Modeling stock market liquidity using macroeconomic variables: Evidence from Sweden

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Abstract

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This paper contributes both to investigating the relationship between the macroeconomic environment and stock market liquidity and to reviewing existing empirical evidence related to this relationship. We develop and examine panel data regression models for stock market liquidity based on macroeconomic factors. Initially, we evaluate the liquidity measures and their viability in respect of the Swedish stock market. By analyzing existing proxies for stock market liquidity through a Principal Component analysis, we manage to obtain a variable that properly incorporates the main features of liquidity and illiquidity. Secondly, we investigate the potential influence on liquidity risk contributed to selected macroeconomic indicators using a panel data regression using both fixed-effects estimations and ordinary least square estimations.

We conclude that macroeconomic factors are important in explaining stock market liquidity on the Swedish exchange. The model results differ substantially depending on explanatory variables included. The results are aligned with previous research and suggest that changes in a limited number of macroeconomic factors are essential in predicting stock market liquidity in Sweden.

***Keywords*:** Stock Market Liquidity; Macroeconomy; Nasdaq Stockholm; Empirical Finance; Econometrics

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1 Introduction

Liquidity, in a financial markets context, is generally a beneficial trait and the term has received increasingly more attention over the past decade. Researchers have attempted to find distinct, composite measures of liquidity that manage to describe the concepts associated with liquidity in a theoretically correct manner. The increasing willingness to avoid systemic liquidity crises and better assess liquidity risk has resulted in a higher demand for empirical research on stock market liquidity and the associated measures. Currently, there is no consistent way to estimate stock market liquidity for all markets and the inherently multifaceted nature of liquidity complicate the risk modeling necessary to make informed investment decisions and it could also lead to difficulties in risk management for investors. High level of liquidity is a desirable property for markets and individual assets, whereas a high level of illiquidity imposes large amounts of risk on investors as it increases transaction cost and acts as an inhibitor of market efficiency. Liquidity in financial markets provides productive allocation of both risk and capital. It is absolutely essential for the functioning of financial markets. Subsequently, stock market liquidity is an important subject for market participants and the key driving factors of liquidity deserve a deeper understanding.

The paper aims to clarify the link between well-known macroeconomic indicators for the Swedish economy and the stock market liquidity in order to facilitate modeling of risk. Initially, the study provides an assessment of some of the liquidity measures for the Swedish stock market and how the multidimensional risk term could be condensed into a fewer number of components containing as much information as possible in terms of the main characteristics of liquidity measures. This first step enables the analysis of the subject of interest – investigating how different macroeconomic factors influence stock market liquidity – which comprises an analysis of the impact of macroeconomic variables on liquidity on the Swedish stock market.

The consensus view from previous research is that the stock market is directly related to the economic growth of a country. In addition, there is evidence suggesting that monetary transmission mechanism effects imposed by central banks impact the aggregate liquidity of stock markets (Fernández-Amadora, et al., 2013). Moreover, there is a well-established relationship between real economic growth in terms of GDP and the performance of the stock market (Seth & Tripathi, 2014).

There are previous studies examining the link between macroeconomic variables and stock market liquidity based on well-known liquidity measures and macroeconomic variables such as inflation, unemployment rate, interest rates, industrial production indices and volatility of the broader market. These papers generally limit themselves to a single geographical market with different attributes compared to the Nordic markets. There is support for a relationship between stock market liquidity and macroeconomic events. Shocks in liquidity have been observed and linked to macroeconomic events impacting the financial systems. In particular, a study with evidence from the Japanese stock market has observed correlation between stock market liquidity and interest rates and inflation (Choi & Cook, 2005). Choi and Cook took a closer look at the Japanese stock market liquidity during the financial crisis in the early 1990's, also known as the lost decade, following an asset price bubble.

There are similar studies examining the power of macroeconomic activity in determining equity market liquidity. A recent study from Nigeria studied the link between macroeconomic variables and the stock market liquidity on some of the largest African exchanges (Igbinosa & Uhunmwangho, 2019). The selected countries were Nigeria, South Africa, Egypt, Mauritius and Morocco. In the analysis of macroeconomic aggregates and stock market liquidity on these markets, fixed-effects panel regression was used. In the analysis, a number of macroeconomic factors were used to the liquidity outcome represented by the standalone dependent variable, turnover ratio with regards to overall market. The final conclusion of this study was that investors should pay close attention to macroeconomic activities because of their substantial potential in impacting liquidity. The previously mentioned study by the International Monetary Fund (IMF) from Japan was more focused on macroeconomic events and business cycle shocks, and their impact on stock market liquidity. By using a vector autoregressive model, Choi & Cook could conclude that Japanese equity markets were highly illiquid and subject to increasingly volatile liquidity shocks during the deflationary period following the financial crisis in the 1990's.

This paper contributes to the subject as it explores the impact of macroeconomic indicators and the stock market liquidity in Sweden by examining data from the Swedish stock market, namely stocks listed on Nasdaq Stockholm main market, using important variables for the state of the domestic economy. We conclude that the short-term rates and the implied volatility indices have a substantial impact on the stock market liquidity in Sweden. The following section 2 Theoretical background provides of a brief explanation of the liquidity term and some of the most popular liquidity benchmarks. In addition, the connection between the macroeconomy and stock markets in general is addressed. The empirical framework is presented in section 3 Data and 4 Empirical method, and is guided by previous research presented in 2.4 Macroeconomy and stock market liquidity. In section 5 Empirical analysis the result of the study will be presented. Finally, a summarizing conclusion will discuss the main findings and takeaways of the study.

2 Theoretical background

In this section, earlier studies on liquidity will be presented. We will also analyze the studies and liquidity proxies to gain a better understanding of different liquidity measures. Furthermore, we will briefly process the link between macroeconomic variables and stock markets in general.

2.1 What is liquidity?

There is no clear-cut definition of liquidity, instead there are several adequate formulations of the term. The general interpretation of liquidity according to the U.S. Securities and Exchange Commission (SEC) is: “How easily or quickly a security can be bought or sold in a secondary market.” Stock market liquidity is described as: “How easily a stock can be bought or sold without substantially impacting the price of the stock.” (U.S. Securities and Exchange Commission, 2021)

There are five typical characteristics/dimensions of a liquid market: depth, breadth, tightness, immediacy and resiliency. Depth describes a market where there exist potential buyers and sellers on both sides of the current trading price. Breadth refers to a market where orders are large in terms of volume and in terms of amount of orders, this implies that trading has limited impact on the security price. Tightness in the market means low transaction costs. Immediacy describes the speed of which orders can be executed and settled which resonates with the clearing and settlement systems. Lastly, resiliency represents a market where order imbalances are corrected rapidly by a flow of new incoming orders (Sarr & Lybek, 2002).

Table 1: Market depth and breadth illustrated by four markets with varying order sizes at different prices. (Sarr & Lybek, 2002).

Size of existing bids

Market	**(1)**	**(2)**	**(3)**	**(4)**
Bid price (SEK)	Thin & Shallow	Thin but Deep	Broad but Shallow	Broad & Deep
100	200	200	1000	1000
98	400	400	1000	1000
96	0	600	0	1400
94	0	600	0	1800
92	0	600	0	3000

Table 1 illustrates the liquidity dimensions breadth and depth. Market 1 is both thin and shallow and thereby the most illiquid while market 4 is both broad and deep and thereby the most liquid market.

2.2 Selected measures of liquidity

As mentioned in the previous section, the definition of liquidity is multidimensional. This multidimensional definition entails several different measures of liquidity. There are measures for both liquidity and illiquidity, where the latter is the opposite of the first. The different measures act as proxies for different aspects of liquidity and illiquidity. The measures could also be divided into two categories: order-based measures and trade-based measures (Aitken & Comerton-Forde, 2002).

2.2.1 Order-based measures

Bid-ask spread is one of the most common measures of stock liquidity. Previously, it has been the focus of a large amount of research on market microstructure and the bid-ask spread is closely followed by investors (Gregoriou, et al., 2005). The bid-ask spread is the difference between the ask price and the bid price. The larger the spread, the more illiquid the stock. The opposite is also true, a liquid stock with many buyers and sellers will have a smaller spread. The bid-ask spread is an order-based measure and it is an implicit measure of the cost of transacting. Moreover, the bid-ask spread is commonly interpreted as the cost an investor must incur to execute a trade instantly. A portion of the bid-ask interval arises from an information asymmetry among investors in the equity market (Venkatesh & Chiang, 1986).

$$Bid - Ask\ Spread = P_{ask} - P_{bid} \tag{2.1}$$

Relative bid-ask spread is closely related to the bid-ask spread with the only difference that it is a relative measure. It works the same way as the bid-ask spread, the higher the value the more illiquid is the stock. Since the measure is relative it is better suited than the absolute measure for comparing liquidity between different assets with different prices. This is because assets with higher prices tend to have a larger absolute spread than cheaper assets (Pereira da Silva, 2014).

$$Relative\ bid\text{-}ask\ spread = \frac{P_{ask} - P_{bid}}{(P_{ask} + P_{bid})/2} \tag{2.2}$$

2.2.2 Trade-based measures

Turnover ratio (TR) is a measure of liquidity, it describes the relation between the turnover in terms of value and the market value of the asset. A high turnover ratio tells us that the stock is liquid and a low turnover ratio describes an illiquid stock.

$$TR = \frac{Turnover\ by\ value}{Market\ value} \tag{2.3}$$

The turnover ratio captures trading frequency, which in turn plays a significant role in liquidity. Therefore, turnover ratio can be used as a valid proxy for measuring stock liquidity (Easley & Maureen, 1992). Another advantage of the turnover ratio is that the data needed to calculate it is easily accessible. Regarding the dimensions of liquidity, the turnover ratio mainly reflects the breadth in the market but also to some extent depth and resiliency (Sarr & Lybek, 2002).

Zero trading days is another illiquidity proxy. It is calculated as the proportion of days with zero returns during a specific time period. This measure assumes that the market is inactive when there is no return (Lesmond, et al., 1999). A high proportion of zero trading days is a characteristic of an illiquid stock. Among all measures of liquidity zero trading days is one of the few that incorporates days without trading and this is why it is an important measure to consider in order to gain a comprehensive understanding of the different aspects of liquidity. The fact that there is no trading in a stock can reveal important information about illiquidity (Easley, et al., 1996).

$$Zero\ trading\ days\ = \frac{\#\ days\ with\ zero\ return\ (during\ the\ period)}{\#\ trading\ days\ (during\ the\ period)} \qquad 2.4$$

The Hui-Huebel liquidity ratio (henceforth LHH) aims to capture the dimensions of price impact, market breadth and resilience (Sarr & Lybek, 2002). LHH can be calculated over a period of time in order to smooth volatility. A liquid asset exhibits a low LHH, more specifically a low LHH captures the dimension of market breadth and a low LHH implies a larger market breadth. The ratio uses the highest and lowest daily price over a given period in the numerator and the turnover ratio for the same period in the denominator. By using the turnover ratio in the denominator, i.e. the volume traded as a proportion of the total value of the actual asset on the market, this ratio manages to capture the resiliency of an asset. However, there are cases when ratios like this one fails to properly dissect the price impact of illiquidity and trades following actual new information. Some claim that the fact that the relationship between price movements and volumes traded is not proportional, results in this ratio and measures similar to it not being able to accurately estimate price movements based on the number of shares traded (Sarr & Lybek, 2002).

$$LHH = \frac{\frac{(P^{MAX} - P^{MIN})}{P^{MIN}}}{TR} \qquad 2.5$$

The Amihud illiquidity ratio (the Illiquidity ratio) is perhaps the most accepted price impact measure within academia. It was introduced by Amihud (2002) and the illiquidity ratio is the daily absolute return to the daily volume in terms of value traded in the same stock, averaged over the number of trading days in the period. Compared to many other liquidity measures, the Illiquidity ratio is computed using widely available data on return and volume. Furthermore, the ratio captures the sensitivity of a particular stock's price to the trading volume. One reason the Illiquidity ratio measure has gained such a traction is the fact that it manages to transform the movement of the stock price to transaction cost (Acharya & Pedersen, 2005). While some liquidity/illiquidity measures can be rather difficult to grasp, the Illiquidity ratio is fairly straightforward (higher trading volume results in lower illiquidity) which – in combination with the advantages with regards to input data availability – has contributed to its popularity and made it one of the most favored measures of liquidity used in literature (Holden, et al., 2014).

$$Illiquidity\ ratio\ =\ Average\ \left(\frac{|r_t|}{Value\ Turnover\ _t}\right) \qquad 2.6$$

2.3 Macroeconomy and equity markets

The relationship between macroeconomic variables and equity markets is subject to extensive research. In this section we present some previous evidence and studies on the topic for some of the most commonly used macroeconomic variables in financial research.

There is a well-known relationship between the equity market and interest rates. Higher interest rates entail an increase in the opportunity cost of holding money which in turn will lead to a substitution between equities and fixed income securities. Higher interest rates will also affect the cash flows of a stocks underlying business in a restrictive way, thus influencing the stock price in a negative way (Nishat, et al., 2004).

The industrial production index describes the development in output of the industrial sector for a domestic economy. The industrial sector consists of sub-sectors such as manufacturing, mining and electricity. Regarding the relationship between equity markets and industrial production, there is an expected positive correlation between industrial production and the equity market. This is because industrial production index influences the expectations on future cash flows which in turn influences asset prices (Fama, 1990).

Similar to the macroeconomic indicators mentioned above, inflation is a macroeconomic indicator that contains information about the state of the economy and the business cycle. Inflation is an increase in the general price level which implies that the value of money is undermined, i.e. you can buy fewer goods and services for the same amount of money (Sveriges Riksbank, 2018). Central banks aim to maintain price stability, and it is often considered to be the most important task for central banks across the world. European Central Bank describes the mission of maintaining price stability as its primary task (European Central Bank, u.d.). Inflation is negatively correlated with real economic activity, which could be interpreted by using money demand theory and the quantity theory of money (Fama, 1981). Extensive research has been documented on both inflationary regimes by itself and the link between the stock market return and expected and unexpected inflation (Stulz, 1986).

In recent years, central banks have used a relatively new monetary policy tool, quantitative easing (QE), in order to stimulate the economy and maintain price stability. It has been widely undertaken by central banks since the 2008 financial crisis and was initially seen as some kind of last resort to ease financial conditions by purchasing assets during recessions. However, QE is today used on a more regular basis to provide market liquidity and maintain price stability (Fawley & Neely, 2013).

2.4 Macroeconomy and stock market liquidity

There is no well-defined link between stock market liquidity and the macroeconomic environment even though evidence suggests there is a relationship. Previous studies on the topic present different macroeconomic indicators that affect liquidity of the stock market in different manners. A study made on the global financial markets liquidity by PwC (2015) mentions a couple of macroeconomic trends that drive the global market liquidity. These trends involve the increase in the size of equity markets and financial markets overall. The growth of the markets creates a growing demand for market liquidity. The study also suggests that the digitalization of the financial markets drives liquidity in the stock markets through a lower cost of trading. The reduction in the cost of trading is assumed to have occurred since it has become easier to link sellers and buyers to each other. Moreover, stability in the monetary environment worldwide supports liquidity globally throughout the economy, according to the study.

Other studies that are more similar to this one focus on a specific geographical region when investigating the relationship between the macroeconomy and the stock market liquidity. Choi and Chook (2005) presents a study on the Japanese equity market where they find evidence for a relationship between shocks in stock market liquidity and macroeconomic events. By using cross-sectional regression models with measures of firms' exposure to liquidity risk as dependent variables and firm-characteristic variables as independent variables they find that larger firms are less exposed to shocks in liquidity while smaller firms are more exposed to the same phenomenon. Furthermore, they examine the relationship between shocks in liquidity and macroeconomic variables using a vector autoregressive model. Using this approach, they find several interesting relationships. Statistically significant evidence shows that a positive liquidity shock results in a decline in interest rates. Another finding shows that stock market liquidity is affected by shocks in the Japanese stock market index "Topix" and shocks in real economic output reflected in, for instance, industrial manufacturing.

A recent study on the topic with focus on African stock markets by Igbinosa and Uhunmwamgho (2019) suggests that the macroeconomic environment determines stock market liquidity. The macroeconomic variables in the study include money supply, exchange rate, inflation and credit to the private sector. The cross-sectional dataset ranges over a ten-year period using turnover ratio as proxy for stock market liquidity and dependent variable as well. Using fixed-effects panel least squares regression they find that macroeconomic variables are statistically significant when explaining stock market liquidity. The choice of model is based on the fact that the fixed-effects model tolerates unbalanced panel data and unobserved heterogeneity. Their key findings suggest that there is a statistically significant positive relationship between inflation and stock market liquidity, meaning that an increase in general price level results in an increase in stock market liquidity. Moreover, money supply and exchange rates show a negative relationship with stock market liquidity. Finally, they agree with Choi and Cook (2005) that macroeconomic factors and stock market liquidity are associated.

3 Data

In this section we present the data used in the study, how it was retrieved and how it has been processed. In addition, the variables used in the analysis are introduced and presented in more detail.

3.1 Data collection

The data necessary to calculate the liquidity measures used in this study is collected from Thomson Reuters Datastream ("Datastream"). All data from Datastream is retrieved on a daily basis. The sample of the study for the Swedish stock market is from June 2001 to January 2021 and includes 89 different companies listed on Nasdaq Stockholm. The selection process is based on market capitalization per January 31st, 2021.

The idea behind the sampling of companies for the study is to select a great variety of companies from different sectors and of different sizes. Initially, the 30 largest companies listed on OMX Stockholm Large Cap, Mid Cap and Small Cap were selected. Since the study's start date is June 2001, companies that were listed after this date were removed and replaced with the following company in terms of market capitalization on the date of selection and with a listing date before June 2001. This method was applied to all three lists in order to obtain 30 companies of each type with regards to equity value. Due to data availability the sample later was reduced to 89 companies consisting of 28 Large Cap, 31 Mid Cap and 30 Small Cap firms which is found in Table 16 in 8.1 Dataset information.

The data covers security-specific data from Datastream for a large universe of public companies on the Nasdaq Stockholm from 2001 to 2021. In addition to the stock price and trading volume data, macroeconomic data was collected from Datastream. It provided the required data for the order-based measures, i.e. ask and bid quotes on a daily basis. Naturally, all data necessary for determining trade-based measures was also available, such as highest/lowest intraday price and turnover by value.

As previously mentioned, we also managed to obtain most of the macroeconomic data from Datastream. The only data collected elsewhere was the rates of 10-year treasury bond and the 3-months treasury bill which we could collect from the Sweden Statistics' database.

3.2 Data processing

For each company relevant data was retrieved including daily price, market value, price high/low, bid/ask quotes and turnover by value. The initial dataset included holidays on which the exchange was closed for trading. However, these days could be difficult to distinguish from normal non-trading days. In order to avoid any misleading impact on the liquidity measures, especially effects on the zero trading days measure, these days were removed from the dataset. Furthermore, the liquidity measures were calculated on a monthly basis as described in the following section, 3.3.1 Liquidity variables.

In the next step, the data for all companies were stacked on top of each other in a falling order based on market capitalization per selection date. Missing data was handled through identifying all rows in the dataset containing missing values. Thereafter, these were deleted from the dataset. The required modification led to a reduction in number observations from 21,004 to 20,791.

Considering the relatively large variation in liquidity values between the companies in the sample, a normalization procedure was necessary to reduce the level of effects caused by differences between company characteristics in the dataset. This process comprised standard deviation computation for each of the liquidity measures and all companies. By dividing all the values by the associated standard deviation for each of the six utilized liquidity measures we obtained a smoother dataset. Furthermore, values that exceeded three standard deviations were set to 3. This normalization process significantly improved the practicality of the dataset as it contributed to more consistent values across the entire dataset.

Furthermore, we examine the viability of the liquidity measures and the variation in the dataset in terms of liquidity by constructing principal components through a step-by-step Principal Component analysis. By using the dataset of 89 firms and over 20,791 observations in total we managed to extract six principal components from the six liquidity measures. The constructed principal components are thereafter used to represent the liquidity of equities listed on Nasdaq Stockholm and will be used in the following panel regression models.

3.3 Variables

In this section we will take a closer look at the variables used in the upcoming regression models in order analyze the link between macroeconomic variables and stock market liquidity. First, we will address the most established and state-of-the-art liquidity measures such as the relative bid-ask spread and the Illiquidity ratio.

Second, we will talk about the selected macroeconomic variables and provide a short background for each of these variables. The selection process of macroeconomic variables was based on the perceived relevance with regards to financial markets and the view of being relevant in a broader context as well.

3.3.1 Liquidity variables

TR is calculated as the sum of the daily turnover in SEK each month divided by the market value of the specific class of shares on the last day of each month. The turnover ratio is closely related to the turnover volume, but unlike turnover it is a relative measure that expresses the trading volume in relation to total market value of the company. In this case the average TR is 0.059 (Table 2) which means that 5.9 percent of the market value on average is being traded on a monthly basis.

Zero trading days is calculated as the number of days with zero returns each month divided by the number of trading days each month. The way this measure is constructed makes it more relevant for more illiquid assets, and could therefore be considered more suitable for companies with lower levels of trading. The average monthly zero trading days for the selected companies is 0.035 overall.

Bid-ask spread is calculated as the average of the daily bid-ask spreads each month. The average observed bid-ask spread for the entire dataset amounted to SEK 1.166. The bid-ask spread is known to suffer from firm size bias which is easily observed in the collected data.

Relative bid-ask spread is calculated as the daily bid-ask spread divided by the average bid-ask quote, and then averaged over each month.

LHH is calculated on a monthly basis as the difference between the highest price and the lowest divided by the lowest price during the period. This quote is then divided by TR over the period.

Illiquidity ratio is calculated as the absolute value of the daily return divided by the turnover in SEK during the same day and then a monthly average is computed.

3.3.2 Macroeconomic variables

Industrial production manufacturing index (henceforth IP) is a measure that tracks the development of the Swedish industrial production on a monthly basis (Sweden Statistics, 2021).

IP data was retrieved on a monthly basis from Datastream. Instead of using the index value as is, we adjusted it by computing the relative change by dividing the index value of the prevailing month by the same month one year prior. The adjustment contributes to making this measure more accurate in describing the actual state of Swedish industrial production as it disregards any potential misleading seasonal differences.

Unemployment rate (UR) is considered one of the most important indicators of the state of a nation's real economy. Unlike some measures tracking economic development, the unemployment rate is fairly easy to understand. It is a statistical measure that describes the development of the Swedish labor market. The underlying population in the statistics include the Swedish population between the age of 15 and 74 years (Sweden Statistics, 2021).

UR data was retrieved from Datastream. The unemployment rate reported on the last day of each month was used in the data set.

Inflation is described in the previous section 2.3 Macroeconomy and equity markets and can be described as an increase in the general price level.

Yield Spread generally equals the difference between the rate on the 10-year treasury note and the short-term rate (e.g. 3 months). In other words, it plots the yield of Treasury bonds against their maturity. The longer the maturity, the higher the yield, as a longer time period often is associated with more risk. The yield spread is a popular forecasting tool among economists as it may predict an upcoming recession. The predicting power of the yield curve has not been empirically established, but it has a track record of relatively accurately predicting economic growth and is definitely a measure that merits further research. Researchers have found evidence of recent changes in the yield spread's ability to properly predict future economic growth (Haubrich & Dombrosky, 1996).

Sweden Statistics' database was used to gather yields of Swedish treasury bonds with a maturity of 3 months and 10 years, respectively. The spread was then determined by subtracting the shorter-term rate from the long-term rate.

Deposit Rate is the rate Riksbanken offers banks when they deposit funds in their accounts and is closely related to the Repo rate.

Repo Rate is the primary monetary policy tool for central banks. Simplified, the repo rate, which is changed by Riksbanken, impacts other interest rates which in turn affect the demand in the economy as well as inflation.

VSTOXX is the most recognized European volatility index and it is closely followed by a wide range of market participants. It measures implied volatility as function of market prices of near-term European equity options, and it is supposed to reflect market expectations regarding future volatility of the underlying asset (Badshah, 2009). This index reflects implied volatility of the broader Eurozone equity market, and will also act as a proxy for volatility of the Swedish stock market in this study.

CBOE Volatility Index is another real-time index that is supposed to capture the expectations for the comparative strength of near-time price changes of the S&P 500, and can be described as the American counterpart to VSTOXX. It is created by the Chicago Board Options Exchange and is one of the most recognized volatility measures globally (Chicago Board Options Exchange, 2021).

3.3.3 Firm-specific variables

In order to properly examine the link between the macroeconomic indicators and the Swedish stock market liquidity, we introduce three firm-specific variables: Market value, return volatility and price-to-book value. Since these variables most likely affect the liquidity of a stock to a rather high degree, they are added as explanatory variables in the panel regression models.

The price-to-book ratio (P/B) is a widely used measure for explaining the value of a publicly traded company as it displays the equity value of the firm in relation to the book value (Jensen, et al., 1997). It is an important factor in describing cross-sectional returns. The firms' price-to-book ratios were collected from Datastream.

Size is another important factor which in this study is represented by market value. The market value in combination with for instance P/B, controlling for the valuation component, is a prominent factor in explaining risk and stock returns. Since the market value variables were significantly larger than the other regressors, a modification of the factor was required. A size variable was created using market value in the following manner:

$$Size_{i,t} = log\left(1 + MV_{i,t}\right) \qquad 3.1$$

Return **volatility** was also considered for each firm in order to control for firm-specific risk. The return volatility for each stock is calculated from the returns for each stock that was collected from Datastream. The return volatility is presented on a monthly basis.

The firm-specific variables are later lagged with a lag of one period in order to avoid cross-sectional dependence in the regression models. This is further discussed in section 4.3 Model description. In Table 2 all variables used in the study are presented. The summary statistics are calculated before the normalization process presented in 3.2 Data processing.

Table 2: Summary statistics for all variables. The sample consist of 20,791 observations for each of the 17 variables.

	St. Dev.	**Mean**	**Min**	**Max**
Turnover ratio	0.059	0.122	0.000	4.575
Zero-trading	0.035	0.105	0	1
Bid-ask	0.516	1.166	0.000	39.414
LHH	12.212	53.694	0.000	5,816.990
Relative bid-ask	0.009	0.018	0.0003	0.516
Illiquidity ratio	5*10^-7	4*10^-6	0	2*10^-4
Industrial production	0.004	0.069	-0.235	0.133
Unemployment rate	0.072	0.011	0.052	0.098
Inflation	0.013	0.012	-0.019	0.044
Deposit rate	0.014	0.017	-0.008	0.054
VSTOXX	0.235	0.093	0.114	0.607
CBOE	0.197	0.096	0.075	0.691
Repo rate	0.014	0.016	-0.005	0.048
Yield spread	0.012	0.008	-0.006	0.033
Price-to-book	2.886	7.568	-87.210	226.470
Return volatility	0.108	0.081	0.000	4.559
Size	7.936	2.481	1.519	14.131

4 Empirical method

In this section we will present our choice of empirical method and describe our approach in more detail. The objective of the study is to examine the relationship between stock market liquidity and macroeconomic aggregates using a quantitative approach. In order to test for the previously stated research question, the empirical analysis has been divided into two sections. The initial stage relies on principal component analysis and aims to identify the underlying trends within stock market liquidity in Sweden. The second part aims to analyze the relationship between the identified trends in liquidity from the previous stage and the selected macroeconomic variables through pooled OLS and fixed-effects estimations for panel data.

4.1 Principal component analysis

Principal Component analysis (PCA) is used to detect patterns in data. It can also be used as guidance in extracting the dominant patterns in a dataset to allow for a reduction in number of dimensions in the data. By using PCA, the number of variables in the dataset can be reduced with only a minor loss of information. In other words, PCA is employed to explain as much of the variability in the data as possible through a new set of orthogonal weights of the initial variables. These weights are in fact linear combinations of the original variables and this approach allows for a smaller set of uncorrelated variables to describe the variation in a larger set of correlated variables (Pereira da Silva, 2014).

The principal components are calculated in order with respect to the maximum possible variation in the original dataset that they can capture. This results in that the first principal component will describe most of the variation in the data and thereby be the most relevant. If the original variables exhibit a strong correlation among them, the first principal component usually represents a common trend in the data. For interpretation purposes, the correlation between one component and the variables can give a hint of what the component represents (Pereira da Silva, 2014).

The implementation of the PCA approach can be divided into four steps. The first step is to compute the covariance or correlation matrix from the six original liquidity measures. In this case, the variables have already been normalized in an earlier step which led to the use of the covariance matrix.

The second step is to compute the eigenvalues, λ, of the covariance matrix and rank them by their value from highest to lowest. Since the largest eigenvalue describes the highest sample variance among all linear combinations of the initial variables it will correspond to the first principal component. The second largest eigenvalue will correspond to the second principal component, and so on. The next step is to rearrange the eigenvectors, *v*, of the covariance matrix in the same order as the eigenvalues have been ranked. This could be written as the optimization problem in Equation 4.1, where *X* is the original dataset.

$$v_i = \underset{\|v\|=1}{arg\,max}\{\| Xv \|^2\} \qquad 4.1$$

The eigenvector, v_i, is called factor loading and as previously mentioned v_1 should capture most of the variation in the data.

Lastly, the original data is transformed along the principal component's axis, meaning, the *i*:th principal component is given by:

$$PC_i = Xv_i \ , \qquad 4.2$$

where *X* is the original data and v_i is the *i*:th eigenvector in the sorted eigenvector matrix.

When the principal components have been implemented the eigenvectors should be orthogonal and the eigenvectors squared should sum to one if it has been implemented correctly. These constraints are illustrated in equations 4.1 and 4.3.

$$v_i v_j' = 0, \text{ if } i \neq j \qquad 4.3$$

The amount of information each principal component contains is of importance. A common procedure to investigate how the information is divided among the principal components is to compare the size of the eigenvalues (one component's captured variance) in relation to the sum of all eigenvalues (all variance in the data). By dividing each eigenvalue with the sum of all eigenvalues the result will be the proportion each principal component captures. Equation 4.4 describes which proportion of the total variances is captured by each principal component.

$$\frac{\lambda_i}{\sum_{i=1}^{n} \lambda_i} \tag{4.4}$$

The purpose of using PCA is to reduce the number of variables, preferably to one or two variables that capture most of the variation in all liquidity proxies. This allows for the creation of a "liquidity variable" that could be used in further analysis.

4.2 Panel data regression

Panel data is a combination of time-series data that tracks an individual over time and cross-sectional data that presents several different individuals at a specific point in time. In other words, panel data tracks different individuals or entities over a period of time. In this study, the different individuals are the different firms and each month represents a point in time in the panel data framework. In summary, our data contains 89 different individuals and 236 points in time. Regarding notation, we denote each firm as i and each month as t.

There are several different regression techniques for panel data. Two common methods are the pooled OLS estimation, which resembles OLS for linear regression models, and the fixed-effects estimation which accounts for unobserved individual effects in order to avoid omitted variable bias (Wooldridge, 2010). Ordinary least squares (OLS) is used for modelling linear relationships. It is a popular technique and also a powerful one (Hutcheson, 1999). The idea behind OLS is to estimate the model coefficients, often denoted β, through minimizing the sum of the squared distance between the fitted values and the observations. The pooled OLS estimator works as the name suggests, it estimates the model coefficients through running ordinary least squares, pooled across i and t (Wooldridge, 2010). The general pooled OLS model is described in Equation 4.5.

$$y_{i,t} = \beta_0 + \beta_1 x_{1,i,t} + \cdots + \beta_n x_{n,i,t} + u_{i,t} \quad 4.5$$

In order for the pooled OLS estimates to be the best linear unbiased estimator (BLUE) and consistent, the unobserved characteristics of the dependent variable have to be uncorrelated with the explanatory variables in the model. If there is correlation, there could be omitted variable bias present in the estimates. Moreover, the pooled OLS model has trouble handling heterogeneity between individuals or groups of individuals. This may cause heterogeneity bias in the estimates from the pooled OLS model (Susmel, 2015).

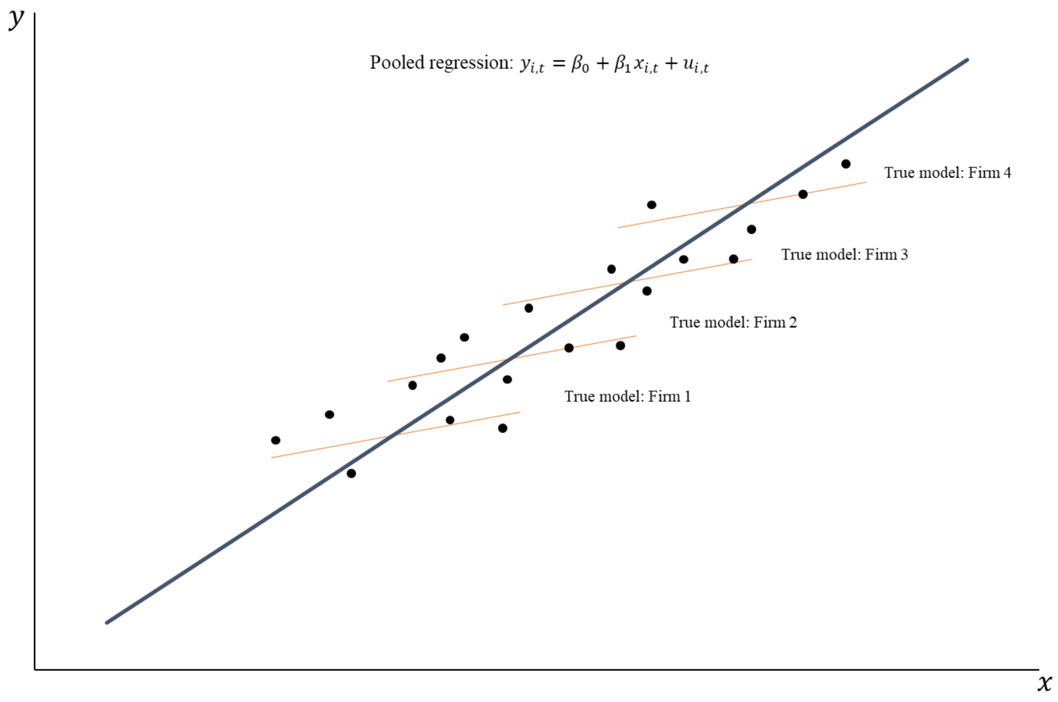

Figure 1: Illustration of heterogeneity bias that might occur in a pooled model.

Fixed-effect (FE) regression is an estimation method often used for panel data that accounts for changes over time within each individual. The fixed-effects controls for time-invariant differences between individuals. By omitting time-invariant characteristics, coefficients can be estimated without bias. This approach allows for capturing unobserved firm characteristics by including a dummy variable α_i in the model (Brüderl & Ludwig, 2014). The general fixed-effects model is described in Equation 4.6.

$$y_{i,t} = \alpha_i + \beta_1 x_{1,i,t} + \cdots + \beta_n x_{n,i,t} + u_{i,t} \qquad 4.6$$

Comparing Equation 4.5 and 4.6, the intercept is what differs in the two models. For the pooled OLS model the intercept is the same for all individuals while the intercept is individual-specific in the fixed-effects model. The individual intercept accounts for unobserved variances within each individual. This is also why the term within-variables estimation is sometimes used to describe fixed-effects estimation.

4.3 Model description

The models used in this study relies on the simpler models presented in Equation 4.5 and Equation 4.6. They are described in more detail below. Equation 4.7 illustrates the pooled OLS model and Equation 4.8 the FE model.

$$y_{i,t} = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_{n-3} x_{m,t} + \beta_{n-2} \gamma_{1,i,t-1} + \beta_{n-1} \gamma_{2,i,t-1} + \beta_n \gamma_{3,i,t-1} + u_{i,t} \qquad 4.7$$

$$y_{i,t} = \alpha_i + \beta_1 x_{1,t} + \cdots + \beta_{n-3} x_{m,t} + \beta_{n-2} \gamma_{1,i,t-1} + \beta_{n-1} \gamma_{2,i,t-1} + \beta_n \gamma_{3,i,t-1} + u_{i,t} \qquad 4.8$$

$$where$$
$$m = 1, \dots, 8$$
$$n = 1, \dots, 11$$
$$i = 1, \dots, 89 \; and$$
$$t = 1, \dots, 236$$

In the equations 4.7 and 4.8 the dependent variable, $y_{i,t}$, is the first principal component calculated using the six different liquidity proxies mentioned earlier. This is because it is likely to capture the common trend in the liquidity proxies and could be seen as a variable for liquidity. The explanatory variables in the models consist of the macroeconomic aggregates presented in section 3.2.2 Macroeconomic variables. These are denoted $x_{m,t}$ and are not firm dependent**.** Moreover, the first index in Equation 4.7 and 4.8 is used to separate the macroeconomic variables from each other. The study investigates the relationship between different liquidity proxies and macroeconomic variables, while simultaneously having data across different firms. Firm-specific attributes are therefore included in the models to better describe the changes in liquidity over time for each firm. These firm-specific variables are denoted $\gamma_{p,i,t-1}$ in both models and are presented in more detail in section 3.3.3 Firm-specific variables. To avoid cross-sectional dependence between the firm characteristic variables and the dependent variable, the firm-specific variables are lagged with a lag of one period (Torres-Reyna, 2007). This lag is represented in the time index, *t*, which is subtracted by one. The firm-specific variables are also separated from each other by the first index. The variable α_i denotes the fixed-effects for each firm in the fixed-effects model and the intercept in the pooled OLS model is β_0. Furthermore, $u_{i,t}$ represents the error term in both regression models.

In order to examine which macroeconomic aggregates that have an impact on the stock market liquidity, several different regression models will be employed. The models differ in terms of the number of explanatory variables that aim to explain the liquidity variable and also in terms of the combination of variables included. Both univariate and multivariate models are used to investigate the relationship between liquidity and macroeconomic aggregates. In order to gain deeper insight to any potential relationship, we will apply both fixed-effects models and pooled OLS models.

The univariate regression models consist of only one explanatory variable, i.e. one macroeconomic variable. This approach will be the first step into investigating how much of the variation in the dependent variable that could be explained by each of the explanatory variables. Multivariate regression models consist of more than one explanatory variable. By using more explanatory variables the explanatory ability often increases compared to univariate models. Nevertheless, redundant variables should not be included in the model. Redundant variables can be identified using the t-test and the coefficient of partial determination which are described in 4.5 Statistical analysis.

Since some macroeconomic variables are strongly correlated, the results can be misleading when used in the same model. One of these variables could be superfluous as they aim to explain the same thing. For example, there are two different variables that describe volatility, namely CBOE and VSTOXX, and these have a correlation of 0.87. In effect, these variables should therefore preferably not be used in the same models.

4.4 Clustered standard errors

For independent and identically distributed residuals, the OLS standard errors are unbiased but when the residuals are correlated across observations there could be potential bias in the estimates. It is easy to overlook correlation in the model errors within clusters in panel data regression. Clusters in financial data can appear, for example, within industries or firms (Petersen, 2009). Not controlling for this within-cluster correlation can lead to too small estimates of the model's standard errors. This in turn implies too narrow confidence intervals and low p-values for the model parameters (Cameron & Miller, 2013). By introducing clustered standard errors, the bias in the estimates can be reduced and possible serial correlation can be avoided. A recent method controlling for these clustered standard errors is to estimate the model without any control for within-cluster errors and then afterwards, obtain "cluster-robust" standard errors. This approach was first proposed by White (1984) and then by Arellano (1987) for fixed-effects estimators in linear panel models.

4.5 Statistical analysis

Various statistical tests are applied to examine the statistical significance of variables, models, and results. These tests will be presented in more detail in the following section and have primarily been employed for the regression analysis.

The t-test is a statistical test used for comparison between the mean value of two groups. It is one of the most commonly used statistical hypothesis tests (Kim, 2015). The result of the test is presented as a p-value. The p-value takes a value between 0 and 1 and if the p-value is below 0.05 the hypothesis can be rejected with a 95% degree of confidence. In this study, the t-test is applied to test whether the explanatory variables in the regression model are significant. To test the significance of variables in a regression model the null hypothesis H_0: $\beta_i = 0$ is used. If the resulting p-value for each hypothesis test is below 0.05 the null hypothesis can be rejected and therefore the variable will be considered statistically significant.

R^2 is a test statistic based on linear regression and ANOVA. It describes the fraction of variance in the dependent variable that is explained through the explanatory variables (Miles, 2014). R^2 is often referred to as "goodness of fit" as it can be seen as a measure of how good the explanatory variables are fit to explain the dependent variable (Camerona & Windmeijer, 1997). The R^2 measure can take a value between 0 and 1. The higher score the better fit is the model to explain the dependent variable as a score of 1 describes a perfectly linear relationship between the dependent and explanatory variables. R^2 is computed as:

$$R^2 = 1 - \frac{\sum_i \ (y_i - \hat{y}_i)^2}{\sum_i \ (y_i - \bar{y})^2} = 1 - \frac{SS_{RES}}{SS_{TOT}} \qquad 4.9$$

In this study, the R^2 measure is used as a performance measure to compare different regression models to each other. The adjusted R^2 is also used in the statistical analysis since this statistic accounts for the number of predictors in the model. The coefficient value decreases when an added variable enhances the model less than expected (Miles, 2014). The idea behind Adjusted R^2 is illustrated below.

$$\text{Adjusted } R^2 = 1 - \frac{(1 - R^2)(N - 1)}{N - p - 1} \qquad 4.10$$

In Equation 4.10 p is the number of predictors and N is the sample size. Furthermore, the coefficient of partial determination, which is closely related to R^2, is used to examine the explanatory ability of different regression models. The coefficient of partial determination provides insight into how much of the variance specific explanatory variables can explain.

The concept behind this coefficient is to compare a full model to a reduced model in terms of explanatory variables. The coefficient provides information about what proportion of variance that cannot be explained in the reduced model. The equation for calculation of the coefficient is shown below.

$$PDC = \frac{SS_{\text{res, reduced}} - SS_{\text{res, full}}}{SS_{\text{res, reduced}}} \tag{4.11}$$

The issue with collinearity or multicollinearity often arises when observational data is analyzed. It is often present in multivariate regression models and can cause difficulties in determining the significance of an estimated coefficient, as well as reducing the significance of the independent variables in the model. Collinearity can be a source of wrongful conclusions about significance of effects and model practicality (Craney & Surles, 2002). The variance inflation factor (VIF) is used to determine the existing level of multicollinearity for each independent variable. It is a useful tool to control for collinearity and determine what variables that should be removed to improve significance among the other factors. One model-specific method that is sometimes used when detecting collinearity is determining a cutoff point for VIF values given by the following equation:

$$VIF_i = \frac{1}{1 - R_i^2} \tag{4.12}$$

However, there is no formal cutoff value or a definite method for determining what VIF values are acceptable and not acceptable. Typically, VIF values exceeding 5 or 10 is considered too large, and is therefore often used as a cutoff point. These values will act as a guideline going forward.

4.6 Scope of the study

We will examine the correlation between the Swedish stock market and some of the most important macroeconomic aggregates by using data from June 2001 to January 2021. The selection of firms is based on criteria with regards to firm size in terms of market capitalization on the selection date. All of the chosen companies are publicly traded companies that have been listed on the Nasdaq Stockholm main market since before the beginning of the time period in focus. Furthermore, the time period was selected based on data availability and due to changes regarding monetary policies and business cycles during the time period which makes it highly interesting to take a closer look at this particular period in time.

5 Empirical analysis

In this section, we present our empirical results and findings. First, we present the results from the principal components analysis followed by a presentation of the primary results in relation to different regression models.

5.1 Principal component results

The principal component analysis was performed on the six normalized liquidity measures according to the steps described in 4.1 Principal component analysis.

Table 3: Factor loadings for each PC.

Measure	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**
TR	0.28	0.81	0.50	-0.02	0.09	-0.12
Zero trading days	-0.75	0.46	-0.31	-0.32	-0.17	-0.01
Bid-ask	-0.27	-0.34	0.70	-0.56	0.00	0.07
Relative bid-ask	-0.43	-0.02	0.39	0.74	-0.32	0.13
LHH	-0.27	-0.12	0.06	0.16	0.47	-0.82
Illiquidity ratio	-0.21	0.06	0.00	0.13	0.80	0.54

Table 3 illustrates the factor loadings for each principal component. By observing PC_1's factor loadings it can be seen that how turnover ratio – the only measure of liquidity – has a positive loading while the illiquidity measures display negative loadings. This is a result of the negative correlation between liquidity and illiquidity. In other words, a decline in liquidity equals an increase in illiquidity. PC_1 exhibits a sensible factor loading and as mentioned in the section 4.1 Principal component analysis**,** the first principal component often captures the common trend in the data, hence the result from the PCA could be considered desirable.

The variable Zero trading days have the largest absolute loading for PC_1 and will therefore influence the first principal component the most. For PC_2, TR has the largest factor loading and will influence PC_2 the most. Since PC_1 contains information from all of the liquidity proxies and captures the common trends in the data, thus reflecting the general trends in stock market liquidity in Sweden.

Table 4: Correlation matrix

	PC1	PC2	PC3	TR	Zero trading	Bid-ask	Relative bid-ask	LHH	Illiquidity ratio
PC1	1.00	0.00	0.00	0.46	-0.91	-0.49	-0.72	-0.66	-0.54
PC2	0.00	1.00	0.00	0.78	0.32	-0.36	-0.02	-0.17	0.09
PC3	0.00	0.00	1.00	0.42	-0.19	0.65	0.34	0.07	0.00
TR	0.46	0.78	0.42	1.00	-0.25	-0.23	-0.23	-0.35	-0.16
Zero-trading	-0.91	0.32	-0.19	-0.25	1.00	0.28	0.50	0.47	0.44
Bid-ask	-0.49	-0.36	0.65	-0.23	0.28	1.00	0.32	0.32	0.17
Relative bid-ask	-0.72	-0.02	0.34	-0.23	0.50	0.32	1.00	0.50	0.37
LHH	-0.66	-0.17	0.07	-0.35	0.47	0.32	0.50	1.00	0.41
Illiquidity ratio	-0.54	0.09	0.00	-0.16	0.44	0.17	0.37	0.41	1.00

Looking at the correlation matrix in Table 4, it can be concluded that the principal components have zero correlation between them. This implied orthogonality between the components confirms that the Principal Component analysis is correctly implemented. Moreover, TR has a negative correlation with all of the other measures of illiquidity implying a desired relationship between measures of liquidity and illiquidity. This implies that PC_1 could be a measure of liquidity since it has positive correlation with the only measure of liquidity and negative correlation with the other five measures of illiquidity. Looking at the first column it can be seen that all liquidity measures influence the estimate of PC_1. The correlation between PC_1 and all the liquidity proxies are relevant as it gives an idea of how the proxies describe stock market liquidity.

Zero trading days have the largest absolute correlation with PC_1 and will therefore look quite similar to PC_1 with the difference that it is mirrored on the horizontal axis. PC_2 contains the second most information and has a large positive correlation with turnover ratio. However, it also has a positive correlation with both zero trading days and the Illiquidity ratio. Since turnover ratio is a measure of liquidity but the other two are measures of illiquidity, PC_2 can't be said to be representative of either liquidity or illiquidity.

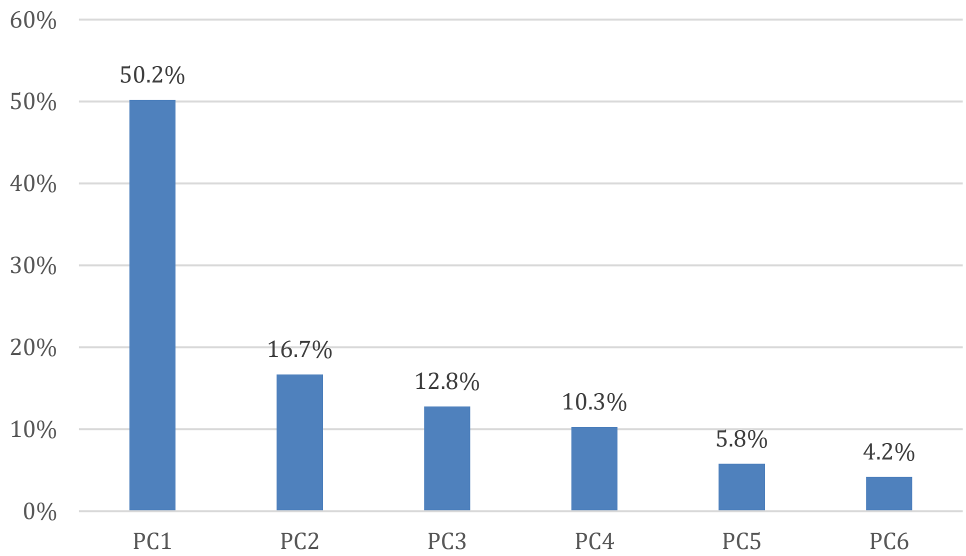

Figure 2: Percentage of variance captured by the principal components.

Figure 2 illustrates the ratio of the eigenvalue of each principal component to the sum of all eigenvalues, and thereby describes the percentage share of the variance in the dataset captured by each principal component (Equation 4.4). As can be seen in the graph, the first principal component manages to describe over 50 percent of the variance which makes it an appropriate dependent liquidity variable in further regression analysis. There is a large gap to the five other principal components in terms of information captured. The other components are on a more similar level in this aspect.

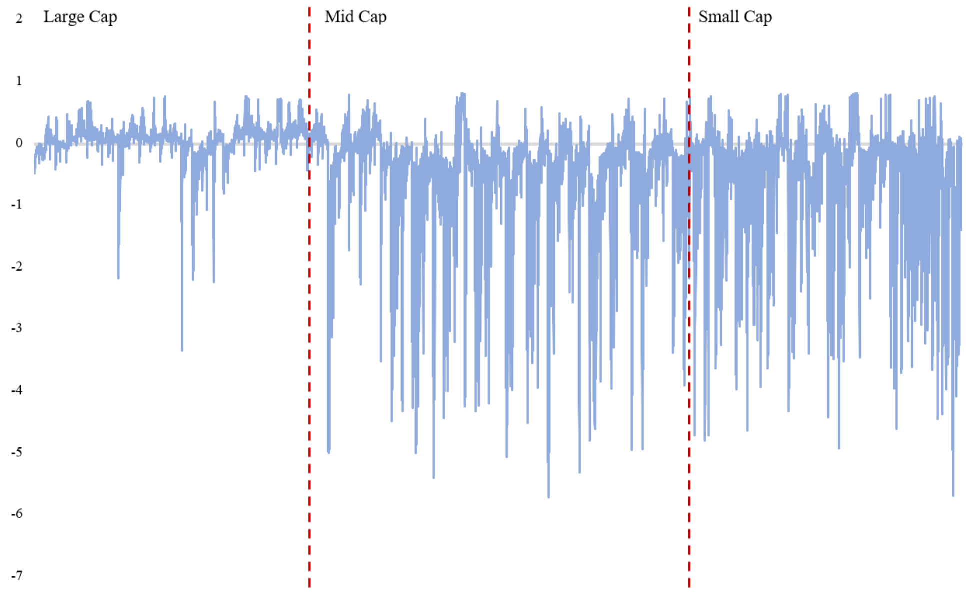

Figure 3: PC_1 values for the entire sample of companies in declining order based on market cap per selection date. The graph comprises PC_1 observations over a total time period of 20,791 months.

It was previously concluded that PC_1 could be interpreted as a measure of stock market liquidity. From Figure 3 it can be concluded that the frequency of downward spikes increases with the number of observations. This indicates that the stocks of firms with a larger market capitalization are more liquid than stocks with a smaller market capitalization. In Figure 3, most Large Cap companies have no downward spikes in PC_1 even though there are a few exceptions. The PC_1 values are generally low for firms with lower market capitalization which is implies that the smallest companies are the most illiquid.

5.2 Regression results

In this section the results from different regression models will be presented. The models are of differing sizes and include different combinations of explanatory variables. The statistical measures used to evaluate the models and compare them includes the R^2 measure, the Variance Inflation Factor and a t-test. The results for the univariate models are presented first, followed by the results for the multivariate models.

5.2.1 Regression models with macroeconomic variables only

Initially, 16 univariate models were constructed. 8 of the models were estimated with an OLS method and 8 models with a fixed-effects technique. The univariate regression models are used in order to get an idea of how each macroeconomic variable influence stock market liquidity. The models can be visualized in Equation 5.1 (FE) and Equation 5.2 (OLS). The results obtained are presented in Table 5 and Table 6. To obtain robustness and avoid potential serial correlation in the residuals we used clustered standard errors. The univariate fixed-effects models presented in Table 5 and Table 6 have the following form:

$$y_{i,t} = \alpha_i + \beta_1 x_{i,t} + u_{i,t} \tag{5.1}$$

$$y_{i,t} = \beta_0 + \beta_1 x_{i,t} + u_{i,t} \tag{5.2}$$

In these univariate models, the sole independent variable is represented by $x_{i,t}$. In both models, both the repo rate and the deposit rate manage to explain the largest portion of the variation as they have the highest coefficient of determination in both the OLS and the FE model. In the univariate FE model, the R^2 is as high as 16 percent (Table 6) which indicates that short-term rates have a significant impact on equity market liquidity.

Table 5: Univariate pooled OLS models. Significant variables are assigned "". The following significance codes are used throughout the entire study: *** significance level of < 0.001, ** significance level of < 0.01 and * significance level of < 0.05*

Model	Inflation	IP	Repo	VSTOXX	CBOE	Deposit rate	Yield spread	UR
β_0	-0.304*** (0.048)	-0.447*** (0.059)	-0.205*** (0.038)	0.132*** (0.030)	-0.084* (0.033)	-0.214*** (0.039)	-0.450*** (0.060)	-1.248*** (0.129)
β_1	-11.090*** (1.193)	0.622*** (0.156)	-17.220*** (1.875)	-2.452*** (0.246)	-1.831*** (0.194)	-16.392*** (1.794)	0.458 (1.048)	11.151*** (1.165)
R^2	0.022	0.002	0.098	0.068	0.040	0.097	0.000	0.018
Adjusted R^2	0.022	0.002	0.098	0.068	0.040	0.097	neg.	0.018

Table 6: Univariate Fixed-Effect models.

Model	Inflation	IP	Repo	VSTOXX	CBOE	Deposit rate	Yield spread	UR
Coefficient	-11.031*** (1.181)	0.637*** (0.158)	-17.174*** (1.867)	-2.464*** (0.247)	-1.841*** (0.195)	-16.350*** (1.786)	0.576 (1.054)	11.055*** (1.165)
R^2	0.037	0.004	0.161	0.114	0.067	0.159	0.000	0.030
Adjusted R^2	0.033	neg.	0.158	0.110	0.063	0.156	neg.	0.025

As anticipated, these two short-term rates are more or less identical in their impact which is a result of the nearly perfect correlation between the variables. Furthermore, the coefficients of the short-term rates variables are negative and therefore assumed to have a suppressing impact on liquidity.

Besides the short-term rates, the volatility indices seem to have the largest ability to single-handedly drive stock market liquidity. The eurozone volatility index VSTOXX display a slightly higher explanatory ability than CBOE which is most likely explained by the fact that the European index acts as a better proxy for the volatility of the market volatility on the Stockholm Stock Exchange. Similar to the short-term rates, an increase volatility generally seems to decrease the stock market liquidity. Since the volatility indices are similar in their characteristics and the fact that financial markets interact globally, the results produced by these variables are similar.

The yield spread variable is not significant in either the OLS or the FE univariate regression model. Although the univariate models with industrial production manufacturing index as the sole independent variable are significant, the associated coefficients of determination are close to zero, 0.2 percent and 0.4 percent, respectively.

In these smaller models, the unemployment rate and inflation are significant with coefficients of determination within approximately 2 – 4 percent. The only non-negative estimated coefficient is the coefficient for unemployment rate, which is notable as it would suggest that an increase in unemployment rate generally would increase stock market liquidity.

The trends and tendencies of the model alternatives, OLS and FE, are similar. However, R^2 is higher across all models when the fixed effect method is used. By using the fixed effects method, we manage to capture a larger portion of the unobserved characteristics of firms included in the data. Hence, the fixed effect regression model becomes appropriate in this context.

To further examine the relationship between the macroeconomic variables and the liquidity proxies, multivariate models are introduced. The multivariate models combine several macroeconomic aggregates into a model in order to improve the explanatory power of the model and thereby better describe stock market liquidity through the macroeconomic aggregates. Both pooled OLS and FE models are presented in Table 7 and Table 9, respectively. The methodology behind the reduction in model size is starting from a model that comprises all variables and then remove insignificant variables. When variables are removed some explanatory power is lost. The degree of the information lost when excluding a variable from the model is described by the partial determination coefficient (PDC). The partial determination coefficient for each model is calculated with respect to model (1), meaning it constitutes the full model in Equation 4.11.

Table 7: Multivariate pooled OLS models.

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
(Intercept)	-0.070	-0.095*	-0.078	-0.070	0.197***	-0.302***	-0.627***
Repo rate	-22.503***	-13.595***	-13.218***	-13.133***	-14.256***	-17.020***	
VSTOXX	-3.134***	-3.084***	-1.685***	-1.668***	-1.637***		-2.420***
UR	4.073***	4.374***	3.987***	2.783***		2.231**	11.322***
Yield spread	-5.863***	-5.287***	-6.051***		-4.779***	-5.430***	-5.312***
CBOE	1.770***	1.597***					
IP	0.328						
Inflation	-1.535						
Deposit rate	8.753						
Adjusted R^2	0.136	0.135	0.128	0.126	0.126	0.100	0.085
PDC		0%	1%	1%	1%	4%	5%

Looking at the full model (model (1)) in Table 7 it can be seen that deposit rate, inflation, IP as well as the intercept are insignificant. In model (2) the insignificant macroeconomic variables have been removed and the adjusted R^2 for this model is similar to the one for the full model. By analyzing the PDC, it can be seen that the removed variables explained almost no variation in the first principal component. The first substantial loss in explanatory power (above 0.5%) caused by the removal of a variable can be seen in model (3) where CBOE has been removed. CBOE was removed due to multicollinearity. The VIF for each independent variable in model (2) can be seen in Table 8.

Table 8: VIF values for model (3) in Table 6.

UR	VSTOXX	Repo rate	CBOE	Yield spread
1.280	4.341	1.360	4.344	1.101

As stated in section 4.5 Statistical analysis the critical value for the VIF is above 5 but with a VIF value of 4.3 and a 1% loss of variation explanation CBOE was removed. In model (3) all coefficients are significant except the intercept. To further analyze the models, one variable is omitted for each of the following models. Among the last four macroeconomic variables, omitting the repo rate results in the worst model in terms of adjusted R^2 and PDC. This is consistent with previous findings from analysis of the univariate models where the model including repo rate yielded the highest "goodness of fit".

The analysis proceed with an examination of the difference between the pooled OLS models and models where fixed-effects estimation is employed. The fixed-effects models are presented in Table 9 and the same principle of starting with a full model and then removing insignificant variables is applied.

Table 9: Multivariate Fixed-Effect models.

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Repo rate	-22.028***	-13.529***	-13.153***	-13.066***	-14.170***	-16.993***	
VSTOXX	-3.155***	-3.104***	-1.702***	-1.686***	-1.655***		-2.433***
UR	4.023***	4.291***	3.910***	2.728***		2.136*	11.210***
Yield spread	-5.698***	-5.142***	-5.918***		-4.670***	-5.290***	-5.172***
CBOE	1.775***	1.600***					
IP	0.332						
Inflation	-1.494						
Deposit rate	8.353						
Adjusted R^2	0.221	0.221	0.208	0.205	0.206	0.161	0.138
PDC		0%	2%	2%	2%	7%	10%

At first sight it can be seen that the same variables are insignificant for the full fixed-effects model as for the full pooled OLS model. Removing the insignificant regressors yields model (2) where all macroeconomic variables are significant. The adjusted R^2 value for model (2) is similar to the full model. In addition, the PDC results indicates that removing variables does not result in any significant loss regarding variation in the dependent variable explained by the predictors. Following the same procedure as for the pooled OLS models, CBOE is omitted from further models due to its correlation with VSTOXX. Thus, removing CBOE results in a PDC of 2%. From model (4) and onwards, the models alternate between omitting one of the remaining variables. Omitting the repo rate results in the lowest adjusted R^2 and the largest PDC as it did for the pooled OLS models. VSTOXX is the second most prominent variable in explaining liquidity according to the results.

The pooled OLS estimation is compared to the fixed-effects estimation by analyzing the results in Table 7 and Table 9. It can be concluded that the coefficients for each variable are rather similar but not identical. The values of the PDC are also larger for each of the fixed-effects models. Another interesting result is that the adjusted R^2 is higher across all fixed-effects models.

5.2.2 Regression models including firm-specific variables

The next step in the analysis is to introduce firm-specific variables. The reason for introducing these variables is to improve the explanatory power of the models. The variables are presented in more detail in section 3.3.3 Firm-specific variables. As mentioned in the section 4.3 Panel data regression, the firm-specific variables are lagged with a lag of one period. As with the previous panel data regression models, additional models are estimated with OLS and FE for the purpose of comparing the results. Initially, models including only firm-specific variables are employed.

Table 10: OLS models including only firm-specific variables. Coefficients are presented as well as coefficients of determination for each model.

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
(Intercept)	-1.876***	-0.220**	-0.467***	-1.793***	-1.800***
Size	0.180***			0.176***	0.175***
Volatility		-2.105***		-0.445	-0.464
Price-to-book			0.007		0.006
R^2	0.259	0.038	0.004	0.261	0.263
Adjusted R^2	0.259	0.038	0.004	0.261	0.263

Table 11: FE models including only firm-specific variables. Coefficients are presented as well as coefficients of determination for each model.

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Size	0.383***			0.356***	0.355***
Volatility		-2.048***		-1.035***	-1.036***
Price-to-book			0.004		0.000
R^2	0.191	0.051	0.002	0.203	0.203
Adjusted R^2	0.188	0.047	neg.	0.200	0.200

In Table 10 and 11 the results from the different regression models are presented. As can be seen, the price-to-book ratio is insignificant for both estimation methods and has the lowest adjusted R^2 among the univariate models. One noticeable difference between the estimation methods is that the volatility variable is insignificant for the multivariate pooled OLS model but significant for the multivariate fixed-effects models. Another interesting finding is that the pooled OLS models have higher R^2 values for all models except the model containing only the volatility variable. The relatively large coefficients indicate that firm-specific attributes are crucial in describing liquidity. The analysis proceeds through combining macroeconomic variables and firm-specific variables in the same regression models. The results from these models are presented in Table 12 and Table 15.

Table 12: Multivariate pooled OLS with firm-specific variables.

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
(Intercept)	-1.588***	-1.527***	-1.570***	-1.601***	-1.589***	-1.274***	-1.806***	-2.021***
Repo rate	-23.566***	-23.950***	-24.034***	-9.395***	-9.014***	-10.230***	-12.274***	
VSTOXX	-2.803***	-2.757***	-2.752***	-2.760***	-1.467***	-1.417***		-1.952***
UR	4.384***	3.886***	4.365***	4.741***	4.234***		2.838***	9.309***
CBOE	1.583***	1.481***	1.476***	1.472***				
Deposit rate	13.851**	14.109**	13.945**					
Inflation	-2.253**	-1.017						
Yield spread	-2.192							
IP	0.273							
Size	0.166***	0.164***	0.164***	0.164***	0.165***	0.164***	0.167***	0.172***
Volatility	0.280							
Price-to-book	0.004							
Adjusted R^2	0.344	0.342	0.342	0.342	0.336	0.334	0.315	0.316
PDC		0%	0%	0%	1%	2%	4%	4%

The same methodology as in 5.2.1 Regression models with macroeconomic variables only is applied in this section when comparing models, meaning that insignificant variables are removed from the model in order to avoid redundancy. In the full model (model (1)) industrial production, volatility and price-to-book ratio are insignificant. Removing the two insignificant macroeconomic variables yields model (2) where inflation becomes insignificant as well. Model (3) includes both deposit rate and repo rate but combining these leads to collinearity. This is concluded by observing the VIF values for model (3) which are presented in Table 13.

Table 13: VIF values for model (3) in Table 12.

UR	VSTOXX	Repo rate	CBOE	Deposit rate	Size
1.282	4.342	276.023	4.324	271.157	1.031

Table 13 indicates that the short-term interest rates are sources of collinearity. By removing the deposit rate from the model, we arrive at model (4). Its VIF values are presented in Table 14. From Table 14 it can be concluded that the most problematic collinearity has been removed.

Table 14: VIF values for model (4) in Table 12.

UR	VSTOXX	Repo rate	CBOE	Size
1.202	4.339	1.385	4.323	1.031

Even though CBOE is statistically significant in model (4) it is removed in further models due to its high correlation of 0.87 with VSTOXX. Their VIF values are in the proximity of the cut-off value of 5 as well, hinting about collinearity between the two volatility indices. In models (5) to (8), all variables are significant and there is no significant multicollinearity issue present. In order to identify to which degree the remaining variables affect the liquidity variable, one of the variables are removed for each model. Comparing the last models, removing the repo rate and VSTOXX contributes to the largest loss of variance explained since removing those yields a PDC of 4%. Model (6), where UR is omitted, has the highest adjusted R^2 of the remaining models which is in line with the other findings, concluding that VSTOXX and the repo rate are superior in explaining the liquidity variable. The analysis proceeds with fixed-effects estimation for models with the firm-specific variables. The results are presented in Table 15.

Table 15: Multivariate Fixed-Effect model with firm-specific variables.

**Variables included in all models.*

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
VSTOXX	-2.565***	-2.530***	-2.540***	-1.286***	-1.286***	-1.250***	-1.449***	
Repo rate	-19.989***	-21.082***	-6.645***	-6.082**	-6.611***	-6.636***		-8.069***
UR	4.109***	3.920***	4.297***	3.926***	4.685***		5.352***	2.827**
Inflation	-2.368**	-1.778*	-1.734*	-1.715*		-3.311***	-4.579***	-1.776*
CBOE	1.528***	1.428***	1.426***					
Deposit rate	12.772*	13.784*						
IP	0.196							
Yield spread	-0.621							
Size	0.237***	0.239***	0.237***	0.247***	0.243***	0.245***	0.300***	0.271***
Volatility	-0.584*	-0.587*	-0.600*	-0.538*	-0.553*	-0.559*	-0.538*	-0.801**
Price-to-book	0.000							
Adjusted R^2	0.276	0.276	0.275	0.266	0.266	0.263	0.256	0.241
PDC		0%	0%	1%	1%	2%	3%	5%

For the full model estimated with fixed-effects, yield spread, IP and price-to-book are insignificant with a 95% degree of confidence. Excluding the insignificant variables causes a negligible loss of explanatory power. CBOE and the deposit rate are later removed due to previously discussed collinearity issues. This leads to model (4) where four macroeconomic and two firm-specific variables are significant. The models that follow omit one of the macroeconomic variables in order to identify which variable(s) affects the liquidity variable the most. In model (8) where VSTOXX is omitted the largest PDC of 5% is recognized. Model (8) also has the lowest adjusted R^2.

Comparing the results of the models including firm-specific variables estimated with pooled OLS and fixed-effects there are some interesting results. All the models estimated with pooled OLS have a higher adjusted R^2 than the models estimated with fixed-effects. The opposite was true for the models without the firm-specific variables. The adjusted R^2 increased for the fixed-effects models when the firm-specific variables were introduced but it has increased even more for the pooled OLS models with the same modification. Since the fixed-effects estimator is designed to capture unobserved firm-characteristics it may already have accounted for some of the information provided from the firm-specific variables. The pooled OLS models on the other hand have not accounted for any firm-characteristics which can explain the dramatic increase in adjusted R^2 when introducing the firm-specific variables. With that said, there could be bias in the pooled OLS estimation, in particular heterogeneity bias could be present. The potential bias is illustrated in Figure 1 and could be a possible factor enhancing the performance measures of the OLS model which is why the FE model might be a more proper choice considering the potential misleading results produced by the pooled OLS model.

5.2.3 Sample of firms

In this section we take a closer look at three Large Cap firms, three Mid Cap firms and three Small Cap firms, all listed on Nasdaq Stockholm. For each type, firms are selected from different industries in order to detect potential differences in model performance between industries. Further analysis of the sample will be conducted using model (4) in Table 15 since it has the highest explanatory ability and do not include any redundant regressors. The model is described by the following equation:

$$PC_{1,i,t} = \alpha_i + \beta_1 VSTOXX_{,t} + \beta_2 REPO_t + \beta_3 UR_{,t} + \beta_4 INF_{,t} + \beta_5 Vol_{i,t-1} + \beta_6 \text{ Size }_{i,t-1} + u_{i,t} \qquad 5.3$$

The resulting values based on the model tends to provide a better fit for companies with a higher market capitalization which can be observed in the residual plots in Figure 7 in 8.2 Complementary regression results in the appendix. Still, the fitted values in Figure 6 tend to be relatively accurate for the selected Small Cap firms.

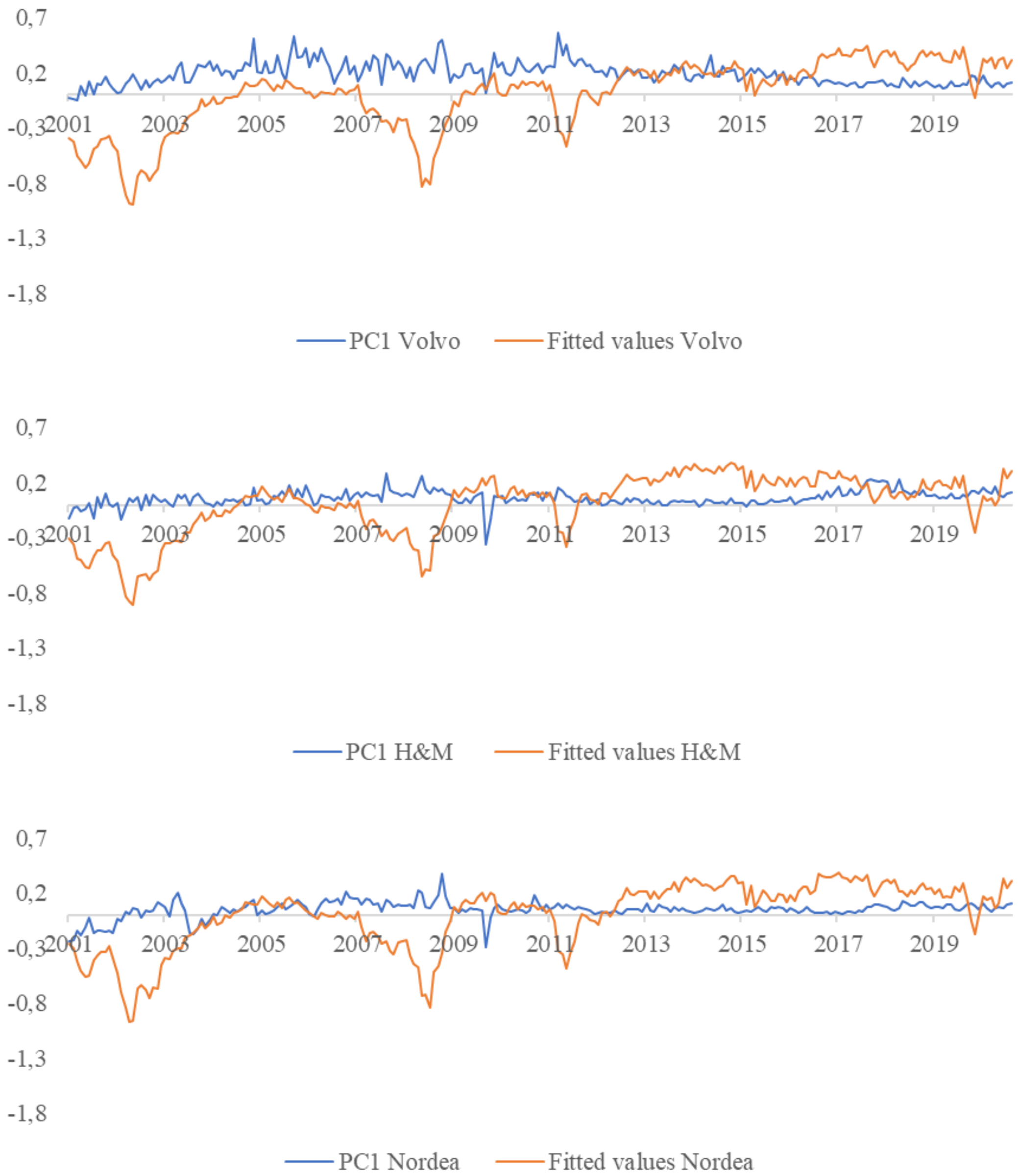

Figure 4: PC1 for a sample of Large Cap firms (Volvo, H&M and Nordea) and corresponding fitted values according to model (4) in Table 15.

The graphs for the Large Cap companies in Figure 4 exhibit a smooth level of liquidity, reflected in the rather constant PC_1 values, over the entire time period. Note, however, that the fitted values for the first principal component do not fall below the actual values since 2012, with few exceptions, which implies that the selected model overestimate the liquidity during this time period. The consistently higher predicted values could be a result of structural changes in the impact of the included variables in the model. Another interesting observation is that PC_1 is consistently non-negative with inception at around 2012. Moreover, the model predicts an illiquidity shock during the 2008 financial crisis for each of the three firms, while the estimated PC_1 indicates the opposite. The same tendencies can be observed following the dot-com bubble during the beginning of the millennium.

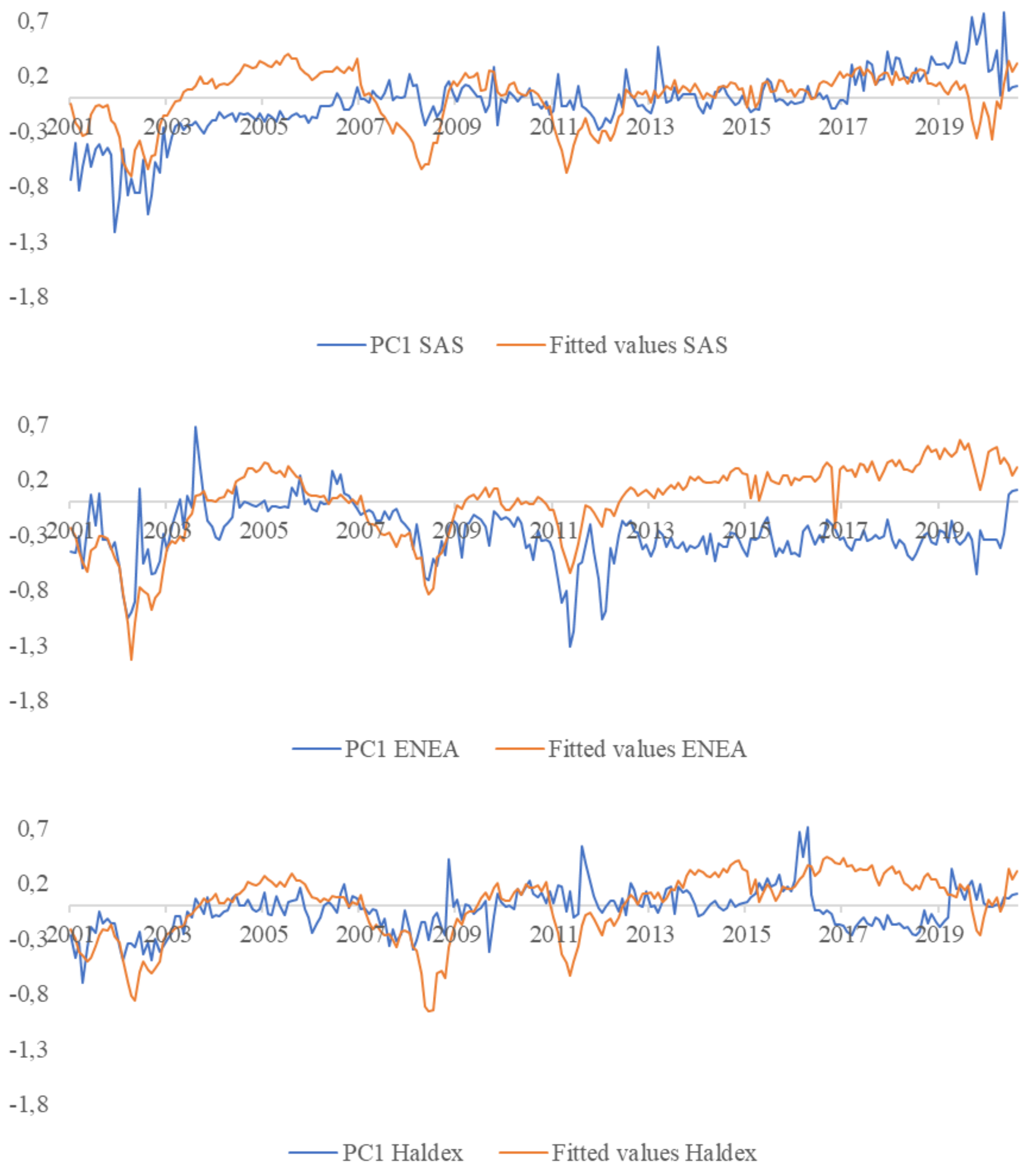

Figure 5: PC1 for a sample of Mid Cap firms (SAS, ENEA and Haldex) and corresponding fitted values according to model (4) in Table 15.

The PC_1 values and fitted values for the selected Mid Cap firms shows that there are common trends among smaller firms which is predicted by the model. The actual liquidity for these smaller firms is noisier with more distinguished spikes which the model manages to capture fairly well. For the selected Mid Cap companies, the PC_1 values are generally lower than the corresponding Large Cap values. By observing the fitted values for ENEA (Figure 5), an IT company, following the dot-com bubble there is a dramatic dip in both PC_1 and the fitted values showing that stock liquidity is likely to be related to the overall industry performance as well.

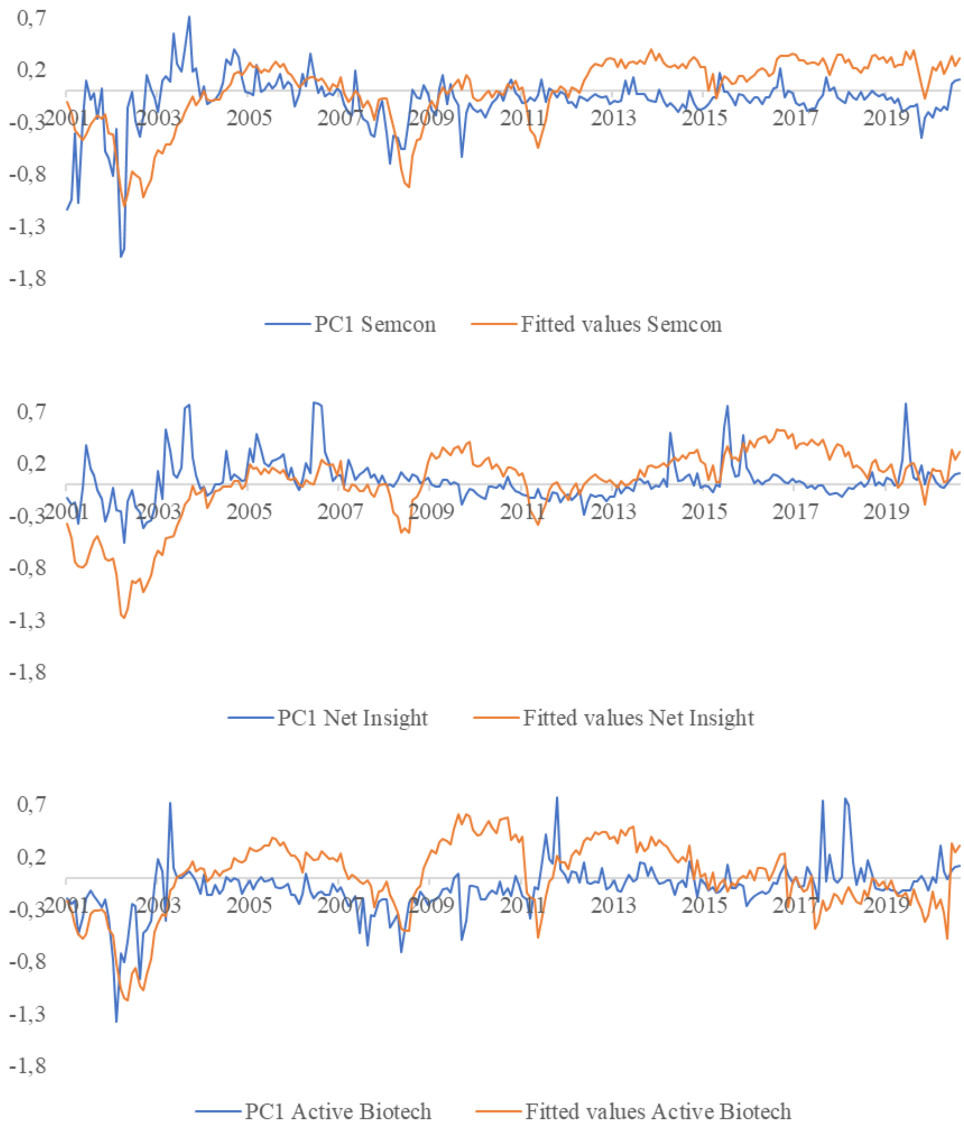

Figure 6: PC1 for a sample of Small Cap firms (Semcon, Net Insight and Active Biotech) and corresponding fitted values according to model (4) in Table 15.

Finally, the PC_1 values and corresponding fitted values for three Small Cap firms are depicted in Figure 6. As can be seen in the Figure 6, a larger portion of the actual values of the first principal component assumes negative values for smaller firms, indicating that generally these shares are more illiquid. The fitted values for Semcon is accurate with regards to both upwards and downwards trends across the entire time period. However, most of the fitted values are larger than the actual liquidity variables since approximately 2012 in the same way the model tends to overestimate PC_1 for the larger companies as well.

The main differences between companies of differences sizes is partly the lower liquidity across the board, and partly the liquidity shocks impacting smaller firms to a much greater extent during shorter period of times. Looking at the nine figures together there are some interesting similarities across all companies. There are three major illiquidity shocks visible for all companies. The first illiquidity shock occurs in conjunction with the burst of the dot-com bubble. The fitted values indicate that there is a dip in liquidity independent of size or industry. On the other hand, the magnitude of the shock seems to be related to size and industry since the fitted values are lower for smaller companies and companies in the IT sector. The second illiquidity shock arrive during the 2008 financial crisis. In this case, the model predictions are more similar across companies. The third and last liquidity shock occur in early 2020 when the covid-19 pandemic brought uncertainty over the stock markets. The shock is visible across all of the companies in the sample. These three macroeconomic events are predicted to have a negative impact on stock market liquidity by the model at first but they are always followed by a quick recovery. The results presented in figures 4-6 present evidence supporting a link between the macroeconomy, macroeconomic events and stock market liquidity.

6 Conclusion

Applying several panel data regression models, with both fixed effects and ordinary least square estimations, this paper investigates the impact of macroeconomic factors on the stock market liquidity on the Stockholm Stock Exchange based on a number of selected macroeconomic indicators.

Previous research provides evidence supporting the relationship between economic growth and stock market liquidity such that economic growth usually tends to boost stock market activity, and subsequently influence market liquidity. Using stock market liquidity of a wide range of selected companies, we find evidence that the liquidity of stocks listed on Nasdaq Stockholm are related to important indicators of the state of the economy.

The key findings of this study are that the macroeconomic indicators included have a significant impact on the stock market liquidity in Sweden, however, only the short-term rate and the volatility of the broader market appear to have any significant potential in affecting stock market liquidity to a greater extent. The empirics also reveal that the stock market liquidity is associated with other indicators such as the unemployment rate and inflation, but these relationships are rather weak. The results regarding the explanatory power of the yield spread, commonly used to predict economic growth, in terms of market liquidity on the Swedish Exchange is ambiguous.

Since the main focus of this study is to document cyclical, long-term changes (over 20 years) in liquidity caused by macroeconomic factors, any potential transitory differences in the behavior of stock market liquidity might be unnoticed. There is noticeable evidence showing that stock market liquidity responds to monetary policy decisions and that liquidity shocks are associated with some macroeconomic events. Note, however, that the explanatory ability of macroeconomic variables with regards to liquidity on the Swedish stock market is limited under normal circumstances. As this study focused on the connection between liquidity of the entirety of the Swedish stock market and macroeconomic factors by using a larger sample of companies, variations among firm characteristics might complicate an accurate analysis of the impact of macroeconomic variables on subsets of firms. Accordingly, separate analyses of firms based on type such as size and sector might show differences in the impact of macroeconomic factors. Similarly, interesting conclusion could be drawn if the analysis was based on specific shorter period of times as it may uncover important evidence regarding the impact of macroeconomic factor at short horizons. In times of economic stress, adjustments in monetary policy and increased market volatility tend to give rise to shocks in stock market liquidity. Smaller firms tend to be more sensitive to changes in the macroeconomic environment as they exhibit larger liquidity fluctuations during economic distress and turmoil.

Naturally, the results are dependent on the data used in the study, as well as the selection of variables that represent macroeconomic factors. The evidence from previous studies advocates for a significant relationship between money supply and liquidity. By including additional factors associated with money supply such as M3, the degree of determination contributed to macroeconomic factors could possibly increase.

In summary, the observed results agree with previous studies suggesting that the stock market liquidity is in fact associated with macroeconomic factors. Even if stock market liquidity primarily is determined by cross-sectional firm-specific variables such as business cycle, industry and size, there is a clear evidence suggesting that macroeconomic aggregates influence the stock market liquidity in Sweden, hence deserving close attention from investors and professionals in the assessment of risk.

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8 Appendix

8.1 Dataset information

Table 16: List of selected public companies included in the sample over approximately 20 years (236 months).

Company	Company #	Industry	Market Cap per 2021-04-21 (SEK m)
AstraZeneca	1	Healthcare	1,172,634
Atlas Copco	2	Industrials	635,037
ABB	3	Industrials	598,409
Investor	4	Financials	552,536
Volvo	5	Industrials	421,354
Ericsson	6	Telecom	387,444
H&M	7	Consumer services	336,393
Nordea	8	Financials	347,202
Hexagon	9	Technology	308,963
Sandvik	10	Industrials	287,631
Assa Abloy	11	Industrials	281,037
SEB	12	Financials	229,831
Swedbank	13	Financials	174,329
Handelsbanken	14	Financials	190,499
NIBE	15	Industrials	154,683
Latour	16	Financials	157,465
Industrivärden	17	Financials	145,500
Kinnevik	18	Financials	132,668
Lundbergföretagen	19	Real Estate	122,239
SCA	20	Basic Materials	110,092
SKF	21	Basic Materials	111,190
Swedish Match	22	Consumer Goods	115,681
Skanska	23	Industrials	95,318
Autoliv	24	Consumer services	83,265
Tele2	25	Telecom	81,852
Electrolux	26	Consumer services	75,486
Getinge	27	Healthcare	73,758
Holmen	28	Basic Materials	69,709
Vitec	29	Technology	13,379
SAS	30	Consumer services	14,576
Bilia	31	Consumer services	15,677
KARO	32	Healthcare	12,242
MTG	33	Consumer services	13,814
Skistar	34	Consumer services	9,821
Fagerhult	35	Industrials	9,232
Beijer Alma	36	Basic Materials	10,389
Heba	37	Real Estate	9,626
Biogaia	38	Healthcare	8,139
Addnode	39	Technology	9,367
OEM	40	Industrials	8,967
Fingerprint	41	Technology	11,030
KNOWIT	42	Technology	6,058
Midsona	43	Consumer Goods	5,534
Elanders	44	Industrials	5,891
Enea	45	Technology	5,198
Probi	46	Healthcare	5,822

Company	Company #	Industry	Market Cap per 2021-04-21 (SEK m)
Clas Ohlson	47	Consumer services	6,029
XANO	48	Industrials	4,782
New Wave	49	Consumer services	6,004
VBG	50	Consumer services	4,611
Proact IT	51	Technology	3,086
Pricer	52	Technology	3,686
RAY	53	Healthcare	3,024
Traction	54	Financials	3,536
BERG	55	Industrials	3,386
Catella	56	Financials	2,608
Haldex	57	Industrials	2,364
IAR	58	Technology	1,877
CTT	59	Industrials	2,305
RROS	60	Basic Materials	1,565
Semcon	61	Industrials	2,123
Kabe	62	Consumer services	1,962
Bergs Timber	63	Basic Materials	2,233
Softronic	64	Technology	1,708
Doro	65	Telecom	1,430
Duroc	66	Basic Materials	1,213
Sintercast	67	Industrials	1,113
Elos	68	Healthcare	1,130
Prevas	69	Technology	923
Svedbergs	70	Industrials	994
Concejo	71	Industrials	960
Net Insight	72	Telecom	934
Profilgruppen	73	Basic Materials	670
Micro Systemation	74	Technology	858
Viking Supply Ships	75	Industrials	-
Medivir	76	Healthcare	454
Novotek	77	Technology	619
Malmbergs Elektriska	78	Industrials	552
Precise Biometrics	79	Technology	488
Midway Holding	80	Industrials	600
Concordia Maritime	81	Industrials	453
Active Biotech	82	Healthcare	313
Lammhults Design Group	83	Consumer services	345
Poolia	84	Industrials	485
Feelgood	85	Healthcare	351
Ortivus	86	Healthcare	204
MultiQ	87	Technology	143
Bong	88	Industrials	138
Empir Group	89	Technology	83

8.2 Complementary regression results

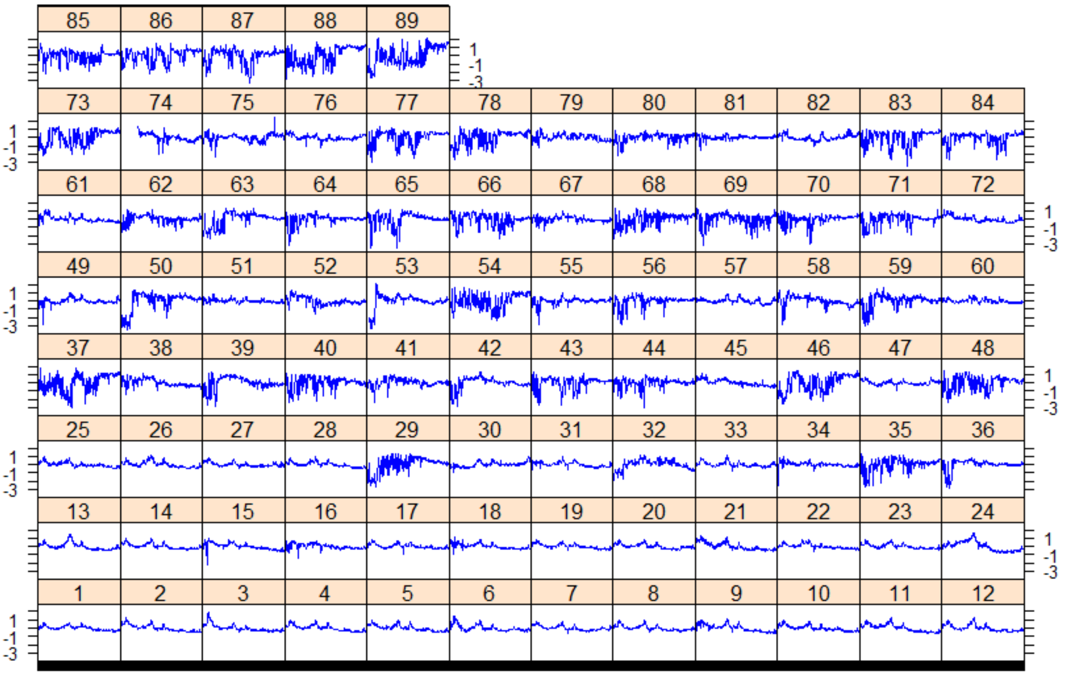

Figure 7: Residual plots for each selected company in the list over selected firms above using model (4) in Table 15.