PREDICTING THE FUTURE WITH STOCK MARKET LIQUIDITY

A STUDY OF THE SWEDISH STOCK MARKET LIQUIDITY AS A LEADING INDICATOR OF THE FUTURE BUSINESS CYCLE

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Abstract:

Using daily stock data from the Stockholm Stock Exchange, this paper investigates the relationship between stock market liquidity and the real economy. We find restricted support for stock market liquidity containing leading information about real economic growth. Our results further document that stock market liquidity does not add significant explanatory value relative to asset prices and stock market volatility. By studying the recessions caused by the financial crisis in 2008 and the Covid-19 outbreak, we show that our model's performance is affected by the origin of the economic downturn examined. Inconsistent with the flight-to-liquidity phenomenon, we manifest that the liquidity of small firms does not have predictive power over large firms. Our research indicates that the forecasting performance of stock market liquidity varies as a consequence of the region, time period, and liquidity proxy employed.

Keywords:

Stock Market Liquidity, Business Cycle, Forecasting, Recession, Sweden

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1. Introduction

In light of today's high inflation, rising interest rates, and concerns regarding a potential economic slowdown, the ability to predict the business cycle is ever so valuable. Information about future economic growth is of importance to central banks, investors, governments and policy-makers, as well as other forecasters. This paper contributes to the area of research concerning the causal relationship between declines in liquidity of financial securities and the future real economy.

There exists comprehensive research on the forecasting ability of asset prices, such as stock returns, interest rates, term spreads and credit spreads. However, part of the findings in the literature examining the forecasting power of different asset prices have been inconsistent and deviated over time which is confirmed by Stock and Watson (2003). Ng and Wright (2013) further advocate that the predictive power of different indicators varies depending on the cause of the economic decline.

One of the latest global economic events that have threatened economic growth and the world economy is the SARS-CoV-2 pandemic, known as Covid-19 (Organisation for Economic Co-operation and Development, 2020). The pandemic impacted the stock market activity, especially at the beginning of March 2020 when stock markets experienced a sharp fall (Yahoo Finance, 2022).

In this study, we investigate whether stock market liquidity can be used as a leading indicator of real economic growth in Sweden. We further examine if the performance of our predictive model with stock market liquidity differs between two different types of recessions, the financial crisis in 2008 and Covid-19 in 2020. We replicate the methodology used in the article *Stock Market Liquidity and the Business Cycle* by Næs, Skjeltorp and Ødegaard (2011). Consequently, the research questions we aim to answer in this paper are the following:

i. Does stock market liquidity serve as a leading indicator of the future real economy in Sweden and does the informativeness of stock market liquidity vary depending on firm size?

ii. Does the predictive ability of stock market liquidity change during different recessions, namely the recessions caused by the financial crisis in 2008 versus Covid-19?

This study extends on previous literature in several ways. Firstly, we contribute to the research by Næs, Skjeltorp and Ødegaard by examining stock market liquidity including a more recent time period. We thus give an updated stance on the relationship between stock market liquidity and the macroeconomic environment. Secondly, we compare the performance of the model proposed by Næs, Skjeltorp and Ødegaard for recessions with different origins. Hence, we contribute to the literature by Ng and Wright (2013) concerning how forecasting models vary in performance depending on the cause of a recession. Covid-19 constitutes a recession that to our awareness has not been analyzed before in this context. Lastly, the current literature on the subject mainly focuses on the U.S. and the New York Stock Exchange (NYSE). Thus, we add to the literature by investigating whether the relationship between stock market liquidity and the business cycle holds for Sweden, which is a small open economy. The Stockholm Stock Exchange has had the highest return globally in the past 50 years followed by the stock exchanges of Copenhagen, Oslo and Helsinki (Credit Suisse, 2020). Out of the Nordic stock exchanges, Nasdaq Stockholm is by far the largest, contains the broadest range of industries and has a more widespread international presence (Nasdaq (2022), Euronext (2022), Word Trade Organization (2021)). Considering this background, we limit our study to the Swedish stock market.

In this thesis, we define stock market liquidity as the cost of trading equities which is in line with Næs, Skjeltorp and Ødegaard. The level of liquidity in the stock market varies and is prone to diminish in economic declines. In order to measure the fluctuations in liquidity, we employ four liquidity proxies using daily stock data of 691 securities from 1999Q4-2020Q1. The liquidity measures' predictive ability of real economic activity is first evaluated using in-sample predictive ordinary least square (OLS) regressions. We find that some of the liquidity measures on their own contain information about future real GDP growth at the 5% significance level. However, in regressions controlling for term spread, credit spread, excess market return, and volatility, we obtain mixed insignificant results for the liquidity proxies. Hence, our results suggest that stock market liquidity does not contain additional information regarding real economic activity relative to asset prices and stock market volatility. Instead, we find the term spread to have the strongest in-sample predictive ability of real GDP growth.

Later, we perform a rolling one-step ahead out-of-sample test. We calculate the squared forecasting error for each quarter and find support for our model performing better during a crisis stemming from the financial market compared to an exogenous shock like Covid-19. The final part of our methodology consists of regressions examining the effect of firm size on the predictive value of the liquidity measures. Overall, we obtain insignificant coefficients for both small and large firms with no additional predictive value stemming from the liquidity variables. Our results do not validate that small firms are more informative about the future business cycle compared to large firms.

Several potential explanations are discussed that relate to our findings. Among these are the turbulent times during and after the financial crisis combined with the monetary policy that prevailed for a large part of our study. Developments in stock market liquidity due to high-frequency trading and algorithmic trading have impacted our liquidity measures' forecasting power. Our findings highlight that the predictive ability of stock market liquidity is dependent on which time period, country and liquidity measure that is studied.

The outline for the remainder of this paper is organized as follows. In section 2, our liquidity measures are explained and previous literature relating to our study is reviewed. Thereafter, in section 3, our empirical hypotheses are presented. Sections 4 and 5 describe the data and methodology as well as the regression variables that we use in order to test the hypotheses. In section 6, we document our empirical findings and section 7 provides concluding remarks.

2. Theoretical Framework and Literature Review

2.1 Theoretical Framework

Similar to Næs, Skjeltorp and Ødegaard (2011), we use four liquidity measures in order to estimate stock market liquidity. The measures are: the relative spread called *RS*, a transaction cost proxy by Lesmond, Ogden and Trzcinka (1999) named *LOT*, Amihud's (2002) *ILR* measure and *Roll* which is a measure of the effective bid-ask spread invented by Roll (1984). The measurements assess the level of illiquidity in the stock market. Hence, low values indicate high stock market liquidity and vice versa. All of the measures are calculated on a quarterly basis.

The liquidity measure *RS* represents the difference in price that the shareholder is willing to sell at and buyer is willing to pay. According to Næs, Skjeltorp and Ødegaard, the measure is given by the best ask price subtracted by the best bid price divided by the mean of the best ask and bid prices. However, due to limitations in data, we use the closing ask and bid prices which serve as good proxies of the bid and ask quotes and are also used by Lesmond, Ogden and Trzcinka. Consequently, we calculate the bid-ask spread as:

$$\frac{Ask - Bid}{(Ask + Bid)/2} \qquad \text{Eq. 1}$$

Lesmond, Ogden and Trzcinka (1999) propose to measure transaction costs by calculating the frequency of zero daily returns. *LOT* is an approximation of the implicit trading cost needed in order for a share's price not to change as the market fluctuates. A zero return occurs when the price change is lower than the trading costs which the investor not to trade. Thereby, stocks with high transaction costs are prone to fluctuate less often in price and have a higher amount of zero returns compared to stocks with lower trading costs.

Roll is a liquidity measure of the implicit spread, further known as the effective bid-ask spread. The measure uses *Scov*, the first-order serial covariance of successive returns, in order to calculate the effective spread. Since the square root only can be calculated for non-negative values, *Roll* will only be defined when *Scov* < 0. However, Harris (1990) proposes a different way of calculating *Roll* for positive serial covariances of successive returns in order to avoid undefined values. As Næs, Skjeltorp and Ødegaard mention, the reasoning of Harris results in an assumption of a negative implicit spread. Hence, it would implicate a negative transaction cost which is irrelevant when looking at trades in equities. Therefore, we choose to keep the below stated definition of the liquidity measure:

$$\hat{s} = \sqrt{-Scov} \qquad \text{Eq. 2}$$

Amihud (2002) finds that by using the liquidity measure *ILLIQ*, known as *ILR* in Næs, Skjeltorp and Ødegaard, the U.S. NYSE expected stock returns are an increasing function of the expected market illiquidity. *ILR* assesses the elasticity of liquidity which refers to price susceptibility to trading volume. The more responsive prices are to trading volume, the lower the liquidity is. The formula of the measure is as follows:

$$IRL_{t,T} = 1/D_T \sum_{t=1}^{T} \frac{|R_{i,t}|}{VOL_{i,t}} \qquad \text{Eq. 3}$$

Where D_T represents the number of trading days available in quarter *T*. $R_{i,t}$ represents the return, where $|R_{i,t}|$ expresses the absolute return, of stock i on day t. $VOL_{i,t}$ denotes the trading volume in SEK. The quota $VOL_{i,t}/|R_{i,t}|$ produces the absolute percentage price change in SEK of the trading volume on day t.

2.2 Literature Review

2.2.1 The Predictiveness of Asset Prices and Volatility

A strand of literature that relates to our study concerns asset prices' predictive ability of real economic activity. Some of the methods used to forecast economic development with asset prices are derived from observing various areas of the debt market. One of the earliest papers on the subject is by Estrella and A. Hardouvelis (1991). They forecast the state of the real economy by using the term structure of interest rates, which is the relation between short and long-term interest rates. The authors show that the slope of the yield curve can be interpreted to forecast changes in real GDP. Similar results are manifested by Hamilton and Kim (2002).

They decompose the spread's forecasting contribution to an expectations effect as well as a term premium effect and show that both components are statistically significant.

A more recent study that confirms the predictive ability and significance of term spread is Gilchrist and Zakrajšek (2012). However, their results illustrate that the corporate credit spread is better at predicting future economic activity compared to the commonly used default-risk indicators. Moreover, they show that their findings hold for forecast horizons of different lengths. Similarly, Saar and Yagil (2015) confirm that the corporate yield spread can predict the future business cycle. However, they document that government spreads serve as better indicators for longer horizons while corporate spreads are superior for short-term trends.

Choudhry, Papadimitriou and Shabi (2016) investigate the link between stock market volatility and the business cycle in the U.S, UK, Canada and Japan. They find that stock market volatility serves as a short-term predictor of the business cycle. Holmes and Maghrebi (2015) show that an increase in the stock market volatility results in a short-term rise in the unemployment rate.

Another line of research concerns stock returns' usefulness as an indicator of the future economy. This field of study is related to ours since it agrees with the forward-looking concept of the stock market. Estrella and Mishkin (1998) find support for stock returns' ability to predict the business cycle which is confirmed by other more recent studies such as Tsouma (2009). However, Stock and Watson (2003) find limited evidence of returns and other asset prices containing leading information about future economic growth. Considering the ambiguous findings regarding the informativeness of asset prices, our thesis contributes to the literature by examining whether another indicator, stock market liquidity, can provide information concerning the future business cycle.

2.2.2 The Predictiveness of Stock Market Liquidity

We examine stock market liquidity in order to forecast the real economy. There are multiple connections between stock market liquidity and the macroeconomy. Investors' expectations concerning the macroeconomy can, according to the flight-to-liquidity hypothesis by Longstaff (2004), cause portfolio changes where the portfolios of investors gravitate towards liquid securities in uncertain economic times. Investment channels represent another way through which stock market liquidity may affect real economic activity. Levine (1991) suggest that a liquid secondary market can promote investments in long-term ventures.

Changes in stock market liquidity have been relatively less studied as a predictor of macroeconomic moods which could be a result of the stock market's volatility relative to debt yields. However, by taking into account fluctuations in stock market liquidity Erdogan, Bennet and Ozyildrim (2015) elaborate on the concept of the term structure of interest rates as a predictor of economic declines. They disclose that by incorporating the change in stock market liquidity yields higher predictability and precision, suggesting advantages of examining stock market liquidity and not solely the yield curve. In addition, despite mixed results on asset prices' predictability, Meichle, Ranaldo and Zanetti (2011) document superior explanatory power of stock market liquidity over the past 20 years.

Chen, Eaton, and Paye (2018) find support for stock market liquidity being predictive of economic conditions when employing several liquidity measures. They use adjusted liquidity measures and show that the alterations improve stock market liquidity as a forecasting instrument.

Using the previously explained liquidity measures, Næs, Skjeltorp and Ødegaard (2011) find that stock market liquidity provides insight regarding prevailing as well as future conditions of the business cycle. Furthermore, their paper documents that the stocks of small companies are more explanatory of the future business cycle since the trades of these stocks are more affected by fluctuations in the economy. Similarly, Apergis, Artikis and Kyriazis (2015) show that stock market liquidity contains useful information of economic activity in the UK and Germany. Consistent with the flight-to-liquidity theory, they also find support for small firm liquidity having stronger explanatory power than large firms. Our thesis extends on the research by studying the predictive power of stock market liquidity with a more recent time series, including Covid-19. Moreover, we examine whether their model for predicting the business cycle holds for the stock market of a small open economy like Sweden. Even though the paper by Næs, Skjeltorp and Ødegaard focuses on the NYSE, they include data on Norway. By using detailed stock ownership data available on the Oslo Stock Exchange, they are able to study portfolio shifts. However, in the rest of the methodology, which constitutes the part that we replicate, the authors only use a simplified version of the method and a shorter time period for the Norwegian market. In addition, since the Norwegian economy is dominated by primarily three industries, oil, seafood, and shipping, inadequate research on stock market liquidity in a small open economy remains (Word Trade Organization, 2021).

2.2.3 Episodic Forecasting Performance

The unlike features of business cycles influence the performance of predictive models and variables. Evidence surrounding parameter inconsistency and episodic performance of models forecasting GDP growth is among others found by Stock and Watson (2003). Giacomini and Rossi (2010), and Rossi and Sekhposyan (2010) further recognize changes in predictive models' performance and relative forecasting ability. An article by Ng and Wright (2013) analyzes how predicting recessions with roots in the financial market differ from downturns caused by other factors such as supply or monetary policy shocks. Forecasting the business cycle is complicated by key predictors shifting depending on the recession's origin. The authors also point out the absence of forecasting methods that function irrespective of the business cycle's nature. Our study contributes to the aforementioned literature by investigating whether the performance of our model with stock market liquidity varies for two different types of recessions, namely the financial crisis of 2008, which was driven by the financial market, and the recession in 2020, which was caused by the virus Covid-19. This comparison is further unique since, as far as we know, stock market liquidity has never been used to forecast the recession caused by Covid-19.

3. Hypotheses

H1: *We hypothesize that stock market liquidity can be used as a leading indicator of real GDP growth in Sweden.*

Findings of Næs, Skjeltorp and Ødegaard (2011), Chen, Eaton and Paye (2018) and Erdogan, Bennet and Ozyildrim (2015) suggest that stock market liquidity serves as a leading indicator of the real economy when mainly focusing on the U.S. Furthermore, research by Meichle, Ranaldo and Zanetti (2011) finds that stock market liquidity is informative when forecasting the business cycle in Switzerland, another small economy. In addition, Apergis, Artikis and Kyriazis (2015) confirms that the stock market liquidity contains robust information about future business cycle in Germany and the UK, when employing similar predictors to those in Næs, Skjeltorp and Ødegaard. Given the previously documented results, we expect to obtain similar results for Sweden.

H2: *We expect our model including stock market liquidity on average to be less predictive of real GDP growth during the Covid-19 recession compared to the recession caused by the financial crisis of 2008.*

We base this hypothesis on the findings of Ng and Wright (2013), and Stock and Watson (2003), which state that leading indicators are of different importance depending on the type of recession studied. The hypothesis is further supported by Næs, Skjeltorp and Ødegaard (2011), Apergis, Artikis and Kyriazis (2015), and Chen, Eaton and Paye (2018) who show that their models including stock market liquidity are able to forecast recessions stemming from the financial markets. The Covid-19 crisis is an exogenous shock and stems from a virus. Hence, we hypothesize that stock market liquidity on average is less informative of the recession caused by Covid-19 since we do not find support for our model encompassing indicators identifying such a downturn.

H3: *We anticipate the liquidity of small firms to be more informative of future real economic activity compared to the liquidity of large firms.*

This hypothesis is supported by the findings of Næs, Skjeltorp and Ødegaard (2011) who show that the liquidity of smaller companies has greater predictive power concerning the future economic environment. Smaller firms are generally less liquid and thus more affected by economic declines compared to larger companies. Apergis, Artikis and Kyriazis (2015) similarly manifest that the liquidity of small-cap firms entails more relevant information than large-cap firms in the UK and Germany. These findings are further in line with the flight-to-liquidity hypothesis by Longstaff (2004). Moreover, Lesmond, Ogden and Trczinka (1999) show that transaction costs decrease with firm size. As a result, smaller firms exhibit a higher number of days with zero returns and the measure *LOT* is higher. Consequently, small company stocks are more illiquid and less traded in times of economic decline.

4. Data

4.1 Stock Market Data

The primary source we use for collecting stock market data is the Swedish House of Finance. Stock prices, trading volume and market capitalization are collected for the Stockholm Stock Exchange for the period 1999Q4-2020Q1. More specifically, the prices we use are the ask price, meaning the lowest price accepted by a seller at the end of the trading day, the bid price, which is the highest price offered by a buyer at the end of the trading day, and the last price, which is the closing price. The trading volume is measured as the total amount traded in the stock in SEK. The consumer price index is gathered from Statistics Sweden in order to adjust for deflation of the market capitalization data. We limit the study to the Swedish Main Market (Nasdaq Stockholm) and companies with a market capitalization above 100 SEK million. Hence, smaller exchanges such as Nasdaq First North Growth Market and Nordic Growth Market are excluded. In addition, to maintain the quality and comparability of the data, we only analyze common shares. To obtain a sound dataset without any extremely illiquid stocks, we remove quarters with less than 20 trading days and years where a stock's price is less than 5 SEK. These data adjustments are in line with the method by Næs, Skjeltorp, and Ødegaard (2011).

Despite that one of our hypotheses aims to investigate Covid-19, the time horizon of our data does not capture the whole period of the pandemic. However, the period leading up to the outbreak and the first quarter of Covid-19 are seized. This is the most important time duration seeing that we want to determine whether stock market liquidity could function as a leading indicator of the real economy. Hence, even though we produce forecasts for the entire Covid-19 recession, the last quarter of the recession is not included in our dataset.

4.2 Macroeconomic Data

Since Sweden does not have any information equivalent to NBER recessions in the U.S., the state of the business cycle is assessed by using the GDP output gap. The GDP output gap is calculated by taking the difference between the actual output compared to the potential output (International Monetary Fund, 2013). Data on the GDP output gap is obtained from Konjunkturinstitutet.

Seasonally adjusted data for real GDP (*GDPR*), the unemployment rate (*UE*), the real consumption (*CONSR*) and the real gross investment (*INV*) data is downloaded from Statistics Sweden. We use these variables as proxies of the real economy and they make up the macro variables that we employ in our regressions.

By taking the difference between the long-term interest rate and the short-term interest rate we obtain the term spread (*Term)*. The short-term interest rate is based on three-month money market rates. The long-term interest rate refers to 10-year government bonds. The Swedish short and long-term interest rates are collected from the Organisation for Economic Co-operation and Development. The U.S. credit spread serves as a proxy for the Swedish credit spread. This is a reasonable approximation considering that the U.S. credit spread closely resembles the spread in Europe (MSCI, 2021). To obtain the credit spread (*Cred),* we calculate the difference between Moody's Baa Corporate Bond Yield and the 30-year treasury yield. The data on the credit spread is obtained from the Federal Reserve Bank of St. Louis and Yahoo Finance. The term spread (*Term)* and credit spread (*Cred*) represent our non-equity control variables.

The excess market return (er_m) is one of our equity market variables. The variable is calculated as the quarterly return of Nasdaq OMX Stockholm 30 (OMXS30) subtracting the short-term interest rate. Data on the index is downloaded from Nasdaq. The cross-sectional average volatility (*Vola)* constitutes stock market volatility and is the second equity market control variable that we use. The volatility is measured as the standard deviation of daily returns of the sample stocks per quarter.

4.3 Regression Variables

The growth in real GDP is our primary dependent variable. Yet, as in the article by Næs, Skjeltorp and Ødegaard (2011), we also run the regressions for other dependent variables which resemble the macroeconomic environment. The market variables include our liquidity measures and control variables. The control variables are employed in order to reduce the influence of extraneous variables in our study. Thus, the control variables aid the assessment of whether liquidity yields information concerning the future macroeconomic outlook. Due to limitations in data, Næs, Skjeltorp and Ødegaard do not use the *RS* measure throughout their study in the U.S. Since we are able to obtain the required data on the measure, we will include *RS* in our study. In accordance with Næs, Skjeltorp and Ødegaard, we perform an Augmented Dickey-Fuller. Thus, we test the null hypothesis that a unit root is present for a variable in a time series, meaning if the variable is non-stationary. The Augmented Dickey-Fuller test leads us to transform some of the variables to stationary by calculating the change. We calculate Pearson correlation coefficients in order to determine the relationship between the variables.

4.4 Summary Statistics and Correlations

In Table 1 we provide an overview of the liquidity measures. Panel A shows the descriptive statistics of the measures including the number of shares and observations per liquidity proxy as well as the means and medians. The liquidity measures are calculated on a quarterly basis between the whole sample period 1999Q4-2020Q1. Subsequently, in Panel B, the pairwise correlations of the liquidity proxies are exhibited.

Table 1. Summary of Liquidity Measures

Table 1 summarizes the four liquidity proxies based on the period 1999Q4-2020Q1. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. Each liquidity measure is calculated on a quarterly basis. In Panel A, the number of shares, observations, means and medians are exhibited. The number of observations is the number of total quarters observed since each stock is observed for multiple quarters. In Panel B, the pairwise correlation coefficients between the liquidity measures are exhibited. The correlation tests correspond to the two-tailed Pearson product-moment correlation coefficient test. Calculations of the pairwise correlation are undertaken once for each quarter and available sample stock. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Descriptive Statistics - Liquidity Measures

Liquidity Measure	Nr of shares	Nr of obs.	Mean	Median
RS	691	22,699	0.018	0.009
LOT	691	22,745	0.167	0.098
Roll	685	20,964	0.466	0.252
ILR	690	22,491	0.175	0.007

Panel B: Contemporaneous Pairwise Correlation Coefficients – Liquidity Measures

Liquidity Measure	*RS*	*LOT*	*Roll*	*ILR*
RS	1***			
LOT	0.6548***	1***		
Roll	0.1878***	0.0915***	1***	
ILR	0.4528***	0.3289***	0.2854***	1***

As Panel A shows, the number of observations differs between the four liquidity measures. *Roll* has the lowest number of shares and observations, which is reasonable since the *Roll* formula generates missing values for *Scov* > 0. The stated number of companies contains firms that are not present throughout the sample period but become listed or delisted. Panel B manifests that all pairwise correlation coefficients are positive and statistically significant at a 1% level. However, the strength of the correlations varies among the different liquidity measures. The highest correlation coefficient is given by *RS* and *LOT*, indicating that they encompass partly the same information and that the implicit trading cost serves as an arbitrary proxy of the actual bid-ask spread, *RS*. Moreover, the correlation between *LOT* and *Roll* is the weakest. This correlation coefficient indicates that *LOT* and Roll measure different aspects of transaction costs, thus entailing a weak relationship between the two liquidity proxies.

In Figure 1, we show the quarterly plotted liquidity measures between 1999Q4-2020Q1. The figure gives a first indication of how the liquidity proxies have developed during the period of our study. There are several patterns in the measures' curves. We can for example observe spikes during 2008-2009 when the financial crisis prevailed.

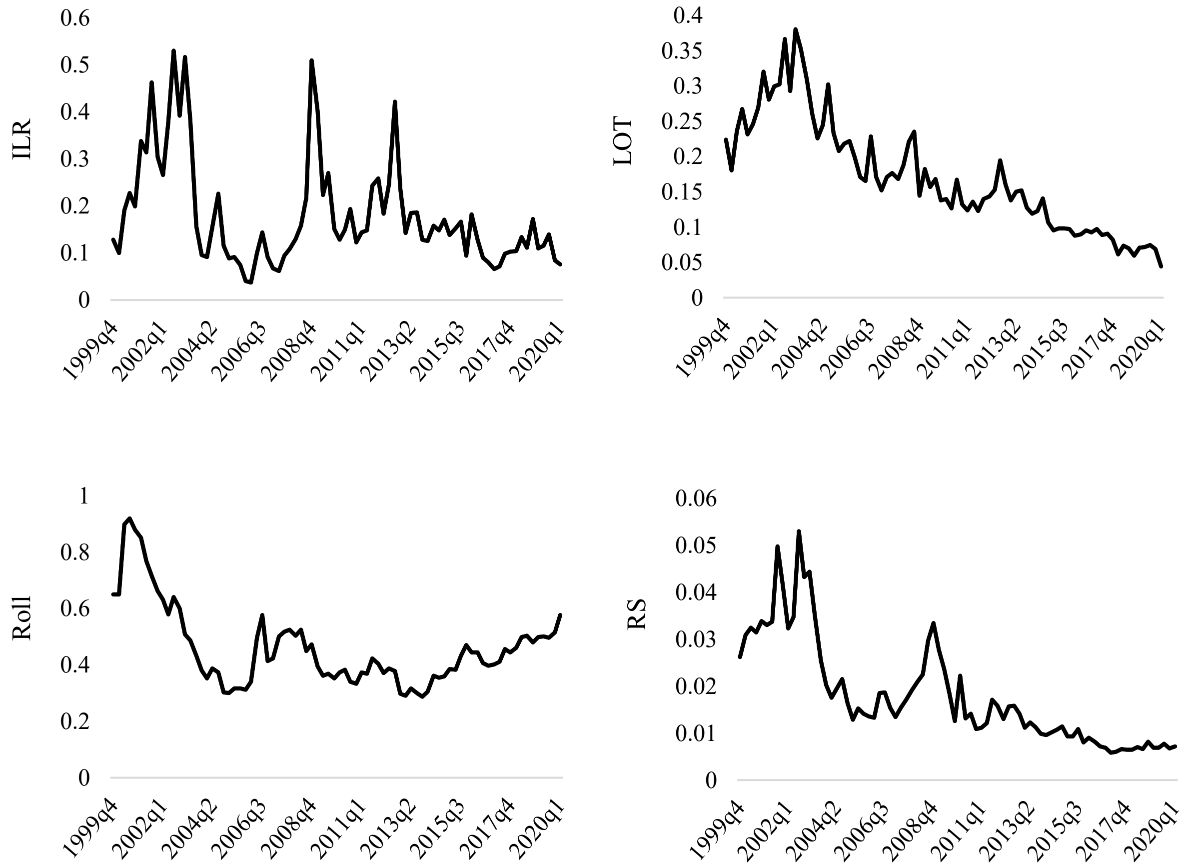

Figure 1. Plotted liquidity measures. The figure shows the equally-weighted liquidity proxies of the available sample stocks on a quarterly basis over the period 1999Q4-2020Q1. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The measures are based on 685-691 securities and 20,964-22,745 observations depending on the measure, more detailed information is found in Table 1.

In Table 2, we present the Pearson correlation coefficients of the macro and market variables as of period t. In Panel A, we see that the correlation coefficients between real GDP growth and the two liquidity measures *dILR* and *Roll* are negative as expected. However, we obtain positive coefficients for the correlations between the other liquidity variables and real GDP growth. The positive sign of the correlation coefficients mean that when illiquidity rises, real GDP increases. Nevertheless, none of the Pearson correlations between the liquidity proxies and growth in real GDP are significant, entailing that they can not be distinguished from zero. There is further some inconsistency in the signs of the correlations between the liquidity measures and the other dependent variables. For instance, the correlations between the growth in the unemployment rate and the liquidity measures are negative which is not in line with our theory. We expect the liquidity measures to rise with increases in the unemployment rate and vice versa. Nevertheless, almost none of the correlations between the liquidity proxies and the dependent variables are significant at a 10% level.

Table 2. Correlations Between Macro and Market Variables

Table 2 contains Pearson correlation coefficients. Panel A includes the correlation coefficients between the macro and market variables observed at time period t, whilst Panel B comprises the correlation coefficients only between the macro variables. The macro variables are the real GDP growth (*dGDPR*), real gross investment growth (*dINV*), unemployment rate growth (*dUE*) and real household consumption growth (*dCONSR*). *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The liquidity measures constitute the equally weighted averages of the sample stocks. The percentage change in *LOT*, *RS* and *ILR* is used. Additional market variables are the term spread (*Term*), the change in credit spread (*dCred*), market volatility (*Vola*) and the excess market return (er_m). The correlation tests correspond to a two-tailed Pearson product-moment correlation coefficient test. The time period studied is 1999Q4-2020Q1, which corresponds 82 quarters. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Market and Macro Variables – Contemporaneous Pearson Correlation Coefficients

	dRS	*dILR*	*dLOT*	*Roll*	*Term*	*dCred*	*Vola*	er_m
Term	-0.183	-0.160	-0.064	-0.199*	1***			
dCred	0.343***	0.462***	-0.104	0.173	-0.397***	1***		
Vola	0.247**	0.338***	-0.028	0.667***	-0.093	0.404***	1***	
er_m	-0.529***	-0.574***	-0.157	-0.471***	0.372***	-0.370***	-0.499***	1***
dGDPR	0.095	-0.046	0.102	-0.042	0.358***	-0.259**	-0.319***	0.105
dINV	0.014	0.089	-0.098	-0.034	0.066	0.033	-0.182	0.034
dCONSR	-0.058	-0.114	0.094	-0.177	0.370***	-0.325***	-0.322***	0.274**
dUE	-0.041	-0.042	-0.035	-0.225**	0.090	0.056	0.205*	0.119

Panel B: Macro Variables – Contemporaneous Pearson Correlation Coefficients

	dGDPR	*dINV*	*dCONSR*	*dUE*
dGDPR	1***			
dINV	0.450***	1***		
dCONSR	0.506***	0.091	1***	
dUE	-0.366***	-0.306***	-0.186*	1***

Among the correlations between the market variables, we find that the term spread is negatively correlated with all liquidity measures, meaning that higher illiquidity correlates with a smaller term spread. If the term spread decreases and becomes negative, the yield curve becomes inverted which is associated with periods of recession. The negative correlation is thus reasonable since decreasing term spreads should coincide with higher stock market illiquidity. Among the correlations between the liquidity measures and term spread, *Roll* is the only statistically significant one. Additionally, in row five, the term spread is significantly and positively correlates with growth in real GDP at the 1% level. The correlation is in line with findings in Estrella and A. Hardouvelis (1991). They show that a positive term spread is related to a future rise in real economic activity. This is further the highest correlation among the market variables and growth in GDP.

The growth in credit spread has a positive correlation with the liquidity measures, except for *dLOT*. Yet coefficients are insignificant for *dLOT* and *Roll*. The logic behind the positive correlation is that credit risk tends to increase during economic downturns causing credit spreads to widen. At 5% significance, *dCred* correlates negatively with the real GDP growth which is consistent with the prior argument and the findings of Gilchrist and Zakrajšek (2012).

In addition, stock market volatility is positively and significantly correlated with *RS* at 5% and 1% with *dILR* and *Roll*. The correlation coefficients indicate that when the stock market volatility is high, stock market liquidity is also high. The negative coefficient between volatility and real growth in GDP is in line with our logic. For the second equity market variable, we notice that the correlation between stock market volatility and the excess market return is negative.

Volatility and excess market return have a negative correlation coefficient at 1% significance level. Thereby, when stock market volatility rises the excess market return decreases. The excess market return correlates negatively with all measures and with the majority of the correlations being significant at 1%. This finding suggests that a lower excess market return is associated with a more illiquid stock market which is in line with the result presented by Hameed, Kang and Vishwanathan (2010). As expected, excess market return correlates positively with growth in real GDP yet not at a significant level.

In panel B, all of the correlations between the macro variables are statistically significant except for *dINV* and *dCONSR*. We attain positive correlations between growth in real GDP, real gross investment and real consumption. Real GDP and real consumption have the highest coefficient. This result is reasonable considering that real household consumption has on average constituted 43%[1] of the real GDP between 1999Q4-2000Q1. This could be compared to the lower correlation coefficient between *dGDPR* and *dINV*, where real gross investments on average have amounted to 23%[2] of real GDP for the same time period. Additionally, the unemployment rate has a negative correlation with all of the other macro variables which is logical considering the nature of the variables, that is, unemployment increases when the economic activity declines.

5. Methodology

5.1 In-Sample Evidence

5.1.1 Predictive Regressions

One part of testing our hypotheses is to evaluate the liquidity measures' forecasting ability in-sample, based on the following predictive OLS regression:

$$y_{t+1} = \alpha + \beta LIQ_t + \gamma' \boldsymbol{X}_t + u_{t+1} \qquad \text{Reg. 1}$$

where y_{t+1} represents the dependent variable where $t+1$ denotes the period one quarter ahead. LIQ_t refers to the stock market liquidity variable computed for quarter t. LIQ is estimated using *dILR*, *dLOT*, *dRoll* or *dRS*. $\boldsymbol{X}_t$ denotes the vector of the control variables *Term*, *dCred*, *Vola*, er_m as well as the lag of the dependent variable. γ' is the vector of the coefficient proxies for the control variables. We run the regression models of all dependent variables for each liquidity measure. The regressions are first computed only with the

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[1] The number has been obtained by taking the real consumption divided by real GDPR for each quarter, then taking the average of all observed quarters.

[2] The number has been obtained by taking the real investment divided by real GDPR for each quarter, then taking the average of all observed quarters.

liquidity variable and the lag of the dependent variable. After that, the term and credit spread control variables are added. Thereafter, we include the volatility and excess market return variables.

As a means to determine the predictive ability of the models, the adjusted R^2, $\bar{R}^2$, is reported for each regression. $\bar{R}^2$ reflects the change in the dependent variable which can be explained by the independent variables. The parameter further takes into account the effect of adding additional control variables to the model. We use the adjusted R^2 to show the liquidity variables' influence on the quality of the forecasting model. Thus, the regressions are executed including and excluding the liquidity variable. In addition, we calculate the variation inflation factor (VIF) for each variable of the regressions to detect multicollinearity.

5.1.2 Granger Causality Test

Although recent findings have supported the hypothesis that it is possible to predict real economy activity by using liquidity proxies, we still undertake the Granger causality Wald test as in Næs, Skjeltorp and Ødegaard (2011) to investigate whether the direction of causality holds for the dataset. Hence, we also determine if the business cycle could impact stock market liquidity. We perform the test using a vector autoregression (VAR) model. Unlike in the Næs, Skjeltorp and Ødegaard article, we conduct the test on the whole dataset simultaneously, excluding subperiods, since our time series is the same length as the mentioned paper's subperiods.

5.1.3 Event Study of Recessions and Stock Market Liquidity

Following the methodology of Næs, Skjeltorp and Ødegaard (2011), we perform an event study to illustrate the fluctuations in liquidity during the emergence of and under recessions. The periods of recession are established by observing the movements in the GDP output gap over our sample period. When GDP growth declines for two successive quarters or more a recession is identified (Ekonomifakta, 2022). However, we limit our event study to recessions with negative growth in the GDP output gap for four successive quarters in order to focus on the more prominent recessions.

A number of calculations are executed for every recession. Firstly, the GDP growth per quarter is calculated for every five quarters before the beginning of a recession, for every five quarters during a recession and for every five quarters after the last quarter of a recession. Secondly, the average GDP growth per quarter before, during and after each recession is computed to obtain the accumulated GDP growth for the event window. This procedure is thereafter repeated for the *ILR* measure, credit spread, term spread, volatility and excess market return. We do not include the other liquidity proxies in the event study which follows the methodology by Næs, Skjeltorp and Ødegaard. Only examining *ILR* is also reasonable considering that we later show that the measure in-sample conforms the most with our theory.

5.2 Assessing the Out-of-Sample Performance

We conduct a pseudo out-of-sample test for all liquidity proxies which is built on Reg. 1 and limited to the main dependent variable, real GDP growth. In line with Næs, Skjeltorp and Ødegaard (2011), we perform rolling one-step ahead regressions and generate quarterly forecasts of real GDP growth using data from a fixed time window of 20 quarters. The quarterly forecasts are constructed by the estimated coefficients retrieved from each rolling regression, and each of the last observed predictor variables of the time window. The first forecast is made for 2004Q4 and is thus based on the estimated coefficients for the window 1999Q4-2004Q3, and the observed predictor variables in 20004Q3. We then re-estimate the model before every new forecast quarter based on the data included in the time window which moves one quarter forward in time with every forecast. We continue with this procedure until the final forecast is made, which is 2020Q1. The liquidity proxies' relative mean squared forecasting errors (MSE) are used to compare and evaluate the liquidity variables' out-of-sample performance. MSE is calculated as follows:

$$MSE = \frac{1}{N} * \sum_{i=1}^{N} (d\widehat{GDPR}_\imath - dGDPR_i)^2 \qquad \text{Eq. 4}$$

Where N is the number of quarters, $d\widehat{GDPR}_\imath$ and $dGDPR_i$respectively represent the forecasted and actual real GDP growth of quarter *i*. In order to test our second hypothesis, we specifically calculate the MSEs of the quarterly forecasts during the recessions in 2008 and 2020 respectively, which allow us to compare the two. Since the recession caused by Covid-19 lasts between 2020Q1-2020Q2, we also conduct a forecast for the second quarter of 2020.

We perform a modified Diebold-Mariano test (MDM) in line with Harvey, Leybourne and Newbold (1998). They suggest comparing the MDM statistic with the Student's t-distribution. Næs, Skjeltorp and Ødegaard motivate the use of MDM since it is believed to have stronger power, in particular for small samples which are fitting for our paper. The aim of performing a DM statistic is to test for the null hypothesis that of equal predictive accuracy that E[$\bar{d}$] = 0 ∀ t, given two competing candidate predictors *k* and *i*. The following equation show how the DM is calculated:

$$DM = \frac{\bar{d}}{\sqrt{(\sigma \frac{2}{d} / P)}} \qquad \text{Eq. 5}$$

Where $\bar{d} = P^{-1} * \sum_t (\varepsilon_{k,t+1}^2 - \varepsilon_{i,t+1}^2)$, *P* is the number of out-of-sample forecast quarters, *h* is the forecast horizon in terms of quarters, $\varepsilon_{k,t+1}^2$ constitutes the squared forecast errors from model 1 containing the candidate predictor *k*, $\varepsilon_{i,t+1}^2$ constitutes the squared forecast errors from the model 2 containing the candidate predictor *i*, and the $\sigma \frac{2}{d}$ constitutes the consistent estimator of the standard deviation of $\sqrt{P\bar{d}}$. The MDM statistic builds on DM and is calculated as:

$$MDM = \left[\frac{P+2h+P^{-1}*h(h-1)}{P}\right]^{1/2} * DM \qquad \text{Eq. 6}$$

Where DM is the original test statistics, *P* is the number out-of-sample forecast quarters, *h* is the forecast horizon in terms of quarters and $(P-1)$ the degrees of freedom from the Student's t-distribution.

Thereafter, we assess the out-of-sample forecasting power of the control variables by using the same one-step ahead rolling procedure. We perform a simplified version of this out-of-sample compared to Næs, Skjeltorp and Ødegaard seeing that we do not calculate the encompassing test (ENC-NEW) nor the F-type test. The reason for this discrepancy is the inaccessible bootstrapped critical values. However, Næs, Skjeltorp and Ødegaard confine this part to the liquidity measure *dILR* since they achieve the most favorable results for that liquidity proxy. As later illustrated, we attain mixed results and thus consider all liquidity measures in these predictions.

Firstly, we compare the MSEs of an unrestricted and restricted model. The unrestricted model contains one of the liquidity proxies and the control variables whilst the restricted model is limited to the control variables. Thereafter, we use an autoregressive model including real GDP growth. The unrestricted model in this case adds one market variable at a time which is then compared to the restricted model only encompassing growth in real GDP.

5.3 The Firm Size Effect on Stock Market Liquidity

The last part of our methodology concerns testing the third hypothesis about the effect of firm size on predictive power of liquidity. The size of a firm is determined by a company's market capitalization on the first trading day of the year. By classifying the size of a firm on the first trading day of the year, unlike on the last trading day like Næs, Skjeltorp and Ødegaard (2011), one less quarter is lost in the calculations. We make this small adjustment seeing that we have relatively little data. The companies are grouped by their market capitalization into four quartiles and the following two variables are created: LIQ_t^{small} and LIQ_t^{large}. The two variables represent the respective groups with 25% of the smallest and largest companies in the dataset. We employ the same control variables used in the previously described regressions except for the lag of the dependent variable which is not included. As a result, we create the following new regression:

$$y_{t+1} = \alpha + \beta_S^{LIQ} LIQ_t^{small} + \beta_L^{LIQ} LIQ_t^{large} + \gamma' \boldsymbol{X}_t + u_{t+1} \qquad \text{Reg. 2}$$

In accordance with Næs, Skjeltorp and Ødegaard we only run the firm size regressions for the main dependent variable, growth in real GDP. However, dissimilar to the mentioned paper, we do not go on to consider differences in turnover between small and large and market participation as an indicator of the business cycle. The reason for this deviation is the limitation in available data.

6. Empirical Results

6.1 In-Sample Results

6.1.1 Predictive Regression Findings

Table 3 consists of four panels with the predictive regressions for each liquidity measure. As illustrated, we achieve mixed results for the different liquidity proxies. We have calculated the VIF for the regression variables, and none of the values are close to, or exceed 10. Hence, we conclude that the deviating result from our regression values are not derived from severe multicollinearity (Pallant, 2013). We begin by discussing the results of *ILR* (Panel A) and the regressions of the main dependent variable, real GDP growth. Thenceforth, the results of the other dependent variables are analyzed before we move on to the next liquidity measure. $\hat{\beta}^{LIQ}$ represents the stock market liquidity coefficient and constitutes one of the liquidity proxies.

Table 3. In-Sample Predictive Regressions

Table 3 presents the output of the predictive regressions for the growth in the dependent variable the coming quarter. The regression model $y_{t+1} = \alpha + \beta LIQ_t + \gamma' \boldsymbol{X}_t + u_{t+1}$ is used where y_{t+1} denotes the dependent variable which constitutes real GDP growth (*dGDPR*), unemployment growth (*dUE*), real household consumption growth (*dCONSR*) or real gross investment growth (*dINV*). The control variables comprise the term spread (*Term*), change in credit spread (*dCred*), market volatility (*Vola*) and the excess market return (er_m). LIQ represents stock market liquidity which is approximated with one of the liquidity measures. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The percentage change in *LOT*, *RS* and *ILR* is used. $\bar{R}^2$ expresses the adjusted R^2. The regressions are based on 1999Q4-2020Q1 and 80 quarters are observed.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: Predictive Regression *ILR*

Dependent variable (y_{t+1})	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{Y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	$\bar{R}^2$	Ex. liq $\bar{R}^2$
dGDPR	0.0042**	-0.0059**	0.2821***					0.1394	0.0741
dUE	0.0011	-0.0004	0.4691***					0.2019	0.2121
dCONSR	0.0063***	-0.0028	-0.1284					0.0113	-0.0034
dINV	0.0086**	-0.0039	-0.1251					-0.0050	0.0042
dGDPR	-0.0020	-0.0044*	0.1329	0.0055***	-0.0001			0.2969	0.2724
dUE	0.0107	-0.0069	0.4795***	-0.0073	0.0245			0.2174	0.2231
dCONSR	0.0008	-0.0036*	-0.2391**	0.0047***	0.0108*			0.1823	0.1569
dINV	-0.0005	0.0054	-0.1320	0.0069	-0.0402*			0.0742	0.0807
dGDPR	0.0030	-0.0032	0.0973	0.0055***	0.0018	-0.2219	0.0040	0.2976	0.2943
dUE	-0.0097	-0.0186	0.4758***	-0.0051	0.0174	0.8044	-0.0007	0.2415	0.2275
dCONSR	0.0032	-0.0010	-0.2745**	0.0041***	0.0110*	-0.0701	0.0002*	0.2110	0.2481
dINV	0.0342**	0.0078	-0.1969*	0.0086*	-0.0225	-1.6321**	-0.0002	0.1291	0.1323

Panel B: Predictive Regression *LOT*

Dependent variable (y_{t+1})	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{Y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	$\bar{R}^2$	Ex. liq $\bar{R}^2$
dGDPR	0.0037**	-0.0101	0.3081**					0.0921	0.0741
dUE	0.0010	-0.0180	0.4689***					0.2072	0.2121
dCONSR	0.0059***	-0.0066	-0.1029					0.0035	-0.0034
dINV	0.0084**	0.0109	-0.1221					-0.0050	0.0042
dGDPR	-0.0020	-0.0070	0.1322	0.0052***	-0.0066			0.2771	0.2724
dUE	0.0113	-0.0217	0.4849***	-0.0081	0.0130			0.2205	0.2231
dCONSR	0.0008	-0.0038	-0.2330*	0.0045***	0.0057			0.1524	0.1569
dINV	-0.0008	0.0133	-0.1184	0.0073*	-0.0318			0.0742	0.0807
dGDPR	0.0032	-0.0053	0.1020	0.0051***	-0.0021	-0.2199	0.0001	0.2927	0.2943
dUE	-0.0438**	-0.0325	0.3746***	-0.0084	-0.0020	2.5101**	0.0009*	0.2759	0.2686
dCONSR	0.0033	-0.0010	-0.2753**	0.0040***	0.0099*	-0.0695	0.0002**	0.2094	0.2196
dINV	0.0331**	0.0106	-0.1815	0.0094**	-0.0137	-1.6137**	-0.0003	0.1240	0.1323

Panel C: Predictive Regression *Roll*

Dependent variable (y_{t+1})	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{Y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	$\bar{R}^2$	Ex. liq $\bar{R}^2$
dGDPR	0.0078**	-0.0089	0.2935**					0.0821	0.0741
dUE	0.0015	-0.0011	0.4683***					0.2018	0.2121
dCONSR	0.0112***	-0.0111*	-0.1394					0.0314	-0.0034
dINV	0.0169	-0.0185	-0.1325					0.0008	0.0042
dGDPR	-0.0012	-0.0021	0.1221	0.0054***	-0.0058			0.2638	0.2724
dUE	0.0165	-0.0123	0.4733***	-0.0078	0.0164			0.2147	0.2231
dCONSR	0.0048	-0.0081	-0.2492**	0.0044***	0.0066			0.1710	0.1569
dINV	0.0024	-0.0053	-0.1279	0.0068	-0.0327			0.0692	0.0807
dGDPR	0.0020	0.0136	0.0413	0.0060***	0.0012	-0.4757*	0.0001	0.3068	0.2943
dUE	-0.0040	-0.1011**	0.3426**	-0.0100*	-0.0196	2.8425**	-0.0004	0.2756	0.2275
dCONSR	0.0035	-0.0016	-0.2736**	0.0040**	0.0097*	-0.0406	0.0002**	0.2095	0.2196
dINV	0.0286*	0.0490*	-0.2188**	0.0111**	-0.0047	-2.4996**	-0.0003	0.1548	0.1323

Panel D: Predictive Regression *RS*

Dependent variable (y_{t+1})	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{Y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	$\bar{R}^2$	Ex. liq $\bar{R}^2$
dGDPR	0.0036**	-0.0086*	0.3166**					0.0977	0.0741
dUE	0.0010	0.0017	0.4696***					0.2019	0.2121
dCONSR	0.0060***	-0.0089**	-0.1166					0.0430	-0.0034
dINV	0.0084**	0.0065	-0.1311					-0.0065	0.0042
dGDPR	-0.0022	-0.0028	0.1339	0.0054***	-0.0048			0.2660	0.2724
dUE	0.0106	-0.0085	0.4814***	-0.0075	0.0187			0.2145	0.2231
dCONSR	0.0008	-0.0087**	-0.2191*	0.0045***	0.0097*			0.1971	0.1569
dINV	-0.0007	0.0232	-0.1276	0.0073*	-0.0424**			0.0944	0.0807
dGDPR	0.0031	0.0014	0.0895	0.0053***	-0.0017	-0.2151	0.0001	0.2853	0.2943
dUE	-0.0087	-0.0239	0.4759***	-0.0062	0.0057	0.7730	-0.0005	0.2278	0.2275
dCONSR	0.0033	-0.0046	-0.2631**	0.0041***	0.0113**	-0.0788	0.0002	0.2202	0.2196
dINV	0.0329**	0.0269	-0.1881*	0.0086*	-0.0226	-1.5551**	-0.0001	0.1482	0.1323

In the first regression of real GDP growth using *ILR*, the liquidity coefficient is negative and statistically significant at the 5% level. The sign of the coefficient is in line with our expectations since we hypothesize that increases in stock market illiquidity should signal a decrease in the growth of the real economy. When including the liquidity variable in the regression, $\bar{R}^2$ almost doubles from 0.0741 to 0.1394. Even though $\bar{R}^2$ is low, *dILR* appears to have a small predictive value when forecasting real GDP growth.

As we add the term and credit spread control variables to the model, $\bar{R}^2$ continues to increase and is higher when *dILR* is included. However, when all control variables are included the *dILR* coefficient loses its significance and the model's predictive value is almost equal to the $\bar{R}^2$ of the model that does not account for the liquidity component. Hence, the unique contribution of the liquidity measure relative to the control variables is small. Instead, *dILR* appears to covary with the control variables. We find that it is mainly the excess market return variable that causes the changes in our regression outcome. This can be explained by the earlier presented descriptive statistics which show that excess market return and *dILR* constitutes the second highest correlation.

For the other dependent variables, we see that *dILR* has the expected coefficient sign in the real consumption growth model. The sign is negative and thus implying that higher illiquidity is linked to lower growth in consumption. However, we do not achieve the expected liquidity coefficient signs in the *dUE* model nor in all of the regressions within the *dINV* model. Instead, the coefficients indicate that higher illiquidity is associated with predictions of lower growth in unemployment and sometimes increased investment growth which is against our theory. Nonetheless, $\hat{\beta}^{LIQ}$ is not significant for any of these regressions. In addition, the *dINV* model has the lowest $\bar{R}^2$ meaning that the model possesses the lowest predictive ability.

In Panel B, we present the regression models for *LOT*. As shown in the first GDP growth regression, *dLOT* enters with a negative yet insignificant coefficient. Hence, the forecasting quality of the liquidity measure in our in-sample data is low. Instead, we find the control variables to be more informative of future economic growth. When we include all of the control variables, adding *dLOT* in the *dGDPR* model does not improve $\bar{R}^2$ relative to the model excluding the liquidity measure. Regarding the other dependent variables, we notice that all of the liquidity coefficients are negative except in the growth in real investments model. Nevertheless, neither of the liquidity coefficients for any of the regressions are significant. The only regression model that improves $\bar{R}^2$ when the liquidity proxy and all of the control variables are included is the growth in the unemployment model.

In Panel C, we recognize that the initial liquidity coefficient of *Roll* in the GDP growth model negative but insignificant. By adding the liquidity variable to the regression $\bar{R}^2$ improves marginally. As we include the control variables, the liquidity coefficient remains insignificant, yet the sign of the coefficient changes and becomes positive. The positive coefficient of the liquidity measure contradicts our theory of high illiquidity corresponding to declines in GDP growth. However, $\bar{R}^2$ remains higher when including the liquidity proxy in the model. As in the models for *dILR* and *dLOT*, the liquidity coefficient surprisingly correlates negatively against the unemployment rate regardless of which control variables are included.

In the real gross investment model including all of the control variables, the *Roll* liquidity coefficient becomes positive and significant at the 10% level. The coefficient on liquidity in the *dUE* model is negative and significant at the 5% level when all variables are included. The liquidity proxy in these two regressions further improve $\bar{R}^2$ compared to the regressions without the liquidity measure. Consequently, two of the models with all the control variables incorporated have significant *Roll* coefficients, yet with the opposite sign than expected.

Finally, in Panel D, we present the predictive regression model of the relative spread. By examining growth in real GDP, we find that the liquidity coefficient is negative and significant at 10% in the first regression. The inclusion of stock market liquidity, in addition, yields a higher $\bar{R}^2$. As we add the term and credit spread variables, the significance ceases to exist. Furthermore, $\bar{R}^2$ decreases when the liquidity measure is incorporated into the regression. These conditions persist when all of the market variables are covered by the model with the only difference being the sign of the liquidity coefficient becoming positive. Seeing that $\bar{R}^2$ including liquidity is lower compared to when excluded, *dRS* does not enhance the forecasting value of the model. Conclusively, the liquidity proxy does not support our hypothesis. In addition, considering that the coefficient is insignificant, the positive sign of *dRS* is less problematic in this case compared to in the *Roll* regressions.

The *dRS* liquidity coefficient is positive for all three regression models with *dINV* as the dependent variable, and shifts from positive to negative in the regression models with *dUE* as the dependent variable. Although the finding contradicts our predictions, none of the liquidity coefficients are significant in the *dUE* and *dINV* models. The *dRS* coefficient in the real consumption model is negative and initially significant. For the real consumption and investment models, $\bar{R}^2$ is higher when stock market liquidity and all of the control variables are included.

We recognize that the term spread is significant at the 1% level in the *dGDPR* model including all variables, regardless of liquidity proxy. The majority of the other control variables do not yield significant results in the *dGDPR* model and if they do it is at the 10% level. This finding aligns with the pairwise correlation in Table 2, where term spread had the highest and one of the most significant correlations with *dGDPR*. In addition, we find that term spread is the variable that contributes the most to $\bar{R}^2$. As a result, the term spread is more explanatory of future GDP growth than the liquidity measures. The second non-equity control variable, the credit spread, is significant to a lower extent. In general, *dCred* is significant in the model of growth in real consumption. Adding the credit spread improves $\bar{R}^2$ but not to the same extent as *Term* does.

Stock market volatility has a negative coefficient in the real GDP growth models for all of the liquidity measures. This result is consistent with the findings by Choudhry, Papadimitriou and Shabi (2016). The volatility coefficient is also negative in the *dCONSR* and *dINV* models. However, the variable is positively correlated with growth in the unemployment rate, which is in line with Holmes and Maghrebi (2015). The second equity variable, excess market return, usually has a negative coefficient in the unemployment model and positive signs in the GDP and consumption model. The variable thus aligns with our theory except from in the *dINV* model in which it has a negative coefficient. However, excess market return is less frequently significant compared to volatility.

6.1.2 Predictive Regressions Discussion

We find limited support for our first hypothesis, that stock market liquidity functions as a leading indicator of real GDP growth. The liquidity measures *ILR* and *RS* contain significant information about future GDP growth when disregarding other forecasting parameters. However, when all control variables are included, we find that the liquidity measures do not provide significant additional predictive power. The results we obtain are thus not in line with our expectations based on previous research by Næs, Skjeltorp and Ødegaard (2011), and Apergis, Artikis and Kyriazis (2015), Chen, Eaton and Paye (2018) etc.

Among the control variables, we notice that the term spread significantly contributes to the informativeness of our GDP growth model. In Appendix Table 13, we show that the term spread has the highest predictive power relative to the other control variables as well as liquidity measures. This finding is in line with previous research that agrees with the term spread being a useful leading indicator of economic activity Estrella and A. Hardouvelis (1991) and Hamilton and Kim (2002).

In addition, we achieve higher $\bar{R}^2$ values in the real GDP growth models when all of the control variables are included compared to Næs, Skjeltorp and Ødegaard. Since $\bar{R}^2$ represents predictive ability, these findings suggest that the GDP growth model applied to Sweden explains a larger fraction of the variance in real GDP growth. Hence, even though $\bar{R}^2$ is still low, we achieve higher predictability than we expected.

We believe that our results differ from the existing literature partly because of the time period that we study. Næs, Skjeltorp and Ødegaard conducted their research using data between 1947-2008. Hence, the majority of, and the time after, the financial crisis are excluded. Considering the impact of the financial crisis, its disturbance on the economy and financial system may have impacted our model (Chen, Mrkaic and Nabar, 2019). Apart from the immediate effect the financial crisis of 2008 had on the stock market activity and liquidity, it was also accompanied by monetary and fiscal policy reforms which prolonged for years after the crisis. The historically low-interest rate environment is one example of how the economic landscape has differed compared to before the financial crisis of 2008 (Riksbanken, 2022). Chordia, Roll and Subrahmanyam (2001), and Fernández-Amador, Gächter, Larch and Peter (2013), find that lower interest rates cause investors to increase their investments in equity and move out of debt securities. As a result, the liquidity in the stock market increases which suggests that the Swedish stock market has been more liquid. The increased liquidity in turn affects our model. As illustrated in Figure 1, all liquidity measures have decreased during our sample period, except for *Roll* which has remained at a stable level. Hence, higher stock market liquidity can be part of the reason why the model underforms and the liquidity measures are less informative in our study compared to Naes, Skjeltorp and Ødegaard.

Several international organizations experienced projection difficulties and profound forecasting errors during and after the financial crisis of 2008. Besides, the forecasting inaccuracy during the period was higher for open economies more dependent on international trade (OECD, 2015). Since Sweden is a small open economy reliant on exports, the country has greater exposure to international shocks which can help explain the lower performance of our model. Another turbulent episode that is not part of the study by Næs, Skjeltorp and Ødegaard is the European sovereign debt crisis. The European debt crisis caused an economic slowdown in 2011 which impacted the stock exchanges around the world (SCB, 2022). The effect on economic activity and investments further constitute disturbances that may impact our liquidity measures and be partly responsible for the deviation in our results.

We find support for this reasoning when running the *dGDPR* regression models for the period 1999Q4-2007Q4 as illustrated in Appendix Table 9. For this time period, *Roll* has a negative coefficient throughout the regressions. Hence, the *Roll* model improves and better aligns with our theory compared to the regressions in Table 3. Liquidity still improves $\bar{R}^2$, yet the $\bar{R}^2$ levels for *Roll* are lower compared to the real GDP growth regressions for the whole sample period. However, they are more similar to the levels manifested by Næs, Skjeltorp and Ødegaard. In the appendix we can also see that the *LOT* model with all control variables has a higher $\bar{R}^2$ when liquidity is included, indicating *LOT*'s improved performance. Neither the *Roll* nor *dLOT* coefficients are significant when all of the control variables are added to the regressions. The insignificance, in this case, could be partly explained by the limited amount of data used to calculate the regressions since the period before the financial crisis leaves less than half of our dataset. The regressions before 2008 do not improve our results of *ILR* and *RS*.

Since Næs, Skjeltorp and Ødegaard use data starting from 1947, other factors than the mentioned crises have also impacted our study. For instance, algorithmic trading, which is the use of algorithms to perform computerized trading, has resulted in more liquid stock markets (Hendershott, Jones and Menkveld, 2011). Specifically, algorithmic trading and high frequency trading has proven to cause a decrease in simple liquidity measures such as the bid-ask spread (Hendershott, Jones and Menkveld, (2011), Riordan, Storkenmaier (2012), Brogaard, Hendershott and Riordan (2014)). The increased liquidity is again confirmed by the decline in our liquidity measures illustrated in Figure 1.

In addition, technological advancements have led to exchanges being able to handle larger trading volumes more easily answering the heightened trading demand. Chordia, Roll and Subrahmanyam (2011) declare that there has been an immense rise in share turnover in the last years, which is related to more frequent and smaller trades. The authors further disclose that the increased trading may stem from reduced trading costs.

Hence, the developments in trading activity may cause the liquidity proxies to lose informativeness and contribute to explaining the weak performance of *LOT* and *RS*. The increased trading activity combined with a decrease in the number of days with zero returns could lead to a less predictive and more noisy *LOT* according to Næs, Skjeltorp and Ødegaard. In Appendix Figure 4 we show how the number of days with zero return has decreased sharply during the sample period, which supports the argument of *LOT*'s impaired explanatory value.

Subsequently, our results indicate that the performance of the liquidity proxies differ depending on the time period examined. This finding is thus consistent with the existing literature by Stock and Watson (2003), Giacomini and Rossi (2010), and Rossi and Sekhposyan (2010), and Ng and Wright (2013).

We further find support for the measures being impacted by the region examined. Galariotis and Giouvris (2015), who use the same methodology as us applied to multiple countries, conclude that the informativeness of stock market liquidity is country-specific. Additionally, they find that the results depend on the choice of liquidity measure which agrees with our findings. Since Næs, Skjeltorp and Ødegaard makes simplifications when examining Norway, it is ambiguous whether the regression model holds for all of the liquidity measures.

6.1.3 Granger Causality Test

Table 4 shows the Granger causality test which examines the direction between the main dependent variable and each of the liquidity measures using one lag. The first shows that we can reject the null hypothesis that *dILR* does not Granger cause *dGDPR* at a 1% significance level. The null hypothesis of the opposite direction cannot be rejected. The result is consistent with the previous predictive regressions for *ILR* as well as our hypothesis that it is possible to forecast real GDP growth with stock market liquidity.

The second row, which displays *LOT*, suggests that the causality between *dGDPR* and *dLOT* is not significant in any direction. We find this result reasonable considering our previous regression results of the measure. Næs, Skjeltorp and Ødegaard (2011) also obtained poor results for *LOT* in the Granger causality test. They propose that the increase in trading activity, which we earlier referred to, can explain why *LOT* does not perform well as a leading indicator. In Appendix Table 11 we notice that before the financial crisis 2008, we are able to reject the null hypothesis that *dLOT* does not Granger cause *dGDPR* at a 5% significance level, while the opposite direction cannot be rejected. Thus, these findings are in line with our hypothesis that stock market liquidity can forecast real GDP growth and the result obtained for the regression model for *LOT* pre-crisis.

In row three, the causality between *dGDPR* and *Roll* is presented. In this case, the null hypothesis that the growth in real GDP does not Granger cause the growth in *Roll* is rejected at the 1% significance level. The reverse causality is not significant and can not be rejected. Hence, the causality results for *Roll* contradict our hypothesis. Nevertheless, this result is not surprising considering the earlier outcome from the predictive regressions of the liquidity proxy. However, before the financial crisis in 2008, we can reject that growth in real GDP does not Granger cause the growth in *Roll* at the 10% significance level. The causality in the opposite direction can be rejected at the 5% significance level, which is consistent with the regression model for *Roll* pre-crisis Appendix Table 9 and aligns with our hypothesis.

The last Granger causality is of *RS* and growth in real GDP. The first null hypothesis, that *dRS* does not Granger cause *dGDPR*, can be rejected at a 10% significance level. While the second null hypothesis is neither significant nor rejected. In short, the Granger causality test in Table 4 supports our hypothesis that stock market liquidity is predictive of GDP growth for two of our liquidity proxies.

Table 4. The Causal Relationship Between Real GDP and Liquidity

In Table 4, the Granger causality Wald tests are presented. Each panel shows the causality between real GDP growth (*dGDPR*) and one of the liquidity proxies. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The percentage change in *LOT*, *RS* and *ILR* is used. The middle column shows the χ^2 for the null hypothesis that stock market liquidity does not Granger cause real GDP growth. The last column shows the χ^2 for the null hypothesis that real GDP growth does not Granger cause stock market liquidity. The tests are conducted for the period 1999Q4-2020Q1 which includes five recessions and 80 quarters and one lag length is applied. *** p<0.01, ** p<0.05, * p<0.1

Liquidity measure	*H0: LIQ* $\nRightarrow$ *dGDPR*	*H0: dGDPR* $\nRightarrow$ *LIQ*
	χ^2	χ^2
dILR	7.196***	1.097
dLOT	2.648	0.564
Roll	1.745	7.126***
dRS	3.162*	0.293

6.1.4 Event Study of Recessions and Stock Market Liquidity

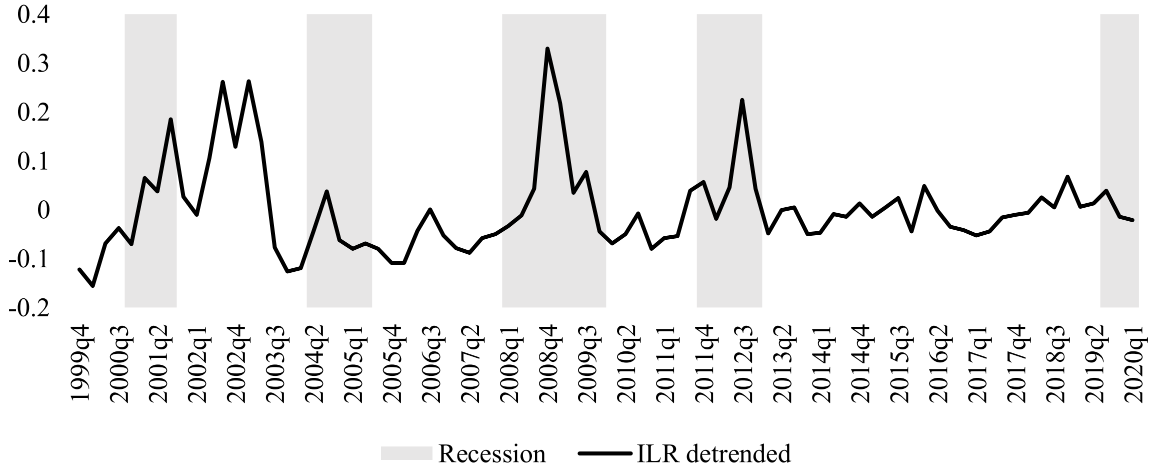


Figure 2. Visualization of stock market liquidity over the Swedish business cycle. The figure illustrates the development in the detrended liquidity measure *ILR* during 1999Q4-2020Q1. *ILR* assesses the effect of trading volume on price. The Hodrick-Prescott filter is employed to detrend *ILR*. The shaded areas signify the five recessions during the time horizon.

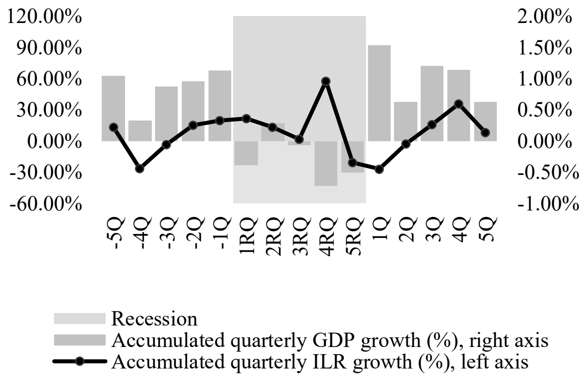
The event study illustrates the predictiveness of *ILR* and is based on five recessions observed in our dataset. Figure 2 demonstrates movements in *dILR*, which is detrended using the Hodrick-Prescott filter, during the period 1999Q4-2020Q1. The figure provides a graphical interpretation of the liquidity measure's predictive power and the shaded bars represent periods of the recessions.

Figure 3 shows the accumulated average real GDP and *ILR* growth during and around periods of recession which again are marked by the shaded area. In Panel A, which only consists of the *dGDPR* and *dILR* parameters, we notice how the growth in *dILR* starts to increase from the fourth quarter before the first recession quarter. Nevertheless, at this stage in the event study, the real economy continues to grow. Thenceforth, *dILR* keeps increasing every quarter until the recession period is realized. The growth of the liquidity measure is on average the highest during the worst recession quarter. At the end of the recession period, stock market liquidity improves and *dILR* decreases which is also consistent with our economic theory. Accordingly, the graph conveys the liquidity proxy's predictive power of economic growth which we earlier manifested in the regression results.

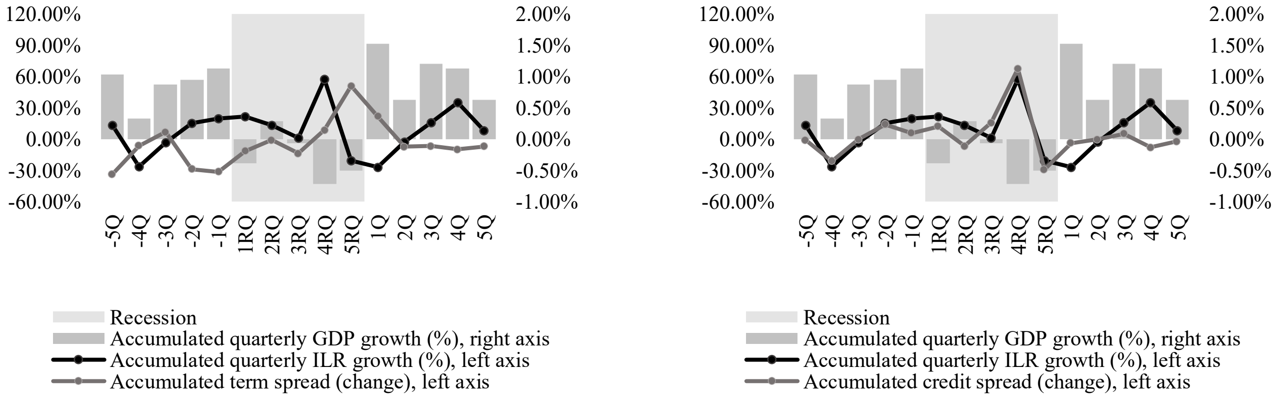
Panel B and C depict the mentioned *dGDPR* and *dILR* relationship as well as the growth per quarter of the control variables, distinguished by the lighter colored lines. In Panel B, the term spread development is illustrated. The term spread starts to decrease from the third quarter before the recession period. The spread then increases from the first quarter before the recession period and later has a sharp increase two quarters before the end of the recession. The credit spread starts to increase from the fourth quarter but then decreases slightly from the second quarter before the recession period. Hence, we can observe that the credit spread is less informative than the term spread, despite that it starts to react one quarter earlier. This result is also revealed in the variable's weaker regression outcome.

From Panel C, we detect that change in volatility on average fluctuates during the quarters before the recession period and then decreases after the last quarter before the recessions start. Excess market return also shifts during the time leading up to the recession. Moreover, the variable increases after the last quarter before the recession episode starts. Thus, as pictured, the predictive ability of stock market volatility and excess market return is weak on average.

Panel A: *ILR* Liquidity Development and GDP



Panel B: Term Spread and Credit Spread Development



Panel C: Volatility and Excess Market Return Development

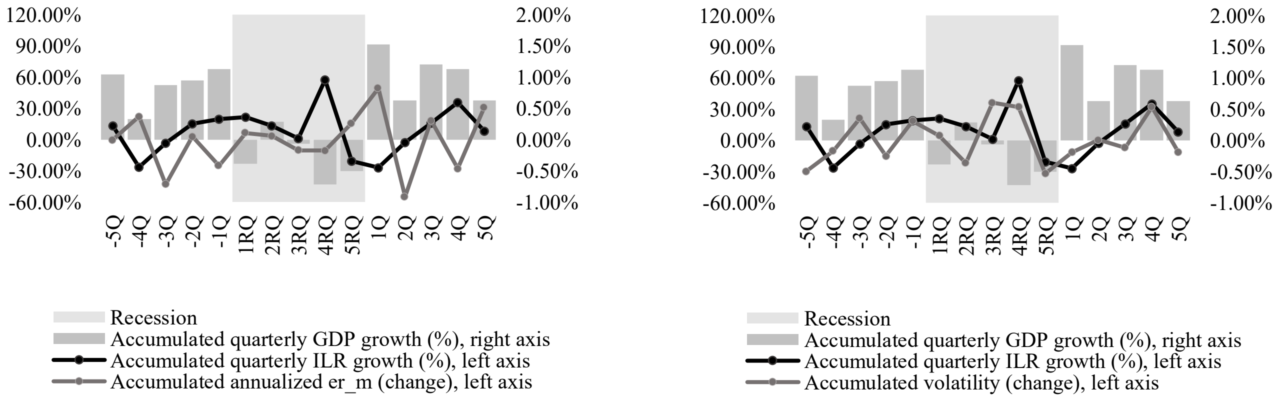


Figure 3. Illustrating growth in the market variables surrounding recessions. Panel A displays the quarterly growth in *ILR*, black line, which measures prices susceptibility to trading volume. The bars represent the average accumulated real GDP growth for every quarter five quarters before, during and after a recession. Panel B and Panel C show the quarterly absolute change in the term spread (*Term*), credit spread (*dCred*), volatility (*Vola*) and excess market return (er_m). The variables are calculated for 1999Q4-2020Q1 which contains five recessions.

6.2 Out-of-Sample Findings

Table 5. Forecasting Ability of Stock Market Liquidity Out-of-Sample

Panel A displays the mean squared forecasting error (MSE) of the liquidity proxies multiplied by 10^3. Panel B shows the relative MSEs between the liquidity measures which are grouped into models. The rolling out-of-sample forecasts real GDP growth per quarter and is based on a rolling estimation window of 20 quarters. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The percentage change in *LOT*, *RS* and *ILR* is used. MSE is calculated for the period 2004Q4-2020Q1, corresponding to 62 quarters.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: MSE of the Liquidity Measures

	dILR	*dLOT*	*Roll*	*dRS*
MSE (x10^3)	0.101	0.097	0.086	0.106

Panel B: Relative Out-of-Sample Forecasting Performance

		Model 2		
Model 1	Statistics	*dILR*	*dLOT*	*Roll*
dLOT	MSE1 / MSE 2	1.037		
	MDM	-0.346		
Roll	MSE1 / MSE 2	1.170	1.129	
	MDM	-1.641*	-1.467	
dRS	MSE 1 / MSE 2	0.952	0.918	0.813
	MDM	0.385	0.619	1.663*

Panel C: Performance of Liquidity Measures Relative Control Variables

Unrestricted Model	Restricted Model	$\frac{MSE_u}{MSE_r}$
dILR, Term, dCred, Vola, er_m	*Term, dCred, Vola,* er_m	1.211
dLOT, Term, dCred, Vola, er_m	*Term, dCred, Vola,* er_m	1.144
Roll, Term, dCred, Vola, er_m	*Term, dCred, Vola,* er_m	1.090
dRS, Term, dCred, Vola, er_m	*Term, dCred, Vola,* er_m	1.145

Panel D: Performance of Market Variables Relative Real GDP Growth

Unrestricted Model	Restricted Model	$\frac{MSE_u}{MSE_r}$
dILR, dGDPR	*dGDPR*	1.025
dLOT, dGDPR	*dGDPR*	1.030
Roll, dGDPR	*dGDPR*	0.955
dRS, dGDPR	*dGDPR*	1.091
Term, dGDPR	*dGDPR*	0.931
dCred, dGDPR	*dGDPR*	1.072
Vola, dGDPR	*dGDPR*	1.089
er_m, *dGDPR*	*dGDPR*	0.808

In Table 5, we present the quarterly one-step ahead out-of-sample results. Panel A indicates that the MSE is the lowest for *Roll* followed by *dLOT*, *dILR* and lastly *dRS*. Hence, *Roll* has the best out-of-sample forecasting performance since the measure's predictions of real GDP growth deviate the least from the actual real GDP growth. The liquidity measures' relative MSEs are documented in Panel B, which confirms *Roll*'s lower MSE compared to the other proxies.

According to MDM-statistics, we are able to reject two null hypotheses at 10% significance level. The null hypotheses that the MSE of *dILR* significantly differs from the MSE of *Roll*, and the MSE of *Roll* significantly differs from the MSE of *dRS.* The MDM test thus indicates that the model containing *Roll* has better forecast accuracy compared to the models of *dILR* and *dLOT*.

Our out-of-sample findings deviate from those of Næs, Skjeltorp and Ødegaard (2011) who find *dILR* to have the lowest MSE. This discovery is not surprising since the in-sample results of the predictor variables also differ from the mentioned article. However, our MSEs appear to be closer in size in comparison to Næs, Skjeltorp and Ødegaard. Only the MSE of *Roll* is significantly lower relative to the other measures. As a consequence, the liquidity proxies appear to perform more similarly out-of-sample in our study on the Swedish financial market.

Panel C shows that the restricted model, which constitutes *Term, dCred,* er_m and *Vola*, performs better in terms of forecasting precision compared to all unrestricted models including the respective liquidity proxies. We find this result reasonable given the in-sample regressions in which the liquidity measures did not yield noteworthy improvements in $\bar{R}^2$ when including all of the control variables.

Panel D presents the mixed results we obtain when employing *dGDPR* as the restricted model, and *dGDPR* as well as each market variable in the unrestricted model. Only the unrestricted model containing *Roll*, *Term* and er_m improves the forecasting ability. *Roll* has the highest out-of-sample performance relative to the liquidity proxies and is predictive before 2008 (Appendix Table 9). Hence, it seems like *Roll* might have been affected during the crisis of 2008, since it serves as an arbitrary predictor of real GDP growth pre and post 2008. As shown in Appendix Table 13, *Term* and er_m perform well in-sample with *dGDPR* which is consistent with the two variables performing better than the restricted model out-of-sample.

Table 6. Predictiveness of Real GDP Growth for Different Recessions

The table shows the mean squared forecasting errors (MSE) multiplied by 10^3 during the quarters of recession caused by the financial crisis of 2008 and Covid-19 pandemic. The first mentioned recession prevails between 2008Q1-2009Q3 and the latter between 2020Q1-2020Q2. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The percentage change in *LOT*, *RS* and *ILR* is used. The MSE is presented for the respective liquidity proxies. The rolling out-of-sample forecasts real GDP growth one quarter in advance and is based on a rolling estimation window of 20 quarters.

	Financial crisis (2008Q1-2009Q3)				Covid-19 crisis (2020Q1-2020Q2)			
	dILR	*dLOT*	*Roll*	*dRS*	*dILR*	*dLOT*	*Roll*	*dRS*
MSE (x10^3)	0.386	0.373	0.325	0.384	2.779	2.848	2.706	2.671

Table 6 shows the mean forecasting error of the respective liquidity measures during the recessions caused by the financial crisis 2008 and Covid-19 in 2020. The GDP output gap indicates that the financial crisis began in the first quarter of 2008. Even though the GDP output gap registers that a slow down in the Swedish economy started in 2019, the recession caused by the pandemic began the first quarter of March 2020.

The MSEs during the recession caused by the financial crisis of 2008 are lower for each liquidity measure compared to the MSEs during the recession following the outbreak of Covid-19. Hence, we find that our model with stock market liquidity on average performs better when predicting the recession in 2008 compared to the recession in 2020. These findings support our hypothesis and the research presented by Ng and Wright (2013) suggesting that forecasting models differ in usefulness depending on the origin of the predicted recession.

6.3 The Predictiveness of Firm Size Liquidity

Table 7 shows the firm size regressions for each liquidity measure. All of the firm size regression variables have passed the VIF threshold of 10 (Pallant, 2013). By examining *dILR* closer, we recognize that the adjusted R^2 excluding the liquidity of small firms is marginally higher compared to when large firms are excluded. $\bar{R}^2$ including both small and large firms is lower compared to when small firms are excluded from the model suggesting that the liquidity of small firms decreases the predictive value of the model. We find similar results for *dRS* with large firms being more informative compared to small firms, as well as the exclusion of liquidity yielding the highest $\bar{R}^2$. In the *dLOT* model, we observe that $\bar{R}^2$ without small firms is greater in comparison to the model in which large firms are excluded. Yet the difference is larger in this case. We also notice that $\bar{R}^2$ including liquidity is higher relative to when the liquidity of all firms is excluded. In row three, we show the results of the liquidity proxy *Roll*. The regression excluding the liquidity of large firms yields a higher $\bar{R}^2$ in comparison to when the liquidity of small firms is excluded. In fact, we see that when small firms are excluded from the model, $\bar{R}^2$ is lower compared to the model excluding liquidity completely. Additionally, $\bar{R}^2$ is the highest when the liquidity of large firms is excluded implying that the liquidity of larger firms decreases the model's forecasting value. These findings indicate that the liquidity of small firms is more useful in forecasting real GDP growth. In this regard, the results agree with our hypothesis. Nevertheless, the sign of the small firm liquidity coefficient is positive which contradicts our hypothesis. The coefficient is further significant at the 5% level making it the only significant coefficient out of the small and large liquidity variables.

Table 7. Firm Size Predictive Regressions

In this table, the GDP growth for the coming quarter is derived from the multivariate OLS regression $y_{t+1} = \alpha + \beta_S^{LIQ} LIQ_t^{small} + \beta_L^{LIQ} LIQ_t^{large} + \gamma' \boldsymbol{X}_t + u_{t+1}$. LIQ_t^{small} and LIQ_t^{large} represent the liquidity variables of the 25% smallest and largest firms according to market capitalization on the first trading day of the year. The rows are divided according to the equally weighted averages of the cross-sectional liquidity proxies. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The percentage change in *LOT*, *RS* and *ILR* is used. The control variables comprise the term spread (*Term*), change in credit spread (*dCred*), market volatility (*Vola*) and the excess market return (er_m). $\bar{R}^2$ is the adjusted R^2. The sample period is 1999Q4-2020Q1 in which 80 quarters are observed. *** p<0.01, ** p<0.05, * p<0.1

Liquidity measure	$\hat{\alpha}$	β_S^{LIQ}	β_L^{LIQ}	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	$\bar{R}^2$	Ex. liq $\bar{R}^2$	Ex. liq S $\bar{R}^2$	Ex. liq L $\bar{R}^2$
dILR	0.005	-0.002	-0.001	0.006***	0.001	-0.287	0.000	0.291	0.297	0.296	0.294
dLOT	0.005	-0.003	0.020	0.005***	0.000	-0.382*	0.000	0.292	0.297	0.298	0.288
Roll	0.009*	0.014**	-0.006	0.005***	0.002	-0.652**	0.000	0.334	0.297	0.290	0.337
dRS	0.004	-0.001	0.001	0.006***	-0.002	-0.261	0.000	0.281	0.297	0.290	0.287

The mixed results from the firm size test do not support our hypothesis and are in conflict with the findings of Næs, Skjeltorp and Ødegaard (2011), Longstaff (2004), Apergis, Artikis and Kyriazis (2015). We begin explaining the results by examining the firm size regressions before the financial crisis of 2008. As shown in Appendix Table 10, the regressions excluding the liquidity of large firms improve the model's predictive ability for *ILR* and *Roll* compared to when small firms are excluded. Moreover, before the crisis, *Roll*'s small firm coefficient was negative and significant at the 5% level. Hence, the faults in the *Roll* regression illustrated in Table 7 are corrected and instead the model is coherent with the existing literature. We can further see that the regressions including both small and large firms improve the model's predictive ability for all measures but *ILR* before the crisis. Although *ILR* is one of the better measures when accounting for the whole time period, the measure performs poorly pre-crisis which aligns with earlier regression pre-2008 and its out-of-sample.

The pre-crisis scenario does not fully explain why the results deviate from our hypothesis. Using data on German, Italian and French stock markets between 1999-2009, Fernández-Amador, Gächter, Larch and Peter (2013) propose a nonlinear effect of monetary policy on the liquidity of stocks. Concerning firm size, they find that smaller firms' stock liquidity in general appears to be significantly more impacted by monetary policy compared to larger firms. Their findings are relevant considering the time period that we study. In light of the 2008 financial crisis, expansive monetary policy was exhibited in Sweden (Elmér, Guibourg, Kjellberg and Nessén, 2012). Except for lowering the interest rate, Riksbanken undertook other measures regarding their lending terms to stimulate the economy. Moreover, monetary policy could have played a role for the years before the crisis as well. For instance, a more expansive monetary policy was undertaken at the end of 2002 with Riksbanken lowering the interest rate gradually (Regeringen, 2003). Although Riksbanken started increasing the rate in 2006, the monetary policy still could be regarded as expansive considering the historical interest rates and the fact that Sweden's interest rate environment was very low in comparison with other countries (Riksbanken, 2006). Hence, the asymmetric effects of monetary policy on stock liquidity can help explain our results.

In addition, existing literature by Galariotis and Giouvris (2015) finds that firm size, in general, does not have any superior informative value when applying the model to multiple countries. Consequently, the element of country, liquidity proxy and time period seem to matter for the firm size findings as well.

Table 8. Firm Size Granger Causality Tests

In Table 8 results from the Granger causality Wald tests are presented. The panels show the causality between real GDP growth (*dGDPR*) and the liquidity proxies for the 25 % smallest respectively 25 % large firms. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The percentage change in *LOT*, *RS* and *ILR* is used. The middle column shows the χ^2 for the null hypothesis that stock market liquidity for small respectively large firms does not Granger cause real GDP growth. The last column shows the χ^2 for the null hypothesis that real GDP growth does not Granger cause stock market liquidity for small respectively large firms. The test is conducted for the period 1999Q4-2020Q1 which includes five recessions and 80 observations with one lag length is applied. *** p<0.01, ** p<0.05, * p<0.1

Liquidity measure	*H0: LIQ ⇏ dGDPR*	*H0: dGDPR ⇏ LIQ*
	χ^2	χ^2
$dILR^S$	6.357**	0.781
$dILR^L$	4.131**	0.695
$dLOT^S$	3.087*	2.938*
$dLOT^L$	0.006	1.494
$Roll^S$	0.024	0.588
$Roll^L$	7.265***	2.506
dRS^S	4.573**	0.017
dRS^L	0.861	0.313

Using one lag, we test the null hypothesis that *dGDPR* does not Granger cause the firm size liquidity measure and vice versa. In Table 8, we see that the only measure for which we can reject the null hypothesis that both small and large firms do not Granger cause real GDP growth is for *dILR* at 5 % significance level. Otherwise, we can only reject the null hypothesis that the liquidity variable does not Granger cause real GDP growth for $dLOT^S$, $Roll^L$ and dRS^S. The results are not surprising provided the findings in the firm size regression model. The null hypothesis that *dGDPR* does not Granger cause stock market liquidity can only be rejected for *dLOT* small firms at 10 % significance level.

7. Conclusion

This study contributes to the existing literature by examining if stock market liquidity contains information about future economic activity in Sweden, capturing two of the most severe crises in modern history. Firstly, some of our liquidity proxies in isolation of other indicators contain significant information about real GDP growth. However, we document that stock market liquidity does not add significant explanatory value regarding the future business cycle relative to the asset price and volatility control variables. We discover the term spread specifically to have significant forecasting power of real GDP growth in-sample. Our findings also show that the regression models with stock market liquidity performed better during the recession caused by the financial crisis in 2008 compared to the recession in 2020 caused by the Covid-19 outbreak. In this paper, we observe that the different liquidity proxies vary in relative performance and in predictive ability over time, which supports the findings of existing literature.

Secondly, inconsistent with the flight-to-liquidity argument, we show that the liquidity of small firms does not have superior forecasting power of real economic activity compared to large firms. We discuss a number of possible explanations behind these results. One of which is derived from the time period of our study which can be characterized by expansive monetary policy, which is proved to have an asymmetric effect on liquidity depending on firm size.

There remain areas of study to be explored. As illustrated by our results, the predictive performance of stock market liquidity varies over time and for recessions with different origins. Since previous literature reports similar findings concerning asset price variables, there is a need for an improved understanding of which indicators are informative of the business cycle. Additionally, digitalization enabling high-frequency trading and algorithmic trading as well as the increased competition between exchanges have driven developments in the equity market in recent years. Hence, another line of interesting future research is how technological advancements in the equity market affect the predictive ability of liquidity measures. Progress in these fields of research would be useful to central banks and other forecasters.

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Appendix

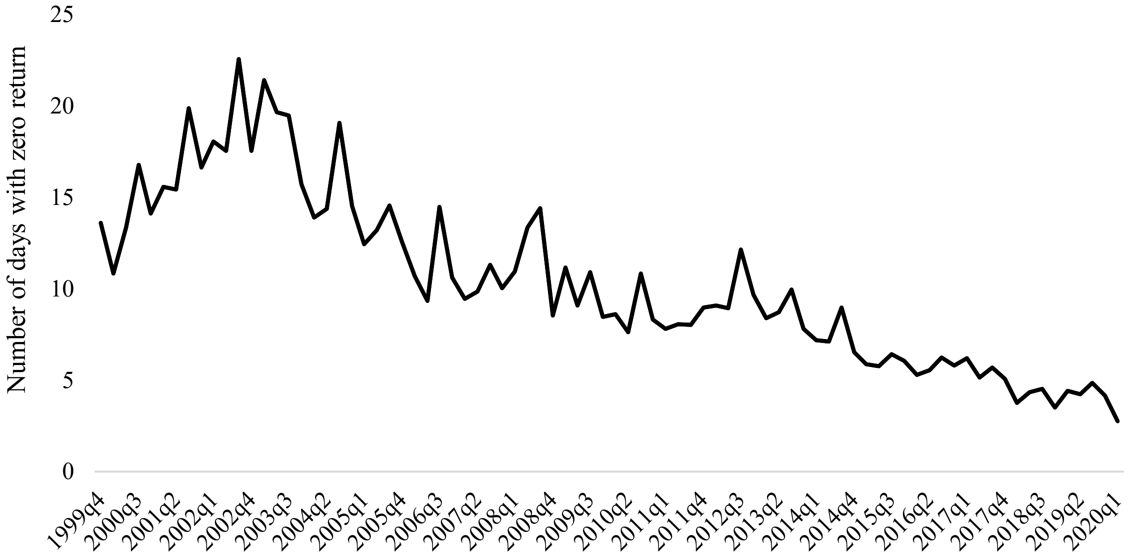

Figure 4. Number of days with zero return. The figures shows the development of zero returns over the time period 1999Q4-2020Q1. Calculated on a quarterly basis based on 82 quarters.

Table 9. Predictive OLS Regressions for Real GDP Growth 1999Q4-2007Q4

Table 9 presents the output of the predictive regressions for the growth in the real GDP the coming quarter. The regression model $y_{t+1} = \alpha + \beta LIQ_t + \gamma' \boldsymbol{X}_t + u_{t+1}$ is used where y_{t+1} denotes the dependent variable which constitutes real GDP growth (*dGDPR*). The control variables comprise the term spread (*Term*), change in credit spread (*dCred*), market volatility (*Vola*) and the excess market return (er_m). LIQ represents stock market liquidity which is approximated with one of the liquidity measures. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The percentage change in *LOT*, *RS* and *ILR* is used. $\bar{R}^2$ expresses the adjusted R^2. The regressions are based on 1999Q4-2007Q4.
*** p<0.01, ** p<0.05, * p<0.1

Liquidity variable	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	$\bar{R}^2$	Ex. liq $\bar{R}^2$
dILR	0.0088***	-0.0016	-0.0935					-0.0381	-0.0160
dILR	0.0031	-0.0021	-0.2080	0.0046*	0.0191			0.0953	0.1057
dILR	0.0064	0.0011	-0.2596	0.0030	0.0177	-0.0228	0.0002	0.1195	0.1504
dLOT	0.0087***	-0.0135*	-0.0761					0.0757	-0.0160
dLOT	0.0038	-0.0156**	-0.2019	0.0040*	0.0240**			0.2361	0.1057
dLOT	0.0066	-0.0126	-0.2077	0.0032	0.0239**	-0.0551	0.0001	0.2083	0.1504
Roll	0.0156***	-0.0116*	-0.1798					0.0666	-0.0160
Roll	0.0111*	-0.0102	-0.2838	0.0031	0.0199*			0.1478	0.1057
Roll	0.0071	-0.0134	-0.2458	0.0023	0.0198*	0.2811	0.0002	0.1624	0.1504
dRS	0.0090***	-0.0001	-0.1340					-0.0523	-0.0160
dRS	0.0033	-0.0036	-0.2567	0.0046*	0.0206			0.0811	0.1057
dRS	0.0066	0.0066	-0.2287	0.0030	0.0124	-0.0293	0.0002*	0.1371	0.1504

Table 10. Firm Size OLS Regressions 1999Q4-2007Q4

In this table, the GDP growth for the coming quarter is derived from the multivariate OLS regression $y_{t+1} = \alpha + \beta_S^{LIQ} LIQ_t^{small} + \beta_L^{LIQ} LIQ_t^{large} + \gamma' \boldsymbol{X}_t + u_{t+1}$. LIQ_t^{small} and LIQ_t^{large} represent the liquidity variables of the 25% smallest and largest firms according to market capitalization on the first trading day of the year. The rows are divided according to the equally weighted averages of the cross-sectional liquidity proxies. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The percentage change in *LOT*, *RS* and *ILR* is used. The control variables comprise the term spread (*Term*), change in credit spread (*dCred*), market volatility (*Vola*) and the excess market return (er_m). $\bar{R}^2$ is the adjusted R^2. The sample period is 1999Q4-2007Q4 . *** p<0.01, ** p<0.05, * p<0.1

Liquidity measure	$\hat{\alpha}$	β_S^{LIQ}	β_L^{LIQ}	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	$\bar{R}^2$	Ex. liq $\bar{R}^2$	Ex. liq S $\bar{R}^2$	Ex. liq L $\bar{R}^2$
dILR	0.005	-0.002	0.001	0.002	0.015	-0.011	0.000	0.091	0.126	0.106	0.108
dLOT	0.007	-0.009	-0.064	0.005*	0.022*	0.168	0.000	0.192	0.126	0.172	0.164
Roll	0.005	-0.027**	0.003	0.001	0.018	0.750**	0.000*	0.242	0.126	0.121	0.270
dRS	0.010	-0.009	0.015**	0.000	0.011	-0.097	0.000*	0.248	0.126	0.228	0.092

Table 11. Granger Causality Test 1999Q4-2007Q4

In Table 11, the Granger causality Wald tests are presented. Each panel shows the causality between real GDP growth (*dGDPR*) and one of the liquidity proxies. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The percentage change in *LOT*, *RS* and *ILR* is used. The middle column shows the χ^2 for the null hypothesis that stock market liquidity does not Granger cause real GDP growth. The last column shows the χ^2 for the null hypothesis that real GDP growth does not Granger cause stock market liquidity. The tests are conducted for the period 1999Q4-2007Q4 which includes five recessions and one lag length is applied. *** p<0.01, ** p<0.05, * p<0.1

Liquidity measure	*H0: LIQ* $\nRightarrow$ *dGDPR*	*H0: dGDPR* $\nRightarrow$ *LIQ*
	χ^2	χ^2
dILR	0.424	0.419
dLOT	4.293**	0.459
Roll	3.948**	3.274*
dRS	0.000	0.343

Table 12. Predictive OLS Regression for Real GDP Growth Excluding Liquidity 1999Q4-2020Q1

Table 12 presents the output of the predictive regressions for the growth in the real GDP the coming quarter. The regression model $y_{t+1} = \alpha + \gamma' \boldsymbol{X}_t + u_{t+1}$ is used where y_{t+1} denotes the dependent variable which constitutes real GDP growth (*dGDPR*). The control variables comprise the term spread (*Term*), change in credit spread (*dCred*), market volatility (*Vola*) and the excess market return (er_m). $\bar{R}^2$ expresses the adjusted R^2. The regressions are based on 1999Q4-2020Q1. *** p<0.01, ** p<0.05, * p<0.1

Liquidity variable	$\hat{\alpha}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	$\bar{R}^2$
dGDPR	0.0030	0.0053***	-0.0013	-0.2160	0.0001	0.2943

Table 13. Predictive OLS Regressions per Control variable for Real GDP Growth 1999Q4-2020Q1

Table 13 presents the output of the predictive regressions for the growth in the real GDP the coming quarter. The regression model $y_{t+1} = \alpha + \gamma' \boldsymbol{X}_t + u_{t+1}$ is used where y_{t+1} denotes the dependent variable which constitutes real GDP growth (*dGDPR*). We regress each of the control variables, which comprise the term spread (*Term*), change in credit spread (*dCred*), market volatility (*Vola*) and the excess market return (er_m), with *dGDPR*. $\bar{R}^2$ expresses the adjusted R^2. The regressions are based on 1999Q4-2020Q1.
*** p<0.01, ** p<0.05, * p<0.1

Market variable	$\hat{\alpha}$	$\hat{\gamma}^{Market\ variable}$	$\hat{\gamma}^{Y}$	$\bar{R}^2$
Term	-0.0029*	0.0059***	0.1323	0.2724
dCred	0.0042***	-0.0140**	0.2406**	0.1196
Vola	0.0113**	-0.3207*	0.2386**	0.0974
er_m	0.0041**	0.0003**	0.2703***	0.1761

Table 14. Predictive OLS Regressions for Real GDP Growth Excluding Term Spread 1999Q4-2020Q1

Table 14 presents the output of the predictive regressions for the growth in the real GDP the coming quarter. The regression model $y_{t+1} = \alpha + \beta LIQ_t + \gamma' \boldsymbol{X}_t + u_{t+1}$ is used where y_{t+1} denotes the dependent variable which constitutes real GDP growth (*dGDPR*). The control variables comprise the change in credit spread (*dCred*), market volatility (*Vola*) and the excess market return (er_m). LIQ represents stock market liquidity which is approximated with one of the liquidity measures. *ILR* estimates the effect of trading volume on price. *LOT* measures the frequency of zero daily returns. *Roll* is given by the square root of the negative first-order serial covariance of successive returns. *RS* is the difference between the closing ask and bid price divided by the average closing ask and bid price. The percentage change in *LOT*, *RS* and *ILR* is used. $\bar{R}^2$ expresses the adjusted R^2. The regressions are based on 1999Q4-2020Q1.
*** p<0.01, ** p<0.05, * p<0.1

Liquidity variable	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{Y}$	$\hat{\gamma}^{dCred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	Ex. Term $\bar{R}^2$
dILR	0.0043	-0.0015	0.2449**	-0.0070	0.0008	0.0002*	0.1641
dLOT	0.0045	-0.0072	0.2454**	-0.0091	-0.0137	0.0002**	0.1764
Roll	0.0042	0.0019	0.2357**	-0.0080	-0.0337	0.0003**	0.1618
dRS	0.0043	0.0016	0.2338**	-0.0087	-0.0006	0.0003**	0.1621