ILLIQUIDITY AND STOCK RETURNS

EVIDENCE FROM THE 2007-2016 PERIOD ON THE STOCKHOLM STOCK EXCHANGE

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Bachelor Thesis
Stockholm School of Economics
2019-05-15

Illiquidity and Stock Returns: Evidence From the 2007-2016 Period on the Stockholm Stock Exchange

Abstract:

In this thesis, we study whether stock specific liquidity help explain stock return variations on the Stockholm Stock Exchange in Sweden over the years 2007-2016 by regressing excess stock returns on liquidity, market excess return, size and value variables. Furthermore, we investigate whether illiquidity premia have differed during the global financial crisis of 2007-2008, compared to four following two-year periods. Our results show that liquidity has not had a statistically significant effect on stock returns for the period of 2007-2016 as a whole. Regression results from the smaller time periods are inconsistent. During the financial crisis and 2011-2012, we find that illiquidity has had a statistically significant negative effect on stock returns. In 2013-2014 and 2015-2016, we find that illiquidity has had a statistically significant positive effect on stock returns. Due to difficulties of accurately measuring liquidity and the uncertainty of market dynamics in financial crises, we cannot conclude whether illiquidity truly has had a negative effect on returns, or if our results are affected by omitted variables and measurement errors. Methods of how to most accurately measure liquidity during both economically stable and unstable times needs to be examined in further research.

Keywords:

Illiquidity, Bid-Ask Spread, Asset Pricing, Stockholm Stock Exchange

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Bachelor Thesis

Bachelor Program in Business & Economics

Stockholm School of Economics

Acknowledgement: *Håkan Thorsell for his support and tutoring and Andreea Enache for her insightful comments and assistance.*

Contents

1. Introduction

If assets are priced rationally, investors demand additional compensation for exposure to additional costs. In addition, if these costs vary over time and are uncertain, risk-averse investors would demand to be compensated for bearing the risk of cost fluctuations. In the existence of an associated risk of holding illiquid assets, which investors demand compensation for bearing, security prices should be affected by illiquidity. Pastor and Stambaugh (2003) propose that high liquidity suggest that investors are able to trade large quantities of a stock at a low cost, without affecting the price. Liquidity is important both for asset pricing, as well as investment strategies.

A source of illiquidity can be exogenous transaction costs; brokerage fees, transaction taxes and order-processing costs. Alternatively, illiquidity can stem from demand pressures and inventory risk. If all market participants are not present at all times or willing to buy, holders of a stock may not be able to sell the stock to a natural buyer immediately. Thus, a buyer of a stock may buy a stock in anticipation of later trading the position. If said buyer is going to be exposed to price changes during the time of inventory, she will demand compensation for this risk. In addition, trading a stock can be costly if one party has private information. Such private information can be about fundamentals or order-flow. As such, stocks exposure to liquidity should affect investors' required return. The cost of capital will indirectly be affected, thus impacting the allocation of real resources in the economy (Amihud et al., 2005).

Liquidity as a determining variable for asset pricing has previously been studied on the basis of market liquidity (Amihud, 2002), as well as what common determinants stock liquidity exhibits (Chordia, Roll and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001). Other studies have examined stock specific liquidity as a explanatory variable of stock return variation (Amihud and Mendelson, 1986; Brennan and Subramanyam,1996; Datar, Naik, and Radcliffe, 1998). The last studies use various measures of liquidity but study the relationship between stock liquidity and return on the U.S. market. The total literature on liquidity in asset pricing is vast and still expanding (Amihud et al., 2005). However, little is known about the effect of stock liquidity on returns on the Swedish stock market. Furthermore, little is known about the determinants of stock specific liquidity in times of financial crisis, and how the corresponding risk help explain return fluctuations. This thesis adds to the existing literature on whether stock specific liquidity help explain stock return variations, by focusing on the Swedish market in times of financial crisis versus when the market is in a normal state.

We study whether stock specific liquidity is a dimension of risk which the market values when pricing assets. Additionally, we study if the effects of liquidity on stock return variation have varied over time to conclude if the importance of liquidity has differed during the global financial crisis period of 2007-2008 compared to 2009-2016. We create and add a liquidity variable to the original Fama and French (1992) variables: Market Excess Return, Size and Book-to-Market Value. Monthly stock returns of firms listed on the NASDAQ Stockholm Stock Exchange, from 1st of March 2007 to 1st of December 2016, are regressed on the Fama and French variables and the created liquidity variable which are assumed to help explain the variation in stock returns. This study finds a positive relationship between the liquidity measure and stock returns. However, this finding is not statistically significant over the whole period. Over time, the illiquidity premium varies greatly. Especially during the time period when the financial crisis of 2007-2008 was the most present. Our results indicate that there are reasons to believe that the estimation of the coefficient is affected by other factors not included or adjusted for in the model.

2. Theory

2.1. Definition of Liquidity and Its Role in Asset Pricing

Sadka and Lou (2011) define the level of illiquidity as the average cost of trading a security. Higher trading costs implies higher illiquidity levels. The liquidity term used in this thesis refers to how easily an investor can trade a specific security (Amihud et al., 2005). Risk associated with liquidity is often connected to its variability and uncertainty and not only the average level of financial liquidity (Persaud, 2003). Commonly used asset pricing models, such as the Capital Asset Pricing Model (CAPM) by Treynor (1962), Sharpe (1964), Lintner (1965) and Mossin (1966), assume zero transactions costs and identical prices for identical future cash flows. This assumption implies that selling a security quickly would have no effect on its price, or put more simply, that there would be no friction on the market. In reality, however, securities differ in how easy they can be liquidated. The difference in the bid-ask spreads between securities such as cash, bonds and stocks differ significantly, showing the existence of market friction.

2.2. Liquidity Measures

2.2.1. Trade-based Measures

Liquidity has been proven to be difficult to measure. While no consensus of a best method exists, previous literature offer a wide range of potential proxies for liquidity. In their study of different liquidity measures, Aitken and Winn (1997) found some 68 proxies for liquidity used in financial and economic literature.

In general, liquidity measures can be divided into two sub-categories; trade-based measures and order-based measures. Commonly used trade-based measures are trading volume, trading value, the number of trades and the turnover ratio, the value of shares traded divided by the market capitalization. The use of such measures has a widespread acceptance, especially among market professionals. However, such measures are ex post as opposed to ex ante measures, meaning that the proxies capture the effect of liquidity after the trade and not before. The trade-based measures indicate what investors have been trading in the past, which does not necessarily indicate what will be traded in the future (Aitken et al., 2003).

2.2.2. Order-based Measures

In contrast to trade-based measures, order-based measures capture the ability to, and associated cost of, trading a security immediately. The bid-ask spread of a stock represents the cost of what an investor must accept in order to trade instantly, and is an order-based liquidity proxy (Aitken et al., 2003). The bid-ask spread is the difference between the bid price and ask price of a security. It is preferred to use high frequency data when applying a bid-ask spread measure of liquidity, but it results in difficulties when analyzing liquidity over an extensive time period or on various international markets, due to computing reasons (Guloglu & Ekinci, 2016). Using average bid-ask spreads estimated with accessible low frequency data makes it easier to study liquidity for a longer time period, as opposed to using intraday data. Many order-based proxies use low frequency data such as daily price or volume (Guloglu & Ekinci, 2016).

2.2.2.1. Closing Percent Quoted Spread

Chung and Zhang (2014) added to the existing research on liquidity proxies by introducing a percent-cost proxy, using low frequency data on closing ask and bid spreads. The spread on day t for a stock is denoted:

$$Closing\ Percent\ Quoted\ Spread = \frac{Closing\ Ask_t - Closing\ Bid_t}{(Closing\ Ask_t + Closing\ Bid_t)/2} \qquad (1)$$

2.3. Liquidity as a Determining Variable in Asset Pricing

Amihud and Mendelson (1986) first tested the hypothesis that the expected return of stocks is a concave function of the bid-ask spread, which posed as a proxy for the liquidity. The study found positive empirical evidence that such a relationship exists. Datar, Naik and Radcliffe (1998) performed an alternative test to Amihud's and Mendelson's, using turnover rate as a proxy for liquidity, and found similar results implying that liquidity plays a significant role in explaining stock return variations. Further studies have confirmed the positive relationship between illiquid stocks and excess return (Amihud et al., 2005). Brennan and Subrahmanyam (1996) estimated measures of illiquidity using intraday data and tested for the relationship between illiquidity and monthly stock return. They found a statistically significant relationship between required rates of return and the illiquidity measures, after adjusting for the Fama and French risk factors and effects of stock price level.

Amihud (2002) researched and found that expected market illiquidity positively affect ex ante stock excess returns over time. However, market liquidity betas are time-varying, implying that the premia vary over time (Kamara, Lou, and Sadka, 2008). Little is known about the source of this variance however (Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes, 2010; Karolyi, Lee, and van Dijk, 2012).

2.4. Commonality in Stock Liquidity

Chordia, Roll and Subrahmanyam (2000) studied the common determinants of liquidity on the US stock market and showed that various stock specific liquidity proxies co-moved with market-wide and industry-wide liquidity, meaning that there existed commonality in stock liquidity. Quoted spread, quoted depth and effective spreads where proxies which exhibited this characteristic. Huberman and Halka (2001) also document the presence of commonality in stock specific liquidity. In times of financial crisis, negative market returns decrease stock specific liquidity and increase commonality in liquidity (Hameed et. al, 2010). The reason behind the increase in commonality in liquidity is partly explained by Cifuentes et. al (2005). The increase is initiated when financial institutions mark their assets to market. When illiquid assets are sold by institutional investors, the market value of said assets will decrease. This will result in a trigger effect of depressed asset prices and increased illiquidity when other financial institutions hold the same assets and thus are forced to sell due to depreciating market prices.

2.5. Asset Pricing Models with Liquidity Risk

2.5.1. Amihud and Mendelson Model

Amihud and Mendelson (1986a) developed a basic asset pricing model where securities are illiquid due to exogenous trading costs. Investors are risk-neutral and have exogenous trading horizons. The model predicts that when an investor purchases a security, she will take future transaction costs into account when valuing the security. In this setting, the required return of the security is the required return for a equivalent liquid security, in addition to the expected trading cost per period.

2.5.2. Liquidity Based Asset Pricing Model (LAPM)

Holmström and Tirole (1998) sets up a model to capture the liquidity effect on asset prices. They expand the original Capital Asset Pricing Model to include a corporate finance aspect. The result is the Liquidity Based Asset pricing model, which includes liquidity as a determining variable in the asset pricing. Later, Acharya and Pedersen (2004) further developed this model by establishing the Liquidity Adjusted Capital Asset Model. In the model, a security's required return is dependent upon its expected return as well as the covariances of its own return and liquidity with the market return and liquidity.

2.5.3. Liquidity Adjusted Capital Asset Pricing Model

In Acharya's and Pedersen's (2004) paper, a liquidity variable was added to the CAPM instead, showing a difference in risk premium between illiquid and liquid stocks of 4.6 percent annually. They concluded that both the liquidity level of the stock and the liquidity risk was priced. Of the 4.6 percent difference in risk premium, 1.1 percent stems from the associated liquidity risk of a stock, while the remaining 3.5 percent was due to the expected liquidity level of the stock. The total liquidity risk premium of 1.1 percent was then attributed to three different sources of risk premia. The first, accounting for 0.08 percent of the premium, is due to commonality in a stock's liquidity with market liquidity, meaning that investors demand a premium for a stock that is illiquid when the market as a whole is illiquid. The second, accounting for 0.16 percent, is due to a stock's return sensitivity to market liquidity, meaning there is an investor preference for high return stocks when the market is illiquid, supported by the findings of Pastor and Stambaugh (2003). The third, accounting for 0.82 percent of the liquidity risk premium, is due to the stock's liquidity sensitivity to market returns, meaning investors are willing to pay a premium for stocks that are liquid when the overall market return is low. They conclude that while risk associated with liquidity contribute to expected return differences, the idiosyncratic level of liquidity based on share turnover of the stock, explains a larger proportion of differences in expected return.

2.5.4. Liquidity Variable in Fama and French Model

In 1992, Eugene Fama and Kenneth French published a paper establishing how the predictability of an assets return increased when adding size and value factors to the market factor used in the CAPM. As an extension to Fama and French's work, Pástor and Stambaugh (2003) studied how expected stock returns are related to the sensitivities of returns to fluctuations in aggregate liquidity, as opposed to the stock specific liquidity which has been studied by previous scholars (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Datar, Naik, and Radcliffe, 1998) Pástor and Stambaugh used a monthly aggregated liquidity measure, based on the average of stock specific measures calculated with daily order flow data. This produced a variable which measures a stock's returns covariance with fluctuations in market liquidity. They found that aggregate liquidity help explain the cross-sectional variance in stock returns over the years of 1966 to 1999. On an average, annual level between 1966 and 1999, there is a premium of 7.5 percent for stocks with higher return sensitivity to the aggregate liquidity levels on the market.

2.6. The 2007-2008 Financial Crisis

A financial crisis can occur in many forms, and while so, they exhibit common elements. Financial crises are multidimensional, thus being hard to characterize using a single indicator. Most crises show signs of substantial changes in credit volume and asset prices, extreme disruptions in financial intermediation and the supply of external financing to various actors in the economy, large scale balance sheet problems as well as large scale government support. In the aftermath of a financial crisis, asset prices and credit growth can remain depressed for a extensive period of time. Crises can also have effects on the real economy (IMF, 2013).

The global economy experienced a systematic failure over the years 2007-2008, which continued when entering 2009. Systematic failure can be considered the widespread failure of financial institutions, or the stagnation of capital flows to the real economy as a result of freezing capital markets. During the years 2007-2009 there was a negative liquidity shock to the U.S. and world capital market, being the largest shock to the worldwide financial system since the 1930's (Acharya et al., 2009). The Swedish stock market fell over 40% over the months between the beginning of 2008 to early December the same year (Österholm, 2009).

3. Method

In this thesis, we test whether stock specific liquidity can help explain return variations on the Swedish stock market by regressing excess return of stocks on size, value, market excess return and liquidity variables. The construction of the different risk variables is based on the work of Fama and French, who showed the significance of company size and book-to-market variables in explaining stock return variations in their research from 1992 (Fama and French, 1992) In this extension of Fama and French's work, we add a liquidity variable to test the role of liquidity in explaining stock return variations on the Stockholm Stock Exchange for the years 2007-2016. First, we perform a regression over the whole time period. Following this, we perform five different regressions for each time period; March 2007 - December 2008; January 2009 - December 2010; January 2011 - December 2012; January 2013 - December 2014 and January 2015 - December 2016.

The liquidity variable is constructed as the difference in return of illiquid and liquid stock portfolios, sorted on a monthly basis. The variable is then added to the monthly Fama and French variables and excess return dataset, forming a panel data structure. We use the fixed effects regression model to perform the tests. The collected data, liquidity measure, liquidity variable and regression model are explained in the following sections.

3.1. Data

Data used in our regressions has been collected from databases held by the Swedish House of Finance and Thomson Reuters. Market capitalization of each stock is collected from the Thomson Reuter Datastream database. Daily share price and bid-ask quotes of all available stocks on the NASDAQ OMX Stockholm from 1st of March, 2007 to 1st of December, 2016 have been collected from the FinBas database. The total number of stocks is 384. Prices and bid-ask quotes are adjusted for corporate actions. The adjustments for corporate actions refer to actions which will impact the sample abnormally. Such corporate actions are typically stock-splits, reverse stock-splits or rights issues which would have effects on the price of a security. These adjustments are already performed by Swedish House of Finance when data is collected.

The bid (ask) quote used in the study, is the highest price a potential buyer (seller) is willing to purchase (sell) the stock for at the end of the day, adjusted for corporate actions to make the quotes comparable over time. We use the last traded share price of the last trading day of each month. Some stocks have not been active during the whole 2007-2016 period, and some stocks lack data due to incomplete databases. Stocks missing data on price, bid-ask quotes or market capitalization are excluded in the months where data is missing.

Monthly Fama and French variables High-Minus-Low (*HML*), Small-Minus-Big (*SMB*) as well as the Excess Return of the market (*RMRF*), defined as the difference between the market return and the return of the 1-month Swedish treasury bill, have been collected from the Fama French database at Swedish House of Finance. Excess return of stock i at month t is defined as the difference between monthly return and the return of the 1-month Swedish treasury bill.

Table 1: Descriptive Statistics of Dependent Variable Excess Return

Variable	Obs	Mean	Std.Dev.	Min	Max
Excess Return	27885	.008	.094	-.267	.382

Descriptive statistics of dependent variable Excess Return for each stock i *at each month* t. *The sample consists of 118 months of data on 384 stocks listed on NASDAQ OMX Stockholm. Stocks missing data on price, bid-ask quotes or market capitalization are excluded in the months where data is missing.*

3.2. The Liquidity Measure

We use the the order-based "Closing Percent Quoted Spread" by Chung and Zhang (2014) as a proxy for stock specific liquidity of the stocks in our data sample. The Closing Percent Quoted Spread is calculated as the difference of the closing ask and closing bid price of a stock, divided by the median of closing ask price and closing bid price for the same time period. We use daily data to calculate a daily liquidity measure for each stock. Following this procedure, we calculate the average monthly spread. Thus, for each day t, the liquidity measure is calculated as:

$$Closing\ Percent\ Quoted\ Spread = \frac{Closing\ Ask_t - Closing\ Bid_t}{(Closing\ Ask_t + Closing\ Bid_t)/2} \qquad (2)$$

Order-based liquidity proxies are preferred over trade-based proxies as they capture the possibility to and associated cost of trading a security immediately (Aitken et al., 2003). Using a low frequency order-based proxy, such as the quoted spread, enables us to study the effect of liquidity on stock returns over a large period of time (Guloglu & Ekinci, 2016).

3.3. The Liquidity Variable

The liquidity variable used to test for the explanatory power of liquidity in stock return variations is defined as the difference in average monthly returns of two illiquid stock portfolios and two liquid stock portfolios. We construct the portfolios on a monthly basis accordingly:

First, the proxy for stock specific liquidity, Closing Percent Quoted Spread, is calculated on a daily basis and then averaged over the past month for all stocks.

Second, all stocks are divided into a “big” (BIG) or “small” (SMALL) group depending on their market capitalization. Stocks with market capitalization lower than the median, are classified as small stocks and are thus placed in the small sized group. Stocks with market capitalization bigger or equal to the median are classified as big.

Further, all stocks in each size group are divided into two additional groups, depending on their average monthly spread, one “illiquid” (ILLIQ) and one “liquid” (LIQUID) portfolio. Stocks with the 30% highest spreads are sorted into the illiquid portfolio, while stocks with the 30% smallest spreads are sorted into the liquid portfolio, in an attempt to isolate the differences in return due to liquidity differences. The remaining 40% in between the top and bottom 30% cut-offs is disregarded in that month. Portfolio formations are conducted in each month, using spreads and market capitalization of the same month, and then held for a month. Average returns are calculated for the portfolios on a monthly, value-weighted basis to reduce the risk of single observations affecting the results abnormally. Thus, four portfolios are constructed, two in each size group. One small illiquid portfolio (S/IL) and one small liquid portfolio (S/L), one big illiquid portfolio (B/IL) and one big liquid portfolio (B/L).

Lastly, the difference in return of the two ILLIQ and the two LIQUID portfolios are calculated as the average return of the two illiquid portfolios subtracted by the average return of the two liquid portfolios. These differences are calculated for each month t of the 118 months in the 2007-2016 period, and constitutes the liquidity variable LIQ.

$$LIQ_t = \frac{(S/IL)_t + (B/IL)_t}{2} - \frac{(S/L)_t + (B/L)_t}{2} \qquad (3)$$

The independent variables for each month t and the excess returns of each stock i for each month t are merged to one dataset. This dataset has a panel structure. We remove the 1st and 99th percentiles of the dependent variable in the regression, excess return, to avoid biased regression results due to large outliers.

3.4. Regression and Hypothesis Test

Individual stock returns of shares listed on the Stockholm Stock Exchange are regressed over time on the market, size, value and liquidity variables using the fixed effects regression model. For the fixed effects model to hold, the dependent variable (excess return of stock i) needs to be measured at least two times and those observations need to be directly comparable. Secondly, the independent variables *RMRF, SMB*, *HML* and *LIQ* need to differ in-between periods for the majority of the sample (Allison, 2009). Both of these assumptions hold.

We conduct our regressions with firm fixed effects. The fixed effects regression model is stated:

$$Y_{it} = \alpha_i + \beta_1 X_1 \ldots + \beta_k X_k + u_{it} \tag{4}$$

Using the fixed effects model, an empirical model of all independent variables except *LIQ* is first estimated accordingly for the whole sample period:

$$R_{it} = \alpha_i + \beta_{RMRF} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + u_{it} \tag{5}$$

Then, another regression model is estimated for the whole sample period, containing the *LIQ* variable:

$$R_{i,t} = \alpha_i + \beta_{RMRF} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{LIQ} LIQ_{T+} u_{it} \tag{6}$$

Where $R_{i,t}$ is the excess return of stock i at month t, *RMRF* the market excess return, *SMB* the size premium, *HML* the value premium and *LIQ* the illiquidity premium. β is the respective coefficients of the premiums and the stock i. The error term is denoted as u and the constant denoted as α.

To answer the research question of whether stock specific liquidity helps explain stock return variation over the sample period, a hypothesis test is conducted. If a illiquidity premium exists, the coefficient for *LIQ* should be positive and statistically different from zero. To test whether the empirical data is in line with the hypothesis of a positive coefficient for the liquidity variable, a double-sided test is conducted at the 0.05 level of significance.

$$H_0: \beta_{LIQ} = 0 \tag{7}$$

$$H_1: \beta_{LIQ} \neq 0 \tag{8}$$

Where the null hypothesis of a zero-effect coefficient is tested against the alternative hypothesis of a positive or negative coefficient for the *LIQ* variable. If the null hypothesis is rejected in favor of the alternative hypothesis, then the effects of the liquidity variable are statistically significant. Thus, to answer the question whether liquidity helps to explain stock return variations, the coefficient of the liquidity variable has to be significantly different from zero.

3.5. Regression Results Over Time

The model containing the liquidity variable is then analyzed over time, to see whether illiquidity premia have fluctuated in the 2007-2016 time period. More specifically, we look at how illiquidity premia might differ in times of financial crisis from times not considered as distressed.

Table 2: Number Months for Each Time Period

Time period	2007-2008	2009-2010	2011-2012	2013-2014	2015-2016
Months	22	24	24	24	24

The table shows the number of months in each time period. For each time period, a separate regression is conducted.

By regressing the liquidity model on stock returns over five different time periods; March 2007 - December 2008, January 2009 - December 2010; January 2011 - December 2012, January 2013 - December 2014 and January 2015 - December 2016, time variability of the illiquidity premium will be displayed in the different coefficients of each period. We define the years 2007 - 2008 as years of financial distress, following the global financial crisis. The following four time periods are considered as non-crisis time periods, with some limitations to the years 2009-2010, during which capital markets are assumed to still recover from the previous financial crisis.

Following the regression over the five time periods, p-values of coefficients and R-squares are averaged over the regressions within each period. We compare the statistics to inquire whether the illiquidity premium and its statistical significance has been more, less or equal during the different periods.

3.6. Robustness Checks

In order to ensure robust and correct regression result, we control and check for common problems that arise when running a fixed effects panel regression. The assumptions controlled for robustness are the assumptions of homoscedastic error terms, no autocorrelation in error terms and no multicollinearity in independent variables.

3.6.1. Hetero- and Homoscedasticity

In order to control for the assumption of homoscedasticity we use clustered standard errors at firm level in the regressions, by using of the robust option in the STATA regression command -xtreg-. If standard deviation of the regression model is non-constant over time, there is heteroscedasticity. If so, coefficients could be estimated inaccurately and with large standard errors (Wooldridge, 2009). Using the robust regression function in STATA manages this issue without producing negative side effects if error terms are in fact homoscedastic.

3.6.2. Autocorrelation in Error Terms

Another assumption is the uncorrelation of error terms. If error terms are in fact correlated over time the bias of the coefficients are unaffected. However, the standard errors could be wrongfully estimated. If standard errors are wrongfully estimated, t-scores of coefficients could potentially be overestimated, making the statistical significance of coefficients larger than in reality. Given the size of the sample for this thesis (N = 27885) and the relatively short time period (t = 118), autocorrelation of error terms is not considered to be an issue.

3.6.3. Multicollinearity

Multicollinearity occurs when the independent variables in a multiple regression are closely correlated with each other, which can result in predictors being able to linearly predict other predictors (Wooldridge, 2009). To ensure that the coefficients of the independent variables are accurately estimated, we check for multicollinearity by making sure none of the independent variables are highly correlated with another.

By producing correlation matrices in STATA, an overview and good sense whether multicollinearity is an issue or not is given. As there is no exact definition or cut-off where multicollinearity is an issue, a more cautious method will be pursued where correlations greater than 0.5 or smaller than -0.5 will be considered problematic. For the cases where the correlation is greater than 0.5, the empirical model will be corrected to account for the issues related to multicollinearity. Adjusting the model for multicollinearity issues can be difficult, since the most effective corrections are to either exclude one of the independent variables or to rewrite the model. In the context of this thesis, we will add new variables that works as functions of the previously correlated variables if problems with multicollinearity exist.

4. Results

4.1. Illiquidity Premium

Sorting stocks into illiquid and liquid portfolios and then creating the *LIQ* variable from the difference in average returns, we see that for 68 out of the 118 months tested for, the illiquid portfolios outperform the liquid portfolios. The average difference in return for the liquidity portfolios amount to 0.010% with a standard deviation of 0.038.

Table 3: Descriptive Statistics of LIQ

Variable	Obs	Mean	Std.Dev.	Min	Max
LIQ	118	.01	.038	-.073	.124

Descriptive statistics of independent variable LIQ over the whole sample time. LIQ is the constructed Illiquid-Minus-Liquid variable. The sample period consists of 118 months.

Sorting the return differences into five different time periods, some fluctuations in the illiquidity premium over time becomes apparent. In March 2007 - December 2008, the illiquidity premium is larger than for the following time period 2009-2010. During the subsequent two time periods, the premium for the illiquid portfolio is even higher, at 0.009% and 0.007% respectively, before it decreases to 0.026%.

Table 4: Descriptive Statistics of Independent Variable LIQ Over Time

Time Period	Obs	Mean	Std.Dev.	Min	Max
2007-2008	22	.005	.035	-.055	.063
2009-2010	24	.003	.046	-.073	.084
2011-2012	24	.009	.028	-.041	.074
2013-2014	24	.007	.034	-.061	.085
2015-2016	24	.026	.045	-.06	.124

Descriptive statistics of independent variable LIQ over the time periods tested for in separate regressions. LIQ is the constructed Illiquid-Minus-Liquid variable.

4.2. Regression Results

In our initial regression (5) on *SMB*, *HML* and *RMRF*, we find that all coefficients are positive and statistically significant. It would suggest that the model is successful in capturing the size and value effect of stock returns.

Table 5: Regression Results for Excess Return on RMRF, SMB and HML

Excess Return	2007-2016
RMRF	0.257***
	(0.0114)
SMB	0.384***
	(0.0144)
HML	0.340***
	(0.0202)
Constant	0.00865***
	(0.000112)
Observations	27,885
R-squared	0.041
Number of Companies	384

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.*
The regression is conducted on the dependent variable Excess Return and the independent variables RMRF, SMB and HML for all observations from 1st of March 2007 to 1st of December 2016. RMRF is the market excess return, SMB is the Fama and French Small-Minus-Big variable and HML is the Fama and French High-Minus-Low variable. The regression model is a fixed effects panel regression with firm fixed effects and clustered standard errors.

When adding the liquidity variable and running regression (6), we find minimal to no support for the explainability of the liquidity variable on stock returns, on the Stockholm Stock Exchange over the time period 2007 to 2016. The coefficient of the liquidity variable *LIQ* is 0.011, which suggests that investors demand higher return for illiquid stocks compared to liquid stocks. However, the standard error and p-value of the coefficient is high, at 0.018 and 0.568 respectively, making the coefficient effects insignificantly different from 0. Additionally, we see that adding the *LIQ* variable to our regression does not increase nor decrease the R-squared, suggesting little to no explanatory power of the liquidity variable.

Table 6: Regression Results for Excess Return on RMRF, SMB, HML and LIQ

Excess Return	2007-2016
RMRF	0.257***
	(0.0115)
SMB	0.383***
	(0.0147)
HML	0.340***
	(0.0202)
LIQ	0.0105
	(0.0184)
Constant	0.00853***
	(0.000248)
Observations	27,885
R-squared	0.041
Number of Companies	384

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
The regression is conducted on the dependent variable Excess Return and the independent variables RMRF, SMB and HML for all observations from 1st of March 2007 to 1st of December 2016. RMRF is the market excess return, SMB is the Fama and French Small-Minus-Big variable, HML is the Fama and French High-Minus-Low variable and LIQ is the constructed Illiquid-Minus-Liquid variable. The regression model is a fixed effects panel regression with firm-fixed effects and clustered standard errors.

4.3. Illiquidity Premium over Time

Dividing the 2007-2016 time period into five separate intervals and running the regression of stock excess returns on *RMRF*, *SMB*, *HML* and *LIQ* for each interval separately, differences in the regression results are noticeable. Looking at the result presented in Table 7, we observe that the period 2007-2008 has a strong negative coefficient on the liquidity variable *LIQ* of -1.027. The coefficient is statistically significant for a double-sided test of the coefficient being equal to zero. The other coefficients are slightly greater than zero, however, both *SMB* and *HML* are not statistically significant on a 5% significance level. The following period, 2009-2010, the coefficient of *LIQ* and *RMRF* are slightly positive but none are statistically significant. From 2011 until 2012, the *LIQ* coefficient turns negative again at -0.383 and with a p-value of 0.000. Regressions for the remaining two time periods, 2013-2014 and 2015-2016, return positive and statistically significant coefficients for LIQ. In 2013 until 2014, *RMRF* is rejected at a 90% significance level.

Table 7: Regression Results for Excess Return on RMRF, SMB, HML and LIQ over different time periods

Excess Return	2007-2008	2009-2010	2011-2012	2013-2014	2015-2016
RMRF	0.0635***	0.0564*	0.325***	-0.00508	0.368***
	(0.0214)	*(0.0334)*	*(0.0241)*	*(0.0409)*	*(0.0360)*
SMB	0.0447*	0.391***	0.690***	0.346***	0.864***
	(0.0228)	*(0.0320)*	*(0.0338)*	*(0.0359)*	*(0.0586)*
HML	0.0814	0.282***	-0.443***	0.386***	0.526***
	(0.0517)	*(0.0357)*	*(0.0623)*	*(0.0507)*	*(0.0403)*
LIQ	-1.027***	0.0443	-0.383***	0.135***	0.312***
	(0.0387)	*(0.0373)*	*(0.0466)*	*(0.0328)*	*(0.0216)*
Constant	-0.0178***	0.0303***	0.00430***	0.0169***	-0.00360***
	(0.000970)	*(0.000735)*	*(0.000497)*	*(0.000713)*	*(0.000728)*
Observations	4,241	5,115	5,509	5,960	7,060
R-squared	0.135	0.042	0.095	0.027	0.090
Number of Companies	256	253	269	291	334

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*
The regressions are conducted on the dependent variable Excess Return and the independent variables RMRF, SMB and HML. Unique regressions are run for each time period March 2007 - December 2008, January 2009 - December 2010; January 2011 - December 2012, January 2013 - December 2014 and January 2015 - December 2016. RMRF is the market excess return, SMB is the Fama and French Small-Minus-Big variable, HML is the Fama and French High-Minus-Low variable and LIQ is the constructed Illiquid-Minus-Liquid variable. The regression model is a fixed effects panel regression with firm-fixed effects and clustered standard errors.

4.4. Robustness Test: Correlation of independent variables

Producing a correlation matrix for the independent variables, we conduct a robustness test of multicollinearity in our model. As two, or more, of the independent variables could possibly correlate, multicollinearity could occur, causing estimation error(s) of one or more coefficients. Looking at the correlation of *RMRF*, *HML*, *SMB* and *LIQ*, we see no correlation greater or smaller than 0.5 and -0.5 respectively. Thus, multicollinearity is not considered an issue.

Table 8: Correlation Matrix of RMRF, HML, SMB and LIQ

Variables	RMRF	HML	SMB	LIQ
RMRF	1.000			
HML	0.246	1.000		
SMB	-0.339	-0.470	1.000	
LIQ	-0.001	-0.022	0.083	1.000

Matrix of correlations between independent variables RMRF, HML, SMB and LIQ used in the regression model. RMRF is the market excess return, SMB is the Fama and French Small-Minus-Big variable, HML is the Fama and French High-Minus-Low variable and LIQ is the constructed Illiquid-Minus-Liquid variable.

5. Analysis

In our findings, we find no statistically significant relationship between stock specific liquidity and return data, meaning that illiquid stocks do not outperform liquid stocks on a statistically significant basis for the whole 2007-2016 time period on NASDAQ OMX Stockholm. Additionally, when looking at shorter time periods, the coefficient of the liquidity variable differs significantly, suggesting that the effect of liquidity on stock return is varying over time.

5.1. Illiquidity Premia in Liquid Markets

According to traditional finance theory, with increased risk investors demand higher compensation for holding these risky assets. As such, the expected return of risky assets is higher than non-risky assets. The lack of support for an illiquidity premium on the NASDAQ OMX Stockholm could be the result of a generally high level of market liquidity, or in other words, very little liquidity risk in general on the Swedish stock market. Previous research has pointed out that a great deal of stock specific liquidity stems from common determinants (Chordia, Roll and Subrahmanyam, 2000; Huberman and Halka, 2001). If Sweden is considered an overall liquid market with high commonality in liquidity, it would mean that many of the stocks exhibit low liquidity risk and that little of this risk stems from stock specific liquidity determinants.

In the regressions of this thesis, stocks are characterized as liquid or illiquid based on the relative level of liquidity. If the overall liquidity risk is low and little of the risk is due to stocks' specific liquidity, it might be difficult to distinguish relative differences in liquidity between stocks. Further, the method for this thesis does not take into account the possibility that an illiquid stock, relative its peers, might still be easy to liquidate for the investor, if the overall market liquidity and commonality in liquidity is high. The consequences of this phenomenon would be low explanatory power of the liquidity variable on returns if the relative difference in liquidity is small, which is in line with our results.

Further, measuring whether an individual stock is, on an absolute or relative level, illiquid or not is difficult due to the abstract nature of illiquidity itself. The main issue in previous literature has been to find a satisfactory measure of liquidity (Amihud et al., 2005). Liquidity is a complex concept and as such, the measure of liquidity used in this thesis could be lacking in capturing the real effect of stock specific liquidity on stock returns, especially if commonality in liquidity is high.

In the question of the pricing of liquidity risk, a possible explanation for the insignificant liquidity variable is that that investors seek additional return for the absolute level of illiquidity rather than if a stock is relatively less liquid than another. If Sweden is considered a liquid market and if there is commonality in liquidity as previous research has confirmed (Chordia, Roll and Subrahmanyam, 2000; Huberman and Halka, 2001), stocks on the Stockholm Stock Exchange would most likely be liquid on an absolute level. In the event that investors value absolute liquidity levels more than relative liquidity, this would result in an insignificant liquidity variable which is based on a measure of relative liquidity. This argument is in line with the results of this thesis.

5.2. Time-variability of the Illiquidity Premium

5.2.1. Negative *LIQ* Coefficient

Between the time periods of our sample, the effects and significance of the liquidity variable on stock return variations fluctuates. During the first and third period, 2007-2008 and 2011-2012, the coefficient of *LIQ* is negative and statistically significant, suggesting that illiquidity has had a negative effect on stock returns during those periods. The sign of the coefficient, as well as the magnitude, makes the causality questionable, since compensation for holding liquid stocks would be on the contrary to traditional finance theory. However, the exhibited negative effects of illiquidity during 2007-2008 could be due to an increase in valuation of liquid stocks during the financial crisis. In times of financial crisis, liquidity levels decrease and market return is low, investor preference for liquid stocks and willingness to pay a premium for these increase (Acharya and Pedersen, 2004). Further, in times of financial crisis, commonality in liquidity increase (Hameed et. al, 2010). This is mainly caused by financial institutions having to sell off assets which have depreciated in value. When a trend of increased illiquidity and decreased asset prices thus is triggered (Cifuentes et. al, 2005), it is possible that previous findings on the positive relationship between illiquidity and stock returns no longer holds.

The causes and consequences of a financial crisis are not easily characterized as crises can occur in different forms (IMF, 2013). Previous research underlined the difficulty of measuring liquidity in general (Aitken and Winn, 1997), and measuring liquidity correctly in times of financial crisis could prove even more so when new market mechanisms might be present. As such, it is possible that during the years of crisis, market wide mechanisms affected stock returns on the Swedish Stock Exchange in ways which the method for this thesis does not capture. Furthermore, a negative *LIQ* coefficient is not in line with previous research on the relationship between stock specific liquidity and returns (Amihud and Mendelson, 1986; Brennan and Subramanyam,1996; Datar, Naik, and Radcliffe, 1998). Thus, this result suggests that the coefficient estimation in this thesis is lacking in explaining the effect of stock liquidity on stock returns, and not that it has existed negative illiquidity premiums (positive liquidity premiums) in 2007-2008 and 2011-2012.

5.2.2. Positive *LIQ* Coefficient

For the periods 2013-2014 and 2015-2016, the regression results suggest that liquidity does in fact help explain stock return variations and that there is a premium for illiquid stocks on the Stockholm Stock Exchange during the years in question. However, the regression from the first of these two periods present a very low R-square as well as a highly insignificant coefficient on *RMRF*. The coefficients are statistically significant however, meaning that liquidity helps explain stock return variations in these periods, but only small fractions of the total variation.

The liquidity coefficient is not statistically significant 2009-2010, suggesting that liquidity has no effect on stock returns during these years.

5.3. Limitations in Proxy Definition

Looking at the definition of our liquidity variable, we find indication to why our regression produces high p-values, different signs and fluctuating size of the coefficient on the liquidity variable.

First, the liquidity variable is based on low frequency data. When using an order-based measure of liquidity, it is preferred to use high frequency data (Guloglu & Ekinci, 2016). Using daily or monthly data strongly reduces the amount of data used and simplifies the model. While this allows for easier computations, it overlooks the effects of liquidity on an intraday level (Guloglu & Ekinci, 2016). As an effect, the accuracy in measurement of the liquidity proxy might decrease, producing less statistically significant regression results as an effect.

Second, the difficulties of defining and measuring liquidity on a general level pose problems in researching its effect on asset prices and returns, as it is ambiguous how investors take liquidity into consideration when valuing stocks. Approximating liquidity as the quoted relative of the bid ask spread on a one-month basis might not fully estimate how investors evaluate liquidity, if the time spectrum used by investors is longer.

Furthermore, some qualities of liquidity, such as free float, is not caught by solely measuring the bid-ask spread. To fully account for stock level liquidity, the amount of stocks not available to the public and on the open market, such as shares held by public institutions or company officers, would have to be accounted for. Using the free float of stocks as an additional measure of liquidity or accounting for it in the overall variable could provide a better measurement of the liquidity level and increase the accuracy of the proxy variable.

6. Conclusion

This thesis intends to provide further knowledge about the relation of liquidity and stock returns on the Stockholm Stock Exchange, as well as analyze how this relationship has differed during the financial crisis compared to afterwards. Specifically, we examine how stock specific liquidity help explain stock return variations on the Stockholm Stock Exchange over the period 2007-2016. Additionally, we study if the effects of liquidity on stock return variation have varied over time to conclude if the importance of liquidity has differed during the financial crisis of 2007-2008 compared to 2009-2016. We conduct this by regressing individual excess stock returns on size, value, market and liquidity risk variables, where liquidity of a stock is measured as the Closing Percent Quoted Bid-Ask Spread (Chung and Zhang, 2014) and Fama and French variables.

In this study, we find no statistically significant effect of stock specific liquidity levels on stock return variation on the Stockholm Stock Exchange over the sample years. An explanation could be that there is low liquidity risk on the Swedish stock market overall, and that potentially only a small fraction of this risk stems from stock specific liquidity determinants captured by our model. Measuring liquidity is difficult, and it is possible that the liquidity measure in this thesis does not capture the stock specific liquidity effect on returns. Additionally, if Sweden is a liquid market and little of the liquidity risk comes from stock specific liquidity sources, all stocks will be liquid on an absolute level. If investors value absolute liquidity levels over relative liquidity, then this could help explain why the liquidity variable used in this thesis is insignificant.

Furthermore, results show that the effects of liquidity on returns strongly varies when dividing the sample into five different time periods. During 2007-2008 and 2011-2012, there seem to have been a premium for liquid stocks over illiquid stocks, contrary to the initial hypothesis of this thesis. Results of other time periods, except for 2009-2010, are in line with previous research, showing a higher return of illiquid stocks and a statistically significant effect of liquidity on stock return variations. The statistically significant negative effect of illiquidity on stock returns 2007-2008 could be due to an increase in investors' preference of liquid stocks during times of financial crisis. However, as our results are inconsistent and vary strongly between time periods, we believe the results are due to problems with the method used in this thesis. A simple liquidity measure has been used, with daily rather than intraday data. This could prove inferior to other studies making use of more complex measures or high frequency data.

Future research should therefore focus on the determinants of liquidity in financial crises, and test for a model which captures the eventual mechanisms of stock-specific liquidity in times of financial crisis. Further, such research should aim to use high-frequency data to capture all dynamics of the effect of liquidity on stock returns.

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8. Appendix

8.1. Creation of Fama and French Variables

The Fama and French variable small minus big (*SMB*) is calculated as the difference in average monthly return of one portfolio consisting of small-cap stocks and one portfolio consisting of large-cap stocks. The high minus low variable (*HML*) is calculated as the difference in average monthly return between two portfolios of high book-to-market equity stocks and two portfolios of low book-to-market equity stocks.

The *SMB* portfolios are constructed by dividing stocks into either a “small” or “big” group, with the stock exchange’s median market capitalization working as the divider between the two. Stocks with below median market cap are classified as “small” and stocks above median market cap as “big”, which creates two portfolios. Stocks in each of the two portfolios are then sub-divided into three groups depending on their equity book-to-market ratio, creating a total of six portfolios. In detail, stocks in the “small” portfolio are divided into either a low, medium or high book-to-market portfolio according to a 30/40/30% split, creating three portfolios: Small/low, Small/medium and Small/high. Following this, the same procedure is then applied to the “big” portfolio, creating the Big/low, Big/medium and Big/high portfolios. The Fama and French variables are then constructed by calculating the average return of the three “small” portfolios minus the average return of the three “big” portfolios, resulting in the *SMB* variable. Similarly, the *HML* variable is constructed by calculating average return of the two “high” portfolios minus the average return of the two “low” portfolios. The portfolio construction and average return difference calculations are repeated each month.

Table 9: Descriptive Statistics of Fama and French Variables

Variable	Obs	Mean	Std.Dev.	Min	Max
RMRF	118	.006	.051	-.182	.216
SMB	118	-.009	.054	-.328	.244
HML	118	.002	.034	-.099	.137

Descriptive statistics of Fama and French variables used in the regressions. RMRF is the market excess return, SMB is the Fama and French Small-Minus-Big variable and HML is the Fama and French High-Minus-Low variable.