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Do stock-level liquidity shocks predict stock returns?

-Evidence from the Swedish stock market

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Abstract

Adopting a methodology similar to Bali, Peng, Shen and Tang (2014), this essay investigates whether stock-level liquidity shocks predict future returns on the Swedish stock market. Liquidity is measured by the relative bid-ask spread. Portfolios with stocks that experienced positive liquidity shocks yield higher returns than portfolios with stocks that experienced negative liquidity shocks. The mean of the slope coefficient for liquidity shocks was significant in stock-level Fama-MacBeth regressions, controlling for beta, size, book-to-market and liquidity level, meaning that liquidity shocks indeed seem to predict higher future returns. Furthermore, it was found that portfolios sorted on relative bid-ask spread show no clear signs of a liquidity premium, indicating that the relationship between returns and the bid-ask spread shocks could be a correlation without causality.

Keywords: stock-level liquidity shocks, liquidity, bid-ask spread, liquidity premium

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1. Introduction

Liquidity takes form in several dimensions. A liquid asset can be described as an asset that can be bought or sold at ease; quickly, with low direct costs, in large amounts, without there being any considerable impact on its own price (Liu, 2006). Its implications on asset pricing have been investigated mainly in two ways. First, there is the asset specific liquidity. Different assets are liquid to different degrees. Given that investors prefer liquid assets, these assets should be priced higher than illiquid ones (Amihud & Mendelson 1986). The price difference between liquid and illiquid assets is referred to as the *liquidity premium*. Second, there is the market wide liquidity, or the *systematic liquidity,* which could be interpreted as the macro perspective of the asset specific liquidity. Fluctuations of systematic liquidity give rise to *illiquidity risk*. Chordia, Roll and Subrahmanyam (2000) defined a form of liquidity risk by introducing *commonality in liquidity,* the covariation between the liquidity of assets and the systematic liquidity. Illiquidity risk can also be defined as covariations between asset returns and the systematic liquidity (Pastor & Stambaugh, 2003). Acharya & Pedersen (2005) derived a model in which the covariation between asset liquidity and the market return factor also is included, in addition to the illiquidity risks introduced by Chordia et al. (2000) and Pastor & Stambaugh (2003).

A new way of examining liquidity is due to Bali, Peng, Shen and Tang (2014). Previous research has mostly focused on stock-level liquidity as a characteristic, and fluctuations in systematic liquidity as a risk source, while fluctuations in stock-level liquidity have received little attention. The findings by Bali et al. (2014) are that positive shocks to stock-level liquidity are associated with higher contemporaneous returns. The findings are in line with earlier research on the liquidity premium. The authors argue that if a stocks' liquidity suddenly increases, the stock price should also increase, as the liquidity premium gets incorporated into the price. However, by examining future returns of portfolios sorted by liquidity shocks, as well as performing predictive cross-sectional regressions of returns on realized liquidity shocks and an extensive list of control variables, they also find that the liquidity shocks predict returns in the next month (and several months ahead), a market under-reaction that seems to be a result of investor inattention and illiquidity in itself. The stocks experiencing liquidity shocks are mainly illiquid stocks with small analyst coverage, which contributes to the delayed reaction in the share price (Bali et al., 2014).

The concept of stock-level liquidity shocks is a largely unexplored area in the asset pricing literature. Following the paper by Bali et al. (2014), this essay aims to shed further light on the

issue of stock-level liquidity shocks, providing new empirical evidence from the Swedish stock market. The sample consists of 412 stocks listed on the main Swedish stock exchange during the period 2001-06 to 2016-07, with monthly data on returns and daily data on bid-ask spreads. Specifically, the aim of this essay is to test the thesis that stock-level liquidity shocks are positively associated with contemporaneous returns, and that they can predict future stock returns. Further, the aim of this paper is to investigate whether there is a liquidity premium using the same measure for liquidity as used when calculating the liquidity shocks. This issue is important since the liquidity premium is a main theoretical argument for the existence of a causal relationship between liquidity shocks and returns.

The main findings are that when sorting stocks into decile portfolios by values of liquidity shocks, the average returns are fairly monotonically increasing across the portfolios, both for contemporaneous and one-month-ahead returns. The one-month-ahead return difference between the top and bottom decile portfolios is 1.3% and 1.2% for equal-weighted and value-weighted returns, respectively. The stocks that experience the largest liquidity shocks are mainly small and illiquid stocks. The predictive power of liquidity shocks is confirmed in cross-sectional regressions of next months' returns on liquidity shocks, controlling for beta, market value, book-to-market ratio and relative bid-ask spread. When including all the variables, the Fama-MacBeth coefficient of shocks to the relative bid-ask spread is 0.333 with a *t*-statistic of 1.894. This implies an average return difference of 1% between the top and bottom decile portfolio sorted by liquidity shocks. Furthermore, when comparing portfolios sorted by the relative bid-ask spread, there is no clear sign of a liquidity premium, which questions its presumed importance in explaining the returns associated with liquidity shocks.

The next section provides some background and discussion of previous research on liquidity. In section III the data is presented along with descriptive statistics. Section IV presents the methodology. Results from performing portfolio analysis and cross-sectional regressions using the Fama-MacBeth method are presented in section V. Finally, section VI provides summary and conclusions, with some suggestions on further research.

2. Literature review

2.1 Liquidity

Recognizing that there are various ways to characterize assets in terms of how liquid they are, early research on the US stock market argued that the perceived liquidity of a stock could affect how investors will price it. In a landmark study, Amihud and Mendelson (1986) derived a model in which the expected returns of assets could be described with a concavely increasing function of illiquidity. The emphasis of their analysis was that trading costs more for illiquid assets than for liquid assets, and that these costs should get incorporated into the asset prices. By using the quoted Bid-Ask spread for measuring trading costs, they provided empirical evidence supporting their thesis. Brennan & Subrahmanyam (1996) made a distinction between variable trading cost and fixed trading cost when analyzing illiquidity. Departing from the microstructure literature, they argued that the price impact of trades was an important indicator of illiquidity, and that this price impact was different across different sizes of trades, hence the variable trading cost. Although the researchers mentioned above approached the problem somewhat differently both empirically and theoretically, the common basic finding from these papers was that there exists an *liquidity premium*, that is, the more illiquid an asset is, the less investors are willing to pay for it, making more illiquid assets yield a higher expected rate of return, all else equal.

2.2 Liquidity risk

The liquidity premium has remained highly relevant throughout the literature on liquidity-related asset-pricing. Once the liquidity premium was established through early empirical evidence, numerous papers investigated the mechanisms by which illiquidity affects asset prices. By emphasizing the commonality and time variation of illiquidity, a new line of research was developed, and the concept of *liquidity risk* made its way into the asset pricing literature. An important study by Chordia et al. (2000) introduced the concept of *commonality in liquidity*. In their paper the authors placed microstructure phenomena in an economy wide context by stating that illiquidity was not just an idiosyncratic, asset specific phenomena, but a wider phenomenon related across assets and over time, where asset specific liquidity covariated with market wide liquidity. The time varying aspect is also emphasized in Amihud (2002), who concluded that

expected stock market illiquidity affected expected stock returns positively, while unexpected illiquidity shocks affected contemporaneous returns negatively. Amihud also suggested that due to an effect of flight to liquidity, it was illiquid assets in particular who were the most sensitive to these fluctuations, adding one more dimension to the illiquidity premium. This relationship was questioned by Lou & Sadka (2011) who found that stocks with high liquidity risk were not necessarily small, illiquid stocks.

Liquidity risk can be interpreted and defined in several ways. Following the results of Chordia et al. (2000), Pastor and Stambaugh (2003) estimated how sensitive stocks' returns are to a measure of aggregated stock market liquidity. They found cross-sectional evidence that stocks with higher sensitivities to the market liquidity had higher expected returns, supporting their thesis that market wide liquidity was a priced state variable. Acharya and Pedersen (2005) derived and tested a liquidity-adjusted capital asset pricing model that took into account three different measures of liquidity risks at the same time. Their model addressed three covariations: (i) between asset specific liquidity and market wide liquidity, (ii) between asset specific returns and market wide liquidity and (iii) between asset specific liquidity and market returns. Liu (2006) used a factor mimicking portfolio constructed by buying the most illiquid stocks and selling the most liquid stocks. Following Liu (2006), Amihud (2014) also used a model with a liquidity mimicking portfolio factor. They both found evidence on a priced liquidity risk.

2.3 Stock-level liquidity shocks

Another way to examine the relation between stock liquidity and returns was provided by Bali et al. (2014). By defining a measure on liquidity shocks at the stock level and using this measure in a cross-sectional setting, they found that the shocks had significant predictive power on stock returns. Since there is well established evidence on a liquidity premium on the US stock market, it comes as no surprise that contemporaneous returns are positively correlated with liquidity shocks. However, the fact that liquidity shocks might predict future returns is somewhat more puzzling, given that liquidity shocks can be observed using publicly available information. Bali et al. (2014) concluded that the market underreacts to stock-level liquidity shocks, possibly due to market frictions, illiquidity and investor inattention. A similar study is described in a working paper by Chordia, Subrahmanyam & Tong (2015), examining the effects of shocks to order flow level and volatility, which are closely related to liquidity. Consistently with the results of Bali et al. (2014) they found that returns could be predicted for several months ahead.

The findings of Bali et al. (2014) indicate that liquidity does not only affect asset prices *per se*, but it also affects *how asset prices are formed.* According to the efficient market hypothesis, prices should always reflect the information available to investors (Zvie, Kane, & Marcus, 2011). However, when there are market frictions, trading is costly and arbitraging is less profitable, making prices adjust slower to public information (Bali et al., 2014). A study by Chordia, Goyal, Sadka, Sadka, & Shivakumar (2009) showed that the post earnings announcement drift was considerably stronger in illiquid than in liquid stocks, and that transaction costs erased a major part of the profits of an arbitrage strategy. Similarly, Hong et al. (2000) found that potential profits of momentum strategies were larger for smaller stocks. Korajczyk & Sadka (2004) also showed that liquidity reduces de facto profits of trading on anomalies. This strand of literature offers some explanation as to why the market seems to underreact to liquidity shocks.

2.4 Measuring stock liquidity

One frequently emphasized feature of stock market liquidity is that it is not easily measured. Illiquidity is a concept with multiple dimensions and the availability on microstructure data is varying. Several measures intended to proxy for illiquidity has been used in the literature, mainly focusing on the three dimensions represented by spread, depth and resiliency.

Amihud & Mendelson (1986) focused on spread by using daily data on relative bid-ask spread, which is the difference between the ask- and bid-prices, over their mid-point value. The bid-ask spread captures the costs of being an impatient trader, in other words, how costly it is to sell or buy an asset *quickly*. If one wants to buy an asset with immediate transaction execution, it has to be bought at the ask price. Analogously, if one wants to sell an asset without waiting, it has to be sold at the bid price. In this way Amihud and Mendelson (1986) argued that the bid-ask spread was a suitable candidate for an illiquidity measure. Brennan & Subrahmanyam (1996) pointed out that a problem with this measure was that for larger amounts of shares, trades often occur outside the quoted spread. This means that the spread does not take the market depth into account.

Recognizing the short-comings of the bid-ask spread, Amihud (2002) proposed a new simple measure of illiquidity, namely the ratio of the absolute value of daily return to the dollar trading volume on that day. It addresses the market depth, and the resulting price impact effect of trades, the basic intuition behind it being that if a small trading volume makes the stock price move largely, then the stock is illiquid. The price impact will then constitute an indirect transaction cost

to the trader, who will have to accept less attractive prices the larger the trade. Amihud has continued to use this measure since first proposed in his paper in 2002, being frequently used by other researchers as well.

Another measure that use volume and return data to capture price impact is the return reversal measure (Pastor & Stambaugh, 2003). However, instead of directly trying to measure the price impact of trading volume as in Amihud's measure, Pastor and Stambaugh focused on the resiliency resulting from illiquidity. They argued that if a stocks return one day is abnormally large (either positively or negatively) simply due to a large trade flow, the stock should experience some return reversal on the following day, as the stock price then would have deviated from its fundamental value. In short, the measure is formed by OLS regressions of next day returns on previous day returns and trading volume. The magnitude of the coefficient for trading volume is used as the liquidity measure (Pastor & Stambaugh, 2003).

Numerous measures of liquidity have been used in addition to the ones mentioned above. A more complete discussion is provided by Goyenko, Holden, & Trzinka (2009), who compares a wide range of different measures previously used in the literature, investigating how they perform in measuring liquidity.

This study will use the relative bid-ask spread as liquidity measure, due to its superior data availability on DataStream.

3. Data

The data on share price, bid- and ask price, book-to-market ratio and market value is collected from Reuters DataStream over the period 2001-06-01 to 2016-06-01 (data on bid- and ask-prices does not appear in DataStream before 2001-06). Share price, book-to-market ratio and market value are monthly data, while bid- and ask-prices are daily data. Share prices are also collected for the period 1997-07-01 to 2001-07-01, for the purpose of estimating market betas. The risk free rate used in this essay is the interest rate on 30-days Swedish treasury bills, which was retrieved for the period 1997-07-01 to 2016-06-01 in monthly observations from the Riksbank website[1].

To make sure that the sample consists of stocks publicly listed on the Swedish main stock exchange (Stockholmsbörsen), stock lists from old issues of Dagens Industri (a Swedish business magazine) were examined as well as information on changes to the lists (including stock name changes, new listings and delistings) from Nasdaq's website[2]. More specifically, the stock lists that made up the main exchange were called "A-listan" and "O-listan" for the period 2001 to 2006. A change was then introduced to the lists and the stocks were divided into three lists called "Large-cap", "Mid-cap" and "Small-cap" for the period 2007-2016. Only stocks that appeared in any of these lists some time during the sample period are included in the sample used in this study. For companies with several stock classes carrying different voting rights, the stocks with superior voting rights are excluded.

3.1 Relative bid-ask spread

This essay uses the relative bid-ask spread as a measure of illiquidity. A limitation to this measure, that larger trades often occurs outside the spread, is noted by Brennan & Subrahmanyam (1996). The quoted bid- and ask-prices for a particular day is defined in DataStream as the last observed prices for that day, which means that it does not cover intraday variations of the spread. A big advantage with this measure is that it only needs data on bid-price and ask-price, which is available for a large set of stocks on DataStream. When searching for trading volume (in SEK), the total sample was restricted to 283 stocks, while data on bid- and ask-prices was available for

[1] (http://www.riksbank.se/en/Interest-and-exchange-rates/search-interest-rates-exchange-rates/)
[2] (http://www.nasdaqomx.com/transactions/markets/nordic/corporate-actions/stockholm/changes-to-the-list)

412 stocks. The daily relative bid-ask spread is calculated from quoted bid- and ask-prices. Daily bid-ask spreads with a value of 0 or less are deleted. A stock's relative bid-ask spread for a given month t, $SPRD_{i,t}$, is calculated as the average of the daily relative bid ask spreads within the month, if there are at least 15 days of data:

$$SPRD_{i,t} = avg\left[\frac{P_{i,d}^{Ask} - P_{i,d}^{Bid}}{(P_{i,d}^{Ask} + P_{i,d}^{Bid})/2}\right], \quad (1)$$

A relatively large value of $SPRD_{i,t}$ indicates that the stock is relatively illiquid.

3.2 Shocks to the relative bid-ask spread

Following Bali et al. (2014), monthly liquidity shocks are defined as the negative of the monthly illiquidity measure, $SPRD_{i,t}$, demeaned by its 12 months preceding average:

$$SPRDshock_{i,t} = -(SPRD_{i,t} - AVGSPRD_{i|t-12,t-1}) \quad (2)$$

The demeaned $SPRD_{i,t}$ is multiplied by -1 for convenience. A large value of $SPRDshock_{i,t}$ indicates that the liquidity has increased. The average monthly number of stocks in the sample that has data on $SPRDshock_{i,t}$ is 244.

3.3 Control variables

The control variables used in the cross-sectional regressions are Beta, Ln_MV, Ln_BM and SPRD. Monthly Beta is estimated for each stock using a rolling window of 60 months. A beta is estimated if there are at least 36 months of return data in the estimation window. The market return factor is the value weighted returns of stocks, less the risk free rate. Ln_MV is the natural logarithm of market value of capital (ordinary shares in issue * share price, MSEK). Ln_BM is the natural logarithm of the book-to market ratio. Both Ln_MV and Ln_BM are based on end of month observations. SPRD is the monthly average of the relative bid-ask spread.

3.4 Descriptive statistics

Table 1 reports summary statistics on the variables used in this study. The mean, median, standard deviation, maximum and minimum values of the variables are cross-sectional estimations for each month, averaged over the sample period (2002-07-01 to 2016-06-01). There seems to be a wide cross-sectional dispersion of liquidity shock-values, with a mean of 0.00088 and standard deviation 0.013, and maximum and minimum values of 0.078 and -0.081.

Table 1

Summary statistics

Variable	Mean	Median	Std. Dev	Max	Min
Ret	0.90	0.12	11.47	0.73	-0.38
SPRD	0.019	0.013	0.023	0.2135	0.0012
SPRD-shock	0.00088	0.00066	0.013	0.078	-0.081
Beta	0.96	0.88	0.53	3.05	-0.15
Ln_MV	7.03	6.92	2.05	12.79	1.44
Ln_BM	-0.62	-0.63	0.92	3.96	-3.98

Return is excess return over the risk free rate, calculated as percentage. SPRD is the monthly average of daily relative bid-ask spreads.

The cross-sectional correlations across the variables are reported in Table 2. For each month I estimate the correlation of the variables across the stocks. These correlation coefficients are then averaged over the sample period. The average correlation between market value and spread is negative (-0.61) which means that smaller firms have a larger spread, indicating that they are more illiquid than larger firms. There is a positive average correlation between contemporaneous returns and liquidity shocks, consistent with the findings of Bali et al. (2014).

Table 2

Correlations

	SPRD	SPRD-shock	Beta	Ln_MV	Ln_BM
SPRD	1				
SPRD-shock	-0.13	1			
Beta	-0.13	-0.01	1		
Ln_MV	-0.61	-0.06	0.06	1	
Ln_BM	0.05	-0.03	0.02	-0.29	1
Ret	-0.05	0.07	-0.02	0.06	-0.09

SPRD is the monthly average of daily relative bid-ask spreads.

4. Methodology

The main methodology in this essay is inspired by the paper by Bali et al. (2014). First, the cross section of returns is analyzed at portfolio level, using univariate sorting by stock-level spread shocks. Second, monthly stock-level cross-sectional regressions are performed using the Fama-MacBeth method. I also search for the liquidity premium by comparing portfolios sorted by liquidity as measured by the relative bid-ask spread.

Forming portfolios sorted by stocks' characteristics is a simple way of examining whether cross-sectional variation of stock characteristics is associated with different rates of return. Stocks are sorted into decile portfolios, that is, ten portfolios containing ten percent of the stocks each. Portfolio 1 contains the stocks with the lowest values in the characteristic of interest, while portfolio 10 contains the stocks with the highest values. The average returns of the portfolios are estimated over the sample period and compared across the portfolios. A problem with this approach is that the examined characteristic could be correlated with some unobserved factor that is not being controlled for.

In addition to the portfolio analysis described above, stock-level cross sectional regressions are performed to further examine the predictive power of liquidity shocks, using the method introduced by Fama-MacBeth (1973). For each month in the sample period, returns in month t +1 are regressed on $SPRDshock_{i,t}$ and four other explanatory variables, using cross-sectional OLS. This yields a 168-month time series for each coefficient. The *t*-statistics for the time series estimated means are used to determine whether they are significantly different from zero. A well-known problem with the Fama-MacBeth method is the issue of errors-in-variables, causing a downward bias in the coefficient for estimated market beta. This is often mitigated by using portfolios of stocks instead of individual stocks as test assets, reducing the noise in beta estimations. However, this would disable the possibility of using individual stock characteristics, giving a smaller dispersion of values in the regression variables.

5. Results

5.1 Portfolio analysis of liquidity shocks

This section performs a cross-sectional analysis by sorting stocks into decile portfolios. First off, I investigate whether contemporaneous returns are higher for stocks that experience positive liquidity shocks than for stocks that experience negative liquidity shocks. Then I sort portfolios based on realized liquidity shocks, to examine if they carry any power in predicting returns. Finally, some characteristics of the portfolios are reported. All returns are calculated as excess returns over the risk free rate.

5.1.1 Contemporaneous returns

In the beginning of each month t, ten portfolios are formed, based on the value of $SPRDshock_{i,t}$ for each stock. It is important to note that these portfolio returns would not be possible to exploit as an investing strategy, since $SPRDshock_{i,t}$ is not known until the end of month t. Portfolio 1 contains the ten percent stocks with the lowest values of $SPRDshock_{i,t}$, while portfolio 10 contains the ten percent stocks with the highest values of $SPRDshock_{i,t}$. The returns of the portfolios are calculated both equally weighted and value-weighted.

Table 3 reports the returns, along with their associated *t*-statistics. The stocks with the lowest values of $SPRDshock_{i,t}$ that is, stocks that are subject to relatively large negative liquidity shocks, clearly have lower returns than the stocks that are subject to relatively large positive liquidity shocks. Portfolio 1 has the lowest equal-weighted (value-weighted) returns of -0.72 (-0.19), while portfolio 10 has the highest returns, 2.59 (2.08). The returns seem to be fairly monotonically increasing over the portfolios. This relationship could partly be due to a liquidity premium, however it is also highly possible that the liquidity-shocks and returns jointly are effects of some unobserved factors or events.

Table 3

Contemporaneous returns

Decile	(Low) 1	2	3	4	5	6	7	8	9	(High) 10	High-Low
Ret (equal weight)	-0.72	-0.32	0.29	0.52	0.79	0.98	1.28	1.59	1.66	2.59	3.3
	(-1.52)	(-0.61)	(0.57)	(0.99)	(1.58)	(2.04)	(2.53)	(3.36)	(3.45)	(4.97)	(8.46)
Ret (value weight)	-0.19	-0.26	0.17	0.16	0.56	0.79	1.25	1.66	1.81	1.89	2.08
	(-0.37)	(-0.56)	(0.35)	(0.34)	(1.15)	(1.56)	(2.56)	(3.28)	(3.67)	(3.66)	(4.82)

Sorted on SPRD-shock. *t*-statistics in parentheses. Returns are calculated for the same month as the liquidity shock. Returns are average monthly returns over the period 2002-07-01 to 2016-06-01, calculated as percentages. High – Low displays the returns of portfolio 10 minus the returns of portfolio 1.

5.1.2 Next months' returns

To investigate whether liquidity shocks have any potential in predicting future returns, 10 portfolios are formed in a similar manner as in the previous section. However, for the purpose of this analysis portfolios are formed *in the end* of month t, based on the *realized* values of $SPRDshock_{i,t}$. In Table 4 the one-month-ahead returns for these portfolios are reported. The returns over month t+1 are still (fairly monotonically) increasing with the level of $SPRDshock_{i,t}$, indicating that the liquidity shocks indeed seem to have some predictive power. The return difference between the top and bottom decile portfolios is still economically and statistically significant, both for equal-weighted (1.3%, t=3.75)) and value-weighted returns (1.2%, t=2.48).

Table 4

Returns 1 month after realized liquidity shocks

Decile	(Low) 1	2	3	4	5	6	7	8	9	(High) 10	High-Low
Ret (equal weight)	0.07	0.56	0.46	0.63	1.14	0.8	1.1	1.22	1.62	1.36	1.3
	(0.14)	(1.07)	(0.91)	(1.29)	(2.21)	(1.59)	(2.36)	(2.56)	(3.36)	(2.78)	(3.75)
Ret (value weight)	0.17	0.59	0.33	-0.01	0.67	0.97	1.12	1.21	1.62	1.37	1.2
	(0.34)	(1.20)	(0.68)	(-0.01)	(1.26)	(1.94)	(2.16)	(2.50)	(3.14)	(2.69)	(2.48)

Portfolios are sorted by SPRD-shock. *t*-statistics in parentheses. Portfolio returns are calculated for month t+1. Returns are average monthly returns over the period 2002-07-01 to 2016-06-01, calculated as percentages. High – Low displays the returns of portfolio 10 minus the returns of portfolio 1.

5.1.3 Portfolio characteristics

Table 5 presents the portfolio characteristics of the liquidity-shock portfolios. There is a wide dispersion of liquidity-shock values, with averages ranging from -0.015 in the bottom decile to 0.016 in the top decile, which is in line with the high standard deviation reported in the descriptive statistics. The portfolios in the top and bottom deciles seem to be mainly small, illiquid stocks, compared to the portfolios located in the middle. Bali et al. (2014) reports a similar pattern in their liquidity-shock portfolios.

Table 5

Portfolio characteristics

	(Low)									(High)
Decile	1	2	3	4	5	6	7	8	9	10
Avg. SPRD-shock	-0.0152	-0.0045	-0.0023	-0.0009	0.0001	0.0011	0.0023	0.0038	0.0063	0.0161
Avg. SPRD	0.0242	0.0143	0.0108	0.0092	0.0098	0.0106	0.0122	0.0149	0.0198	0.0355
Avg. Mkt. Share	4.93%	10.06%	14.25%	16.91%	15.41%	12.37%	10.35%	7.97%	5.75%	2.01%

Portfolios are sorted on SPRD-shock. *t*-statistics in parentheses. Avg. SPRD is the average of $AVGSPRD_{i|t-12,t-1}$ across the stocks in each portfolio.

5.2 Cross-sectional regressions

The results of the Fama-MacBeth regressions are presented in Table 6. The monthly cross sectional regressions are of the same form as Bali et al. (2014), with excess returns of month t+1, regressed on liquidity shocks, and other variables of month t. The regressions include an intercept ($\propto_{t+1}$). First, I only include SPRD-shock and Beta in the regressions:

$$R_{i,t+1} = \propto_{t+1} + \gamma_{1,t+1} * SPRD_{i,t}^{shock} + \gamma_{2,t+1} * \beta_{i,t} + \varepsilon_{i,t+1} \quad (3)$$

The average of the coefficient for SPRD-shock is positive with an estimated value of 0.363 and it is significant in a two-tailed test at the 5 % level (t=2.085). Beta is positive but not significant (t=0.195). The small value of Beta could be due to the errors-in-variables issue, causing the coefficient to be biased towards zero.

Next, the variables Ln_MV and Ln_BM is included, to control for market value and book-to-market:

$$R_{i,t+1} = \propto_{t+1} + \gamma_{1,t+1} * SPRD_{i,t}^{shock} + \gamma_{2,t+1} * \beta_{i,t} + \gamma_{3,t+1} * Ln\_MV_{i,t} + \gamma_{4,t+1} * Ln\_BM_{i,t} + \varepsilon_{i,t+1} \quad (4)$$

This reduces the average coefficient for SPRD-shock to 0.342, but still being significant at the 5 % level (t=2.004). The largest impact of the two control variables seems to come from Ln_BM, with a highly signinficant estimated average of 0.007 (t=5.461). Ln_MV has a positive though non-significant average coefficient. Finally, the liquidity level (SPRD) is added to the regressions:

$$R_{i,t+1} = \propto_{t+1} + \gamma_{1,t+1} * SPRD_{i,t}^{shock} + \gamma_{2,t+1} * \beta_{i,t} + \gamma_{3,t+1} * Ln\_MV_{i,t} + \gamma_{4,t+1} * Ln\_BM_{i,t} + \gamma_{5,t+1} * SPRD_{i,t} + \varepsilon_{i,t+1} \quad (5)$$

When adding SPRD to the regressions the SPRD-shock coefficient average is reduced to 0.333 with a t-statistic of 1.894, significant at the 10% level in a two-tailed test. The average of the coefficients for SPRD is negative but not significantly different from zero. The sign of SPRD was expected to be positive, since illiquid assets should yield higher returns than liquid assets, if there is a liquidity premium. In an essay by Lunina & Dzhumurat (2010) the authors find a positive (yet insignificant) coefficient for illiquidity as measured by the relative bid-ask spread. This motivates a sub-period robustness check. In this study, the same method outlined above over the sub-period 2002-07 to 2010-07 is performed, including all variables in the regressions (the time period used by Lunina and Dzhumurat is 2004-04 to 2010-04). The sign of SPRD is now positive (0.119), though non-significant (t=0.770). This result is similar to the findings of Lunina & Dzhumurat (2010). The average coefficient of SPRD-shock and Ln_BM are still positive and significant.

An economic interpretation of the coefficient estimate of SPRD-shock can be made by comparing it to the portfolio characteristics reported in Table 5. The difference of the average value of spread shocks between the top and bottom decile is 0.031. Multiplying this with the coefficient estimate (0.33) for SPRD-shock implies a return difference of 1%.

While this study use four additional variables, Bali et al. (2014) use a list of 24 control variables in the cross-sectional regressions. It could be that the liquidity shocks are correlated with other variables not controlled for, causing an over-estimation bias of its coefficients.

Table 6

Coefficient averages from cross-sectional regressions

	Sample period			Sub-period
SPRD-shock	0.363	0.342	0.333	0.493
	(2.085)	(2.004)	(1.894)	(2.382)
Beta	0.001	0.000	-0.001	0.003
	(0.195)	(-0.096)	(-0.245)	(0.646)
Ln_MV	-	0.001	0.000	0.000
	-	(0.812)	(0.480)	(-0.055)
Ln_BM	-	0.007	0.007	0.009
	-	(5.461)	(5.446)	(4.780)
SPRD	-	-	-0.044	0.119
	-	-	(-0.296)	(0.770)

t-statistics in parentheses. The sample period covers 2002-07 to 2016-06 while the sub-period covers 2002-07 to 2010-07.

5.3 Looking for the liquidity premium

One argument stating that contemporaneous returns of stocks should be affected positively by positive shocks to liquidity comes from the illiquidity premium. If there is an illiquidity premium, illiquid stocks have a higher expected rate of return than liquid stocks. If the liquidity of a stock increases, the price of that stock should also increase, due to the liquidity premium. The evidence on a liquidity premium is largely established in the empirical research on the US market, over several liquidity measures, the relative bid-ask spread being one of them. However, for the Swedish market the empirical research is not as extensive, motivating the analysis carried out in this section.

To find out whether liquidity is priced I sort portfolios by the stocks' relative bid-ask spreads. Interestingly, I do not find any clear cut evidence on a liquidity premium when measuring liquidity with the relative bid-ask spread. Table 5 reports returns of portfolios sorted by their level of liquidity, as measured by $SPRD_{i,t}$ and the 3-, 6- and 12-month averages of $SPRD_{i,t}$.

Table 7

Portfolios sorted on SPRD, equal-weighted

Decile	(Low) 1	2	3	4	5	6	7	8	9	(High) 10	High-Low
1 month	0.76	0.77	1.06	0.92	1.23	1.04	1.00	0.85	0.79	0.39	-0.36
	(1.77)	(1.60)	(2.21)	(1.72)	(2.24)	(2.10)	(2.06)	(1.61)	(1.56)	(0.75)	(-0.84)
3 months	0.61	0.91	0.99	1.08	1.06	0.95	0.74	1.26	0.82	0.32	-0.29
	(1.39)	(1.94)	(2.06)	(1.97)	(1.91)	(1.98)	(1.53)	(2.25)	(1.64)	(0.53)	(-0.69)
6 months	0.60	1.03	0.89	0.94	1.08	0.65	0.80	1.28	0.88	0.49	-0.11
	(1.36)	(2.09)	(1.87)	(1.71)	(2.03)	(1.35)	(1.62)	(2.43)	(1.81)	(0.94)	(-0.25)
12 months	0.62	0.97	0.86	1.06	0.98	0.59	0.88	1.04	0.87	0.71	0.10
	(1.36)	(1.98)	(1.80)	(1.88)	(1.79)	(1.24)	(1.77)	(2.10)	(1.85)	(1.35)	(0.21)

The portfolios are sorted by the monthly liquidity measure (1 month) and different averages of the monthly measure (3, 6 and 12 months averages).

This questions the thesis that the observed returns associated with $SPRDshock_{i,t}$ are motivated by a liquidity premium. For robustness I also resort portfolios each 3, 6 and 12 months instead of each month. In this way the potential effect of different holding periods is controlled for. Table 8 reports the returns of these portfolios. The returns of the lowest decile portfolio seem to be lower than the other portfolios in all cases, however, the returns are not conclusively increasing across the portfolios.

Table 8

Portfolios sorted on SPRD, different re-sorting intervals

Decile	(Low) 1	2	3	4	5	6	7	8	9	(High) 10	High-Low
3m resort	0.61	0.98	1.02	0.84	1.16	0.93	0.83	1.07	0.86	0.61	-0.01
	(1.40)	(2.02)	(2.19)	(1.55)	(2.14)	(1.86)	(1.68)	(2.11)	(1.64)	(1.17)	(-0.02)
6m resort	0.60	0.91	0.92	1.03	0.90	0.90	0.80	1.17	0.96	0.70	0.10
	(1.34)	(1.91)	(1.91)	(1.90)	(1.72)	(1.73)	(1.60)	(2.36)	(1.90)	(1.37)	(0.24)
12m resort	0.65	0.92	0.79	1.07	0.85	0.91	0.77	1.07	0.80	0.69	0.04
	(1.36)	(2.04)	(1.68)	(1.92)	(1.63)	(1.71)	(1.53)	(2.29)	(1.73)	(1.33)	(0.09)

Portfolios are sorted based on the average SPRD over the preceding 3 months. The portfolios are resorted each 3, 6 and 12 months respectively, which means that three different holding periods are examined.

Table 9 reports some characteristics on portfolios sorted by relative bid-ask spread. Noticeably, the lowest decile portfolio contain an average market share of 67% which is considerably larger than any of the other portfolios. The negative relationship between size and bid-ask spread displayed in table 9 is consistent with the findings in the descriptive statistics. This is in line with the notion that larger firms are more liquid than smaller firms. However, this also indicates that there is no sign of a size premium either. In contrary to this result, Foye (2015) finds a size premium on the Swedish stock market over the period 1997-2013. It could be that sorting on size in particular would yield different results. Foye (2015) also uses a slightly smaller sample of stocks.

Table 9

Portfolios sorted on SPRD, characteristics

	(Low)									(High)
Decile	1	2	3	4	5	6	7	8	9	10
SPRD	0.0024	0.0039	0.0060	0.0086	0.0114	0.0145	0.0177	0.0214	0.0278	0.0484
Market share	66.87%	18.20%	6.16%	3.29%	1.92%	1.30%	0.78%	0.66%	0.51%	0.31%

Portfolios are sorted based on the average SPRD over the preceding 12 months.

6. Conclusion

The main findings from this study are that when forming portfolios with stocks sorted by liquidity shocks, both contemporary and one-month-ahead returns are found to be increasing with liquidity shocks, giving support to the thesis that stock-level liquidity shocks are positively associated with contemporaneous and future returns. The one-month ahead equal-weighted and value-weighted return difference between the top and bottom deciles are 1.3% and 1.2%, respectively. The stocks in the top and bottom deciles of these portfolios are small, illiquid stocks.

The results from the portfolio analysis are confirmed in stock-level cross sectional regressions using the Fama-MacBeth methodology controlling for beta, book-to-market, market value and liquidity. When including all variables in the regressions, the average of the coefficient for SPRD-shock is positive with an estimated value of 0.333, which implies a return difference of 1% between the top and bottom deciles of portfolios sorted by spread shocks. While the results from the portfolio analysis and the Fama-MacBeth regressions are supportive to the thesis of Bali et al. (2014), this study does not employ an as extensive list of control variables, which leaves room for the possibility of omitted variables.

The mechanisms behind the liquidity shocks and their relationship to returns remain an unexplored topic. Since one of the possible explanations is the liquidity premium, return differences across portfolios sorted by the relative bid-ask were examined. However, there is no strong evidence confirming any liquidity premium, which questions the presumed causal relationship behind liquidity-shocks and returns.

The ability to predict returns is not in line with the efficient market hypothesis, which states that asset prices should always reflect all available information. This could partly be explained by the fact that the liquidity shocks mainly occur for the most illiquid stocks. Since arbitrage opportunities are limited when trading is costly, price adjustments will be slower for illiquid assets. Another possible explanation could be that there is some unobserved priced risk factor correlated with the liquidity shocks.

It is important to note that the conclusions that can be made from this study are limited to the relatively short time period and also to one single measure of liquidity (the relative bid-ask spread). A suggestion for further research on the Swedish stock market is to compare results

from different measures for liquidity and also longer periods of time, if possible. It could also be of interest to include more control variables in cross-sectional regressions, to rule out alternative possible factors behind the returns.

More research needs to be done on what the causes are behind stock-level liquidity shocks. It would be interesting to disentangle the relationship between liquidity shocks and returns, since it does not seem unreasonable to assume that the correlation is not entirely causal.

The literature on liquidity and its implications on asset pricing has continued to evolve over the last three decades, making it an ever intriguing field of study. Since the stock-level liquidity shocks constitute a whole new approach, it is a topic that probably will gain considerable attention in future research.

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