Illiquidity and Stock Returns:

Empirical Evidence from the Stockholm Stock Exchange

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Abstract:
In this paper we use a quantitative method to study if illiquidity contributes to explaining variations in stock returns across stocks and across time on the Stockholm Stock Exchange during the period 1990-2010. We find support for the hypothesis that excess stock market returns increase with the expected illiquidity of the stock market. In addition, we find that unexpected increases in stock market illiquidity have a negative effect on contemporaneous stock prices. We find limited support for a cross-sectional relationship between illiquidity and cross-sectional risk-adjusted returns. The relationship appears to be stronger for stocks of smaller firms than for larger firms and also appears to have become weaker over the time period of our sample. The linkage between stock illiquidity and returns is well documented in the asset pricing literature, but research has primarily been conducted on American stock exchanges. The idea behind an illiquidity factor in asset pricing is that investors should not only require compensation for the risk of holding capital assets but also for the costs of trading capital assets.

Keywords: Illiquidity, Asset Pricing, Stockholm Stock Exchange, Bid-Ask Spread, Price Impact

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1 Introduction

1.1 Background

"Investors prefer to commit capital to liquid investments, which can be traded quickly and at low cost whenever the need arises. Investments with less liquidity must offer higher expected returns to attract investors. In equilibrium, the expected returns on capital assets are increasing functions of both risk and illiquidity"

Amihud and Mendelson (1991, p.56)

How the risk of an investment should affect its expected return is a central question in finance. Capital asset pricing theory is based on the idea that risk-averse investors require compensation for taking on risk. Thus, their required expected returns should increase with the riskiness of the asset. Sharpe (1964) suggests that risks that can be diversified away in a large portfolio should not be priced; meaning that only the systematic component of risk should affect required returns. In contrast, Fama & French (1992) find empirically that the market capitalization and the market-to-book value of equity are important factors for explaining variations in stock returns. While neither Fama & French (1992) nor Sharpe (1964) explicitly account for transaction costs, Amihud & Mendelson (1991) argue that investors require compensation for the costs they incur to immediately trade an amount of assets. The cost of immediacy in supply and demand is referred to as illiquidity costs. Amihud & Mendelson (1986) propose that illiquidity should be priced because illiquidity costs, unlike idiosyncratic risk, do not cancel out in large portfolios.

In line with Amihud & Mendelsons (1986) argumentation, research has found that proxies of illiquidity costs contribute to explain variations in returns across stocks. Amihud & Mendelson (1986), Datar, Y Naik, & Radcliffe (1998), and Amihud (2002) all find that illiquidity has a positive effect on risk-adjusted stock returns on the American stock market. Similar findings have been documented on other markets, including the London stock exchange (Florackis, Gregoriou, & Kostakis, 2011) and the Spanish stock exchange (Marcelo & Quirós, 2006).

While these studies indicate that investors require compensation for the costs associated with holding an illiquid stock, empirical evidence from the American stock market (Chordia, Roll, & Subrahmanyam, 2001) and the Hong Kong Stock Market (Brockman & Chung, 2002) indicates that the illiquidity of individual stocks co-moves over time. Thus, research has studied whether time-series variations in the overall illiquidity level of an exchange affects returns. Amihud (2002), Acharya & Pedersen (2005) and Pástor & Stambaugh (2003) find that expected market illiquidity contributes to explain variations in stock returns over time on the American stock market, while Marcelo & Quirós (2006) presents similar result on the Spanish stock market.

1.2 Motivation and contribution

The purpose of this paper is to study if illiquidity costs contribute to explain variations in stock returns on the Stockholm Stock Exchange over the period 1990-2011. In this paper, we answer two main questions:

1. Does illiquidity contribute to explain variations in stock returns across stocks?
2. Does the illiquidity of the aggregated stock market contribute to explain variations in stock returns over time?

We argue that these questions are of interest to investors as well as companies on the Stockholm Stock Exchange. If illiquid stocks yield higher stock returns, institutional investors such as life insurance companies and pension funds with long investment horizons could benefit from investing in illiquid stocks. The reason is that the illiquidity costs should be of relatively small magnitude due to the length of their investment horizons. A cross-sectional illiquidity effect on stock returns would also be a motivation for Swedish companies to increase the liquidity of their stocks to reduce their costs of capital. For example, companies with illiquid stock could contract with market-makers whose purpose is to increase the liquidity of the stock.

An additional motivation for our study is that previous studies on the Stockholm Stock Exchange have found that the prediction accuracy of the CAPM and the Fama & French three factor model is limited, for example Novak & Petr (2010), Asgharian & Hansson (2002) and Östermark (1991). Thus, it seems reasonable that stock returns are also affected by other risk factors. As the Stockholm Stock Exchange shows large variations in illiquidity costs across stocks and over time, illiquidity is an interesting factor to investigate.

Previous research has focused on the American stock markets, although some research has been conducted on other stock markets such as the Spanish, the Japanese and the British stock markets. While previous research has found that both cross-sectional variations in illiquidity and time-series variations in illiquidity affect stock returns, we have only found one study on illiquidity and stock returns on Swedish stock data. Westerholm (2002) studies the most actively traded stocks on the Stockholm Stock Exchange over the period 1990-1995. In line with research on other stock exchanges, such as the NYSE, he finds that illiquidity costs have a positive effect on cross-sectional stock returns. We extend the research by investigating a larger sample of stocks over a longer period of time and also by employing other illiquidity proxies than Westerholm (2002). In addition, we study if variations in illiquidity over time affect excess stock returns, which to our knowledge has not previously been studied on the Stockholm Stock Exchange. Thus, we contribute by investigating if the illiquidity effect documented on other stock exchanges is generalizable to the Stockholm Stock Exchange, which should be of particular importance to investors.

1.3 Disposition and summary

The paper proceeds as follows. In the second chapter, we describe different aspects of illiquidity and motivate our choice to focus on market tightness and market depth. These aspects are related to the costs of executing orders on the stock exchange. We also explain the two main components of illiquidity costs: waiting costs and costs of asymmetric information. To understand under which conditions illiquidity would affect stock prices, we continue by contrasting two theories on the linkage between illiquidity and asset pricing.

In the third chapter, we discuss empirical research on the illiquidity-return relationship and develop three hypotheses:

1. *The risk-adjusted return of individual stocks is positively related to stock illiquidity*
2. *The excess return of the stock market portfolio is positively related to the expected average illiquidity of the market.*
3. *The excess return of the stock market portfolio is negatively related to unexpected increases in the illiquidity of the market.*

These hypotheses are supported by evidence from foreign stock exchanges but have not been tested on Swedish stock market data. In the fourth section, we develop economic models to test our hypotheses. These models are based on the idea that investors make investment decisions on the first of April based on information about risk and illiquidity that is publicly available at the investment date. In addition we motivate our choice of illiquidity proxies and risk factors. We use relative bid-ask spreads to proxy for market tightness and a measure of price impact costs, ILLIQ, to proxy for market depth. These measures are calculated from daily stock data which we have collected from Thomson Reuters DataStream. To reduce the risk that our results are due to inappropriate risk adjustments, we use two parallel model specifications to adjust for risk: CAPM augmented with size and momentum factors, and the Fama-French three-factor model with a momentum factor.

In the fifth chapter, we describe the statistical models we use to test our hypotheses. The first hypothesis is tested with an OLS panel regression. We regress the excess monthly stock return of each stock on the illiquidity and risk characteristics of each stock, and obtain one coefficient for each stock characteristic and month. We compute the coefficient for the whole period as the average of the monthly coefficients. The second and third hypotheses are tested with a time-series regression. We regress the average excess stock return of the market on measures of the expected and unexpected illiquidity of the market. The regression results are adjusted for heteroscedasticity and autocorrelation in regressions where these effects are present.

The results of our regressions are discussed in chapter six. We find weak support for the hypothesis that illiquidity has a positive effect on risk-adjusted cross-sectional stock returns. The coefficient of the relative bid-ask spread is stable between regressions with different risk-adjustments although it is only statistically significant in the regression where we use the augmented CAPM to adjust for risk. The coefficient of the price impact measure, ILLIQ, is not economically and statistically significant in any of our risk specifications. Thus we find no support for the hypothesis that price impact costs, as expressed by ILLIQ, affect cross-sectional stock returns. The hypothesis that expected illiquidity has a positive effect on excess stock returns and unexpected illiquidity has a negative effect on excess stock returns is supported in the regressions where we use relative bid-ask spreads as a proxy for illiquidity. The results of the regression with price impact costs, ILLIQ, indicate that unexpected ILLIQ has a negative effect on stock returns whereas the coefficient of expected ILLIQ is not statistically significant.

In chapter seven, we conclude that the market risk premium appears to include compensation for expected illiquidity costs. We also conclude that differences in illiquidity between stocks appear to have a limited effect on stock prices and that the effect appears to be weaker than in the American stock exchanges. We also find that the effect appears to be stronger in smaller companies and that it appears to have decreased in strength over the time period of the sample.

2 Theoretical framework

In Section 2.1 we elaborate on the concept of illiquidity and distinguish between different aspects of illiquidity. We continue by presenting two theories that emphasize the two main components of illiquidity costs: waiting costs (Demsetz, 1968) and asymmetric information (Kyle, 1985). While our study makes no distinction between these costs, the theories are useful to understand why illiquidity costs arise and to understand our choice of proxies. In Section 2.3, we contrast two theories with different predictions on the effect of illiquidity on cross-sectional stock returns.

2.1 Definition of illiquidity

Illiquidity includes different components which are related to the costs of executing transactions in the capital markets. Amihud & Mendelson (1991) suggest that illiquidity costs represent the difference between the actual transaction price and the price that would have prevailed in the absence of a transaction. As it is impossible to determine the price that would have prevailed in absence of a transaction, research has studied different aspects of illiquidity costs. The aspect of illiquidity costs that is most commonly addressed in the literature is the cost of immediate order execution. For small order quantities, the cost of immediate order execution is reflected in the spread between the bid and the ask price (Amihud & Mendelson, 1991). For any degree of illiquidity, the cost of execution of large order quantities tends to increase with the order quantity. The cost of executing large orders is reflected in the impact of order flow on the execution price, and price impact costs can be interpreted as the effective spread on large transactions (Amihud & Mendelson, 1991).

Black (1971, p. 30) describes a liquid market as a market where:

"There are always bid and asked prices for the investor who wants to buy or sell small amounts of stock immediately.

The difference between the bid and asked prices (the spread) is always small.

An investor who is buying or selling a large amount of stock, in the absence of special information, can expect to do so over a long period of time at a price not very different, on average, from the current market price.

An investor can buy or sell a large block of stocks immediately, but at a premium or discount that depends on the size of the block. The larger the block, the larger the premium or discount."

In line with this description, Kyle (1985) defines a liquid market as a market characterized by *depth*, *tightness* and *resiliency*. The depth of the market reflects the order quantity that the market can absorb without affecting prices. If the market is deep, investors can trade large order quantities without affecting prices. The tightness of the market reflects the cost of immediately turning around a small position. If the market is tight, investors can always trade at the bid and ask price and the spread between these prices is small. Resiliency reflects the speed with which stock prices converge to the underlying value of the stock after a price chock that is not related to the underlying value of the stock. If the market is liquid, investors immediately place orders to take advantage of temporary mispricing and thus the resiliency is high. (Kyle, 1985)

In this paper, we focus on market tightness and market depth. Much of the previous research on the illiquidity-return relationship has focused on these aspects, and one possibility would thus be to extend the research by focusing on resiliency. On the other hand, the research on market depth, market tightness and stock returns is limited on the Stockholm Stock Exchange. Therefore, we extend the research by studying another sample than those of previous studies. By focusing on market depth and market tightness we will also be able to base our method on the methods used in previous research and compare our results to those of previous studies.

2.2 Components of illiquidity costs

Research suggests that illiquidity costs include one component associated with immediacy in supply and demand (Demsetz, 1968) and one component associated with asymmetric information (Kyle, 1985). Although Demsetz (1968) studies bid-ask spreads whereas Kyle (1985) studies price impact costs, research suggest costs of immediacy in supply and demand and asymmetric information affect both of these measures (Glosten & Harris, 1988) (Brennan & Subrahmanyam, 1996). We will not decompose our measures of market depth and market tightness into these components. Nevertheless, it is useful to understand the concepts of immediacy in supply and demand and asymmetric information to concretize the concept of illiquidity costs. In addition, the studies by Demsetz (1968) and Kyle (1985) are considered seminal studies within the area of capital asset illiquidity.

2.2.1 Waiting costs

Demsetz (1968) shows that illiquidity costs arise in equilibrium because the demand and supply curves do not represent always present market orders. Investors thus incur costs since they cannot count on immediately finding counterparties willing to transact at the prevailing market price. Demsetz (1968) proposes that the spread between the bid and the ask price reflects compensation to market participants that stand ready and waiting to meet orders of investors who require immediate order execution. Conversely, the spread reflects the price investors incur for immediate order execution. Investors who stand ready and waiting place limit orders and investors who require immediate order execution place market orders. Limit orders are executed at the price specified by the investor when a matching order arrives whereas market orders are executed immediately at the best available price. Liquidity is thus provided by investors who accept to stand ready and waiting. As these investors incur waiting costs, they will always require a better price than investors that require immediate order execution.

As matching limit orders and matching market orders do not generally arrive at exactly the same point in time, limit orders are matched with market orders (Demsetz, 1968). The ask price is determined by the intersection of the demand curve of market buying orders and the supply curve of limit selling orders. Likewise, the bid price is determined by the intersection of the demand curve for limit buying orders and the supply curve of market selling orders. Demsetz (1968) proposes that the bid-ask spread is negatively related to the trading activity on the market. This is because higher trading frequency results in lower waiting costs on limit orders and thus investors will be prepared to pay less for immediate execution.

In order-driven markets, liquidity is solely provided by market-participants that place limit orders. Thus, immediate order execution of market orders is dependent on other investors' willingness to place limit orders. However many markets operate with market-makers who are obliged to quote bid and ask prices to make trading possible at all times. To make trading possible even when there is no matching limit and market orders, market-makers hold inventories of short and long positions in stocks. As the market-makers require compensation for their waiting costs and other inventory costs, they charge a premium for immediately filling incoming market buying orders and require a discount for immediately filling incoming market selling orders (Demsetz, 1968).

The Stockholm Stock Exchange shares many characteristics with order-driven markets. Trading is organized such that investors submit either limit orders or market order to exchange member firms. The member firms can submit orders to the central order book as brokers for their customers and as dealers for themselves. Thus they can hold inventory to act as market-makers to their customers but they have no obligation to quote prices. In the central order book, the prices of limit sell orders represents ask quotes whereas the prices of limit buy orders represent bid quotes. The limit orders are stored in the order book and are automatically filled by market orders according to the price-time principle. That is, the limit orders with the best price are executed first and afterwards, in the event of price parity, according to the time of their arrival in the central order book (Hollifield, Miller, & Sandås, 2004). Liquidity providers, which are hired by companies to quote prices on their shares at all times, were first allowed in year 2002 (Söderberg, 2009).

2.2.2 Costs of asymmetric information

Kyle (1985) relates illiquidity to asymmetric information among investors and trading frequency. He distinguishes between informed investors with private information about the value of the stock and uninformed investors who lack such information. The trades of the informed investors are motivated by arbitrage opportunities whereas uninformed investors trade randomly. As market-makers have the same information set as the uninformed traders and cannot distinguish between informed and uninformed investors, they incur losses from trading with the informed investors. To make zero profits, the market-makers recover these losses in their trades with the uninformed investors. Thus uninformed investors make losses on average. It is important to note that the model is adopted for quote-driven markets. However, Brockman & Chung (2002) find that investors who place limit orders alter their prices in the same manner as market-makers when they expect informed trading. Thus, the logic behind the model adopted by Kyle (1985) is still applicable to understand the illiquidity costs related to asymmetric information on order-driven markets.

Kyle (1985) suggests that market-makers set prices as a function of the order quantities placed by informed and uninformed traders. As uninformed investors trade randomly, the market-maker interprets changes in order quantity as an indication of informed trading. Thus they increase their prices in response to increases in order quantity. As informed investors are aware of the price-setting strategy of the market-maker, they consider the impact of their order quantity on the prices established by the market-maker. Kyle (1985) shows that the profit-maximizing order quantity of the informed investors is related to the frequency with which trading take place. If trading does not take place continuously, the informed investors place order such that their private information is gradually incorporated into prices. If trading is continuous, private information is gradually incorporated into prices at a constant rate. Thus the market-maker does not expect that changes in order quantity are due to informed trading. In other words, the compensation required by the market-maker for trading with informed investors does not vary with order quantity. Thus investors can trade large amounts of stocks without affecting the prices established by the market-maker.

2.3 Illiquidity costs and stock returns

In this section we contrast two different views on illiquidity costs and asset pricing. Amihud & Mendelson (1986) argue that illiquidity costs should have a large impact on cross-sectional stock returns whereas Constantinides (1986) argues that illiquidity only should have a small impact on stocks prices.

Amihud & Mendelson (1986) model investors with different holding periods and stocks with different bid-ask spreads. They argue that investors require compensation for investing in stocks with high spreads. However, the spread is more costly for investors with short holding periods than it is for investors with long holding periods, since investors amortize the cost of the spread over their holding periods. In equilibrium the expected stock returns increase with the cost of the spread, but the relationship between expected stock returns and illiquidity costs is concave. The reason is that long-term investors, who amortize the spread over long periods, benefit from holding stocks with higher expected returns and higher spreads. For short term investors, the cost of the spread would eliminate any excess return from holding illiquid stocks. As long-term investors amortize the spread over longer periods, they require less compensation for increases of the spread than short-term investors require for a corresponding increase. Thus, the spread has a smaller impact on the expected returns of high spread stocks, held by long-term investors, than on the expected returns of low spread stocks which are held by short-term investors. Amihud & Mendelson (1986) refer to this effect as a clientele effect.

Amihud & Mendelson (1991) suggest that illiquidity costs should have a relatively large effect on stock returns. This is because each investor that holds a specific stock expects to incur illiquidity costs for which the investor requires compensation in terms of higher return. Thus, the premium on the return of illiquid stocks reflects the present value of the aggregated illiquidity costs investors incur during the life of the stock. As stocks have no maturity date, the illiquidity effect on stock returns reflects up to an infinite stream of illiquidity costs. Amihud & Mendelson (1989) suggest that the impact of illiquidity costs on required returns is consistent with the idea that investors require compensation for risks that are not diversifiable in large portfolios. Investors that want to hold a particular stock will have to pay the bid-ask spread in the buying and selling process. Furthermore, the illiquidity costs of a portfolio of illiquid stocks do not cancel out, like idiosyncratic risk. Thus, investors cannot reduce their illiquidity costs through holding well-diversified portfolio of illiquid stocks.

In contrast, Constantinides (1986) argues that illiquidity costs are diversifiable in portfolios that consist of illiquid and liquid stocks. Thus illiquidity costs should only have a small impact on expected stock returns. As opposed to Amihud & Mendelson (1986), Constantinides (1986) suggests rational investors diversify their portfolios by holding high spread stocks and low spread stocks. He argues that investors pursue a buy and hold strategy for illiquid assets whereas they rebalance their portfolios by trading liquid assets. Thus the cost of the spread affects the trading frequency and trading volumes rather than the required expected returns of investors. As investor can reduce the cost of the spread by holding well-diversified portfolios, the spread should only have small impact on stock returns (Constantinides, 1986).

3 Hypothesis generation

In this chapter we discuss previous empirical research on the relationship between illiquidity and stock returns which we use to generate our hypotheses. We aim to give a varied view by including studies on different stock exchanges and different time periods, although most of the previous research is conducted on American stock data. In addition, we have included studies that use different proxies for illiquidity costs. As we do not aim at giving an exhaustive review of the research field we do not discuss related research streams. One related research stream decomposes illiquidity costs into costs associated with asymmetric information and costs associated with waiting costs to study the impact of each component on stock returns, see for example Brennan & Subrahmanyam (1996), Duarte & Young (2009) and Easley, Hvidkjaer, & O'hara (2002).

3.1 The impact of illiquidity costs on stock returns

In the previous sections we have discussed different aspects of illiquidity and compared two theories on how illiquidity should affect investors' required returns. Amihud & Mendelson (1986) propose that investors require compensation for investing in illiquid stocks which translates into higher risk-adjusted stock returns. Throughout this paper, risk refers to risk factors other than illiquidity. Empirical research has employed a variety of proxies to test the relationship proposed by Amihud & Mendelson (1986) on data from different stock exchanges and time periods.

Amihud & Mendelson (1986) use the bid-ask spread as a proxy for illiquidity costs and study stocks traded on the NYSE over the period 1961-1980. They find that excess stock returns increase with bid-ask spreads after controlling for systematic risk and the size of the companies. In contrast, Eleswarapu & Reinganum (1993) and Chen & Kan (1989) find no significant relationship between bid-ask spreads and risk-adjusted stock returns of NYSE stocks. This is remarkable since the studies are highly similar except for differences in sample selection criteria and risk-adjustment methods. Amihud & Mendelson (1986) exclude stocks that have not survived during a period of eleven years whereas the sample selection criteria of Eleswarapu & Reinganum (1993) are more encompassing. As opposed to Amihud & Mendelson (1986), Chen & Kan (1989) allows the premium for systematic risk to vary over the estimation period. Nevertheless, Eleswarapu (1997) finds support for a positive relationship between excess stock returns and relative spreads on the Nasdaq Stock Exchange over the period 1973-1990. Research suggests that one potential explanation for the mixed results on the NYSE stock data is that quoted spreads tend to overstate the actual illiquidity costs incurred by investors (Datar et al., 1998) (Eleswarapu, 1997). Petersen & Fialkowski (1994) compute effective spreads from detailed intraday transaction data on NYSE stocks and find that the quoted spreads exceed the effective spreads. They suggest that orders are executed inside the quoted spread because market orders are sometimes matched with other market orders rather than with limit orders as suggested by theory. Furthermore, investors can place hidden limit orders which are not included in the quoted spread. If market orders are matched with hidden limit orders and obtain a better transaction price than the quoted price, the quoted spread overstates actual trading costs (Petersen & Fialkowski, 1994). As the detailed transaction data used by Petersen & Fialkowski (1994) is not readily available for long periods of time, researchers have used other proxies such as trading activity and price impact costs to avoid the measurement problems associated with the spread (Datar et al., 1998).

Datar et al. (1998) study stock pricing and illiquidity on the NYSE over the period 1961-1992 and use trading activity as a proxy for liquidity. They measure trading activity as the share turnover, which is calculated as the number of shares traded divided by the number of shares outstanding. In theory, the share turnover is negatively related to the waiting costs of limit orders and thereby also negatively related to the bid-ask spread (Demsetz, 1968). Furthermore, Kyle (1985) proposes that high trading frequency reduces the likelihood that changes in order quantity are due to informed trading. If the trading frequency is high, the price impact of large order quantities is small which reduces the cost of placing large orders. Datar et al. (1998) find that the share turnover has a negative effect on stock returns adjusted for differences in size, book-to-market value and systematic risk. In line with Amihud & Mendelson (1986), they conclude that risk-adjusted stock returns increase with illiquidity.

Research on illiquidity and stock pricing has also found that risk-adjusted stock returns increase with price impact costs. Amihud (2002) studies NYSE stocks over the period 1964-1997 and develops the price impact measure ILLIQ to proxy for illiquidity. ILLIQ is specified as the absolute stock return divided by the dollar trading volume of the stock. The idea behind the measure is that the dollar trading volume in the stock will have a large impact on the stock price if the stock is illiquid. High ILLIQ is costly because investors cannot trade large order quantities at the prevailing market price. This proxy is associated with the depth of the market, in the sense that high ILLIQ is related to low market depth. Amihud (2002) finds that stock returns increase with ILLIQ after adjusting for systematic risk, size, stock price volatility and momentum effects. Florackis et al. (2011) document similar findings on the London Stock Exchange over the period 1991-2008 but measure price impact costs as the absolute return divided by the share turnover rather than the share trading volume.

We have only found one study on illiquidity and stock pricing on the Stockholm Stock Exchange. Westerholm (2002) uses amortized spreads as a proxy for illiquidity and study the 80 most actively traded stocks on the Stockholm Stock Exchange over the period 1990-1995 and stocks traded on the

Helsinki Stock Exchange over the period 1987-2000. The amortized bid-ask spread accounts for both the magnitude of the spread and the average holding periods of investors that hold the stock where the average holding period is measured as the share turnover. This proxy is based on the idea that the cost of the spread is larger for investors with short holding periods since they trade more frequently. If the average holding periods of investors differ between stocks with similar spreads, Chalmers & Kadlec (1998) argue that the spread alone would overstate the illiquidity costs of the stock with long average holding periods relative to the stock with short average holding periods. Westerholm (2002) finds that stock returns adjusted for systematic risk, market-to-book value and size increase with amortized spreads on the Swedish and Finnish stock markets.

The logic behind amortized spreads as a proxy for illiquidity has however been questioned since stocks with lower trading frequency will be considered more liquid than stocks with higher trading frequency if the stocks have similar spreads (Loderer & Roth, 2005). In empirical and theoretical research, the trading frequency in the stock is generally considered a proxy for liquidity rather than illiquidity. For example, Demsetz (1968) shows that illiquidity costs decrease with trading frequency and Datar et al. (1998) use trading frequency as a proxy for liquidity. Given the small sample size and the criticism of the illiquidity proxy used by Westerholm (2002), we argue that it is interesting to test the hypothesis that risk-adjusted stock returns increase with illiquidity on the Stockholm Stock Exchange, using a larger sample and other risk proxies than Westerholm (2002). We thus define our first hypothesis as:

Hypothesis 1a: risk-adjusted stock returns increase with illiquidity on the Stockholm Stock Exchange.

The literature that has been discussed in this section is summarized in Table 1. The proxies used to study illiquidity in this study are discussed in section 4.1.

Authors	Illiquidity proxy	Stock Exchange	Period	Priced?
Amihud and Mendelson (1986)	Relative spreads	NYSE	1961-1980	Yes
Eleswarapu (1997)	Relative spreads	Nasdaq	1973-1990	Yes
Chen and Kan (1995)	Relative spreads	NYSE	1961-1980	No
Eleswarapu and Reinganum (1993)	Relative spreads	NYSE	1961-1990	No
Westerholm (2000)	Amortized spreads	Stockholm and Helsinki	1990-1998	Yes
Amihud (2002)	|Return| to volume	NYSE	1964-1997	Yes
Florackis et. al (2011)	|Return| to turnover	London	1991-2008	Yes
Datar et. al (1998)	Share turnover rate	NYSE	1961-1992	Yes

Table 1: A selection of research on the cross-sectional relationship between illiquidity and risk-adjusted stock returns. The expression "Priced?" is to be interpreted as whether the study concluded that support was found for a cross-sectional relationship between stock returns and illiquidity.

3.2 The impact of market illiquidity on returns

While the research presented in the previous section indicates that cross-sectional stock returns increase with different measures of illiquidity, research has also studied how variations in illiquidity over time affect stock returns.

Amihud (2002) suggests that investors should not only require compensation for choosing illiquid stocks over liquid stocks. Investors should also require compensation for holding stocks when the illiquidity of the stock market is high. If the expected illiquidity of the stock market is high, investors should require higher expected stock returns for choosing stocks over risk-free securities. Amihud (2002) thus argues that the excess return of the market portfolio of stocks over the returns of risk free securities include compensation for the expected illiquidity of overall stock market. This argument is based on the proposal that stocks are not only riskier than risk-free securities but also more illiquid. Amihud (2002) proposes that the expected illiquidity of the stock market has a positive effect on required stock returns. Moreover, he proposes that unexpected illiquidity has a negative effect on contemporaneous stock returns. The idea behind this proposal is that investors revise their expectations about the illiquidity of the market in response to unexpected illiquidity. If the illiquidity of the stock market suddenly increases, investors will expect higher illiquidity in future periods and therefore require higher expected stock returns. This implies that they will be willing to pay less for investing in stocks which translates into lower contemporaneous stock returns. Amihud (2002) tests these propositions on NYSE stock data over the period 1963-1997. He uses price impact costs, measured as ILLIQ, to proxy for illiquidity and finds that excess stock returns increase with expected ILLIQ and decrease with unexpected ILLIQ.

Research has also found that stocks whose illiquidity is more sensitive to variations in the illiquidity of the market yield higher stock returns (Acharya & Pedersen, 2005). Acharya & Pedersen (2005) study stock returns and illiquidity on the NYSE, measured as ILLIQ, over the period 1963-1999. In line with Amihud (2002) they also find that unexpected illiquidity results in lower stock prices and higher future returns on individual stocks. Similar findings have been documented on the Spanish stock market (Marcelo & Quirós, 2006) (Martínez, Nieto, Rubio, & Tapia, 2005) and the London Stock Exchange (Florackis et al., 2011).

These findings are consistent with research that indicates that illiquidity costs of individual stocks co-vary over time which is referred to as commonality in illiquidity. Chordia, Roll, & Subrahmanyam (2001) study NYSE stock data and find that illiquidity measures of individual stocks co-vary over time in response to changes in macro-economic factors. They suggest that commonality in illiquidity could arise if macro-economic factors affect the illiquidity costs of the overall stock market. For example, changes in interest rates could induce investors to reallocate their holdings between stocks and bonds which could increase the trading activity on the overall stock market and thereby reduce the inventory costs of market-makers. Commonality in illiquidity has also been found on stock exchanges that operate without market-makers. Brockman & Chung (2002) study measures of spreads and depth over the period 1996-1999 on the Hong Kong Stock Exchange, which is purely order-driven. They find that commonality in spreads and depth is an important component of illiquidity but that the effect tends to be smaller than in quote-driven markets. The findings of commonality in illiquidity measures across stocks suggest that illiquidity has a component that cannot be eliminated through diversification. This is analogous to the CAPM which suggests that risks associated with the performance of the overall stock market cannot be diversified away.

We formulate hypotheses 2a and 2b as:

Hypothesis 2a: Excess stock market returns increase with expected market illiquidity

Hypothesis 2b: Unexpected changes in market illiquidity results in lower contemporaneous excess stock market returns

The literature that has been discussed in this section is summarized in Table 2.

Authors	Illiquidity proxy	Stock Exchange	Period	Priced?
Amihud (2002)	Price impact costs	NYSE	1964-1997	Yes
Acharya and Pedersen (2005)	Price impact costs	NYSE and AMEX	1963-1999	Yes
Marcelo and Quirós (2006)	Price impact costs	Spanish*	1994-2002	Yes
Florackis et. al (2011)	Price impact costs	London	1991-2008	Yes
Martínez et. al (2005)	Price impact costs, bid-ask spreads	Spanish*	1991-2000	Yes

Table 2: A selection of research on the relationship between market illiquidity and market returns. Spanish refers to the the Spanish Continuous Market. The expression "Priced?" is to be interpreted as whether the study concluded that support was found for systematic illiquidity risk being a priced factor.*

4 Economic model

In this section we develop economic models to test the hypotheses that illiquidity affects cross-sectional and time-series stock returns. We also motivate our illiquidity proxies and the proxies we use to adjust for risk factors that have been documented to affect returns, such as systematic risk.

Our first hypothesis is based on the idea that investors consider risk and illiquidity costs when they form expectations about required returns and form portfolios. As investors lack ex-ante information about the risk and illiquidity of stocks during the investment period, we assume that they base their investment decisions on information that is publicly available prior to their investment period. Our model is built on the assumption that investors make investment decisions shortly after they gain access to the annual reports. As the annual reports are generally available at the end of March, we assume that investors re-structure their portfolios at the beginning of April. Thus we assume that investment decisions made on April 1 are based on information from the previous 12 months. Under these assumptions, we investigate if illiquidity factors and risk factors contribute to explain monthly excess stock returns. The time perspective of the model is illustrated in Figure 1.

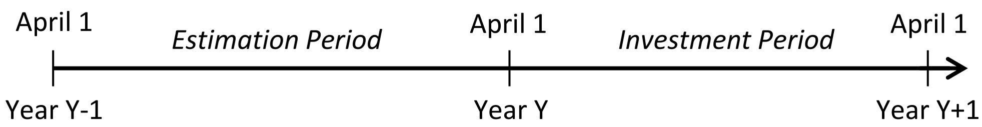

Figure 1: Estimation Timeline, hypothesis 1

Our second hypothesis is based on the idea that investors are concerned about the future expected illiquidity of the stock market. Under our hypothesis, investors' required returns increase with the expected illiquidity of the market. We assume that investors use information from the previous year to forecast the illiquidity of the coming year. Our third hypothesis concerns the effect of unexpected illiquidity on stock prices. We refer to unexpected illiquidity as the difference between realized illiquidity and the expected illiquidity. Our model is based on the assumption that investors respond to unexpected illiquidity by revising their expectations about the illiquidity in future periods. We assume that investors require higher expected returns in future periods if the illiquidity in the current period is higher than expected. Under our hypothesis, buyers will therefore require lower stock prices to compensate them for the relatively high illiquidity in future periods. This results in lower contemporaneous stock returns and higher future stock returns.

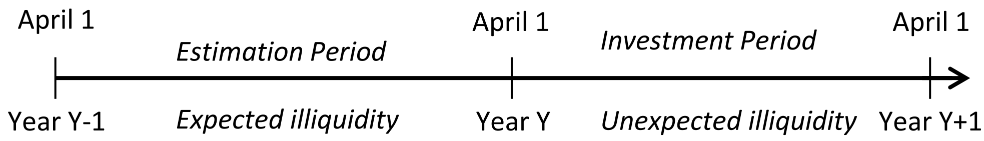

Figure 2: Estimation Timeline, hypothesis 2a and 2b

4.1 Illiquidity measures

Illiquidity has many aspects and Amihud (2002) argues that all aspects of illiquidity cannot be captured by one single proxy. As we study market tightness and market depth, we have chosen one proxy for each of these aspects. We use relative bid-ask spreads to proxy for market tightness and price impact costs to proxy for market depth. These proxies have been used in a number of previous studies and are based on readily available data. The choice of proxies is motivated further in the following sections.

4.1.1 Relative Bid-Ask Spread

The tightness of the market is associated with the cost of immediately turning around a small stock position. As the spread between the bid and the ask price is a direct measure of the costs associated with immediate order execution, we use the bid-ask spread to proxy for market tightness. We measure the bid-ask spread as the difference between the ask price and the bid price divided by the bid price. This measure is referred to as the relative bid-ask spread. In general terms, the relative bid-ask spread is specified as the bid-ask spread divided by a benchmark price. The benchmark price can be either the closing price, the bid price or the midpoint between the ask and bid price. The different benchmark prices yield highly similar relative spreads and we have opted to use the bid price as suggested by Loderer & Roth (2005).

The relative bid-ask spread has been used by a number of researchers to study the relationship between illiquidity and stock pricing, for example Amihud & Mendelson (1986) and Eleswarapu (1997). Furthermore, empirical research has found that the relative bid-ask spread is negatively correlated with different characteristics of liquidity such as trading volume, the number of shareholders and the stock price continuity (Amihud & Mendelson, 1986).

We calculate the relative bid-ask spread from daily data on bid and ask prices. As discussed by Petersen & Fialkowski (1994), the spread will overstate actual trading costs if orders are executed inside the bid-ask spread which has been problematic in empirical research on NYSE stock data. Petersen & Fialkowski (1994) propose that orders may be executed inside the spread if market-makers do not always display the best public limit orders and if some market orders are matched with market orders rather than with limit orders. We do not know to which extent orders are executed inside the spread at the Stockholm Stock Exchange. As investors can place hidden limit orders which are not visible in the central order book it is however possible that our spread measure overstates actual spreads. Furthermore, buying and selling orders are automatically matched in the central order book and therefore market orders might be matched with other market orders. This would have an impact on our results, especially if our spread measure is not highly correlated with the actual spreads faced by investors. However, the estimation procedure of Petersen & Fialkowski (1994) requires detailed data on orders and quotes which is not available in DataStream. Therefore we use quoted spreads as an approximation of actual trading costs.

Previous research has also used amortized bid-ask spreads and measures of trading activity to proxy for illiquidity costs. As described in Section 3.1, amortized spreads account for the magnitude of the spread and the average holding period of investors that hold the stocks. Chalmers & Kadlec (1998) measure the amortized spread as the relative spread multiplied by share turnover where share turnover is a proxy for investors' average holding periods. This measure is however problematic since the share turnover might proxy for the liquidity of the stock rather than investors' average holding periods. For example, Demsetz (1968) shows that the bid-ask spread is negatively related to the share turnover of the stock and Datar et al. (1998) use a share turnover measure as a liquidity proxy. We argue that the relative bid-ask spread is a cleaner measure since it does not mix different measures that are associated with the illiquidity of the stock. Trading activity measures, on the other hand, have been found to capture effects of momentum and value strategies (Lee & Swaminathan, 2000). For example, Lee & Swaminathan (2000) suggest that stock with high share turnover earn lower returns because they share characteristics with glamour stocks. Furthermore, trading activity is an indirect proxy for liquidity whereas bid-ask spread is a more direct proxy of illiquidity costs.

4.1.2 Price Impact

We use the price impact measure ILLIQ as a proxy for market depth. ILLIQ was developed by Amihud (2002) to study whether illiquidity affects variations in stock returns across stocks and across time. The measure is specified as the daily absolute stock return divided by the daily trading volume denominated in currency units. The measure is based on the idea that order volume has a larger impact on the stock price if the illiquidity is high. Price impact is costly since the investors cannot execute large orders at the market price without affecting the transaction price. Amihud (2002) suggests that ILLIQ can be interpreted as the effective spread of executing large orders.

Our motivation for using ILLIQ is that the measure is related to market depth and the cost of executing large orders. Furthermore, the measure has been used by a number of previous studies on the illiquidity-return relationship, for example Amihud (2002) and Acharya & Pedersen (2005). Amihud (2002) studies the effect of ILLIQ on cross-sectional stock returns as well as the effect of expected illiquidity on excess stock returns. As the measure proved useful to investigate these relationships, we argue that it makes sense for us to use the same proxy. A similar measure, the Amivest liquidity ratio, which is the inverse of ILLIQ, has been used by for example Amihud, Mendelson, & Lauterbach (1997) and Berkman & Eleswarapu (1998). An alternative to ILLIQ is the return-to-turnover measure proposed by Florackis et al. (2011). This measure is similar to ILLIQ but has a measure of the share turnover rate rather than trading volume in the denominator.

One draw-back of price impact measures in general is that they are based on asset returns, which means that these measures could incorporate information that may not be directly related to illiquidity. ILLIQ incorporates price volatility in its numerator, and an asset may thus mistakenly be estimated as illiquid simply because its price volatility is high (Easley et al., 2002). As in Amihud (2002) we therefore use the standard deviation of the stock price as a control variable in all our cross-sectional regressions that include ILLIQ to alleviate this potential issue.

In line with Amihud (2002) we estimate ILLIQ from daily data. The reason for doing so is that the daily data required for estimating the measure is available over long periods of time. Goyenko, Holden, & Trzcinka (2009) suggest that using daily volumes and returns is justified only if all trades during the trading day are of identical size. Their comparison of price impact measures based on intraday data and ILLIQ, however, indicates that the measures are highly correlated.

4.2 Risk adjustment

Research has found that excess stock returns are affected by a number of different risk-factors whereof illiquidity is one factor. To investigate if illiquidity contributes to explain excess stock returns we need to hold other risk factors constant, to ensure that the estimated illiquidity-return relationship remains after controlling for previously documented risk factors. In the absence of an appropriate risk-adjustment our estimated relationship might be due to correlation between our illiquidity proxies and factors that account for other sources of risk. As both the relative bid-ask spread and ILLIQ contains stock price information, these measures might be correlated with excess returns for other reasons than illiquidity concerns. Chen & Kan (1989) discuss this issue and even claim that the results of Amihud & Mendelson (1986) might be due to inappropriate risk-adjustments. We therefore control for a number of previously documented risk-factors and other factors which has been shown to affect stock returns. The risk adjustments discussed in this chapter apply only to the cross-sectional model, since adjusting for risk factors such as systematic risk would not make sense in the time-series model. For example, the CAPM beta of the market portfolio is always one, and the average market capitalization in itself has no theoretical link to market returns over time.

To reduce the risk that any estimated relationship between illiquidity and excess stock returns is an artefact of inappropriate risk-adjustments, we use two different models to adjust for risk:

1. CAPM augmented with factors that account for momentum and company size. This risk-adjustment corresponds to the risk-adjustments of Amihud (2002).
2. Fama-French three-factor model (market risk, market capitalization and book-to-market ratio), augmented with a momentum factor. This is one of the dominant models in asset pricing research (Subrahmanyam, 2010)

The risk factors included in the models are motivated below.

Sharpe (1964) proposes that investors require compensation for risks that cannot be diversified in a large portfolio of stocks. *Systematic risk* is specified as the sensitivity of stock prices to the excess return of the market portfolio. In the context of the CAPM, investors solely require compensation for systematic risk since idiosyncratic risks can be diversified away in a large portfolio. As the CAPM is the cornerstone of asset pricing and a common first step in risk adjustment, we adjust for systematic risk.

Fama & French (1993) extend the CAPM with two additional risk factors: the size of the company and the book-to-market value of the company. The three-factor model is based on the empirical finding that cross-sectional stock returns are better explained by a combination of the market beta factor, SMB ("Small minus Big") and HML ("High minus Low") (Fama & French, 1993). SMB refers to the additional returns earned by stocks with low market capitalization over stocks with high market capitalization, and HML refers to the additional returns earned by stocks with high book-to-market-value ratios over stocks with low book-to-market-value ratios (Fama & French, 1993). The market beta factor can be interpreted as a proxy for systematic risk.

Size and book-to-market value are included as risk proxies because of their empirical relevance. The latter is of particular interest in the context of liquidity, because size as defined by the market capitalization is strongly negatively related to different measures of illiquidity. In the full sample period of this study, the estimated correlation between size and the bid-ask spread variable is -0.49, and the correlation between size and mean-adjusted illiquidity is -0.22. This is problematic because it means that any effect of illiquidity could be due to its function as a proxy for size, which strongly supports the need to adjust for differences in size between firms.

Previous research suggests that the explanatory power of the market beta, market capitalization and book-to-market ratios that have been found to explain cross-sectional differences in returns on other stock exchanges internationally tends to be low when used to predict returns on the Swedish market. Asgharian & Hansson (2002) study panel data and find that the market beta is not a statistically significant factor. Their findings on the relationship between market capitalization and book-to-market-ratios and returns yield similar results, although they find them significant with the expected sign in some of their model specifications. Westerholm (2002) and Östermark (1991) find similar results. Although these results cover different time periods than our sample, their overall implication on the expected results of the risk adjustment is that the coefficient sign of each variable is expected to follow the international norm, but the variables are not expected to be significantly different from zero. We have opted to use these variables despite this expected relationship because of the widespread use in the literature as well as the lack of a stronger model at this point in time.

Research has found empirical support for a relationship between past and future returns (Jegadeesh & Titman, 1993), which is commonly referred to as *momentum*. As relative bid-ask spreads contain information about past stock prices and ILLIQ contains information about past returns and trading volumes, these measures might capture momentum effects. This implies that any estimated positive returns to illiquidity may in fact represent a momentum effect rather than an illiquidity effect. In order to adjust for the potential effects of momentum we have included two measures of lagged stock returns.

Theoretical research suggests that illiquidity and stock price volatility are positively related (Amihud, 2002). As the return measure in the numerator of the ILLIQ contains information about the price volatility of the instrument, Amihud (2002) suggests that the measure might capture potential effects of idiosyncratic risk on stock returns. Thus we include *stock price volatility* to reduce the risk that any estimated relationship between ILLIQ and stock returns contains a premium related to stock price volatility.

Table 3 summarizes our choice of illiquidity and risk proxies along with their expected effect on returns and references to literature on which the proxies are based. The proxies are explained in Section 4.1 and the variable estimation procedure is described in Section 5.2.

Category	Variable	Expected sign	Reference
Illiquidity	Relative Bid-Ask Spread	Positive	Amihud & Mendelson (1986)
	Price Impact (ILLIQ)	Positive	Amihud (2002)
Risk Factors	Market Model Beta	Positive	Scholes & Williams (1977)
	Market Capitalization	Negative	Fama & French (1992)
	F&F Small Minus Big	Positive	Fama & French (1993)
	F&F High Minus Low	Positive	Fama & French (1993)
	F&F Market Coefficient	Positive	Fama & French (1993)
Momentum	LRET100	Positive	Amihud (2002)
	LRET100R	Positive	Amihud (2002)
Volatility	STDEV	Positive	Amihud (2002)

Table 3: List of variables

5 Method

In this section we describe the data and statistical models we use to test our hypotheses. We also describe how we estimate the illiquidity measures and risk factors discussed in the previous section. Our method is based on the method used by Amihud (2002), but incorporates additional illiquidity proxies and risk factors.

5.1 Sample Characteristics

We study the effect of illiquidity on stock returns for stocks traded on the Stockholm Stock Exchange in the period 1990-2011. The Stockholm Stock Exchange encompasses OMX Stockholm, AktieTorget and First North. The time period is chosen on the basis that we want to cover several macroeconomic cycles to study if variations in illiquidity over time affect expected excess stock returns. Our sample contains 1220 companies which exhibit large variations in illiquidity, size and riskiness.

All equity instruments that fulfil the following criteria are included in the sample:

- Listed in DataStream
- Classified as the major equity instrument for its underlying asset
- Alive at any time during the period 1990 to 2010

The first criterion is necessary since our sample size and time resources do not allow us to collect and combine data from different sources. The data provided by DataStream appears sufficiently encompassing to approximate the population. The second criterion is required to ensure that stocks which represent the same underlying entity are not counted twice. In order to avoid survivorship bias, both stocks that are currently listed and stocks that were unlisted at some point during the sample period are included. Thus the third criterion implies that we do not require companies to survive the whole period to be included in the sample.

Stocks that were traded less than 100 days during year y-1 were excluded from the sample of year y to improve the reliability of our risk and illiquidity measures. Thus, stocks that are highly illiquid are not part of the sample which implies that our results are not generalizable for these stocks.

Table 4 contains the amount of observed stocks that fulfil our sample selection criteria, listed per year. Observations are filtered out from the sample if they lack data in the variables market capitalization, returns in all months of the year, or both the illiquidity proxies. Observations that are filtered out in this manner are not included in tables 4, 5 and 6.

Year	Stocks
1990	48
1991	57
1992	60
1993	68
1994	109
1995	122
1996	124
1997	149
1998	197
1999	223
2000	259
2001	294
2002	289
2003	267
2004	272
2005	292
2006	318
2007	362
2008	403
2009	404
2010	418

Table 4: Amount of cross-sectional observations per month in each year

The total number of monthly observations of stocks is 56 822. Since the panel is unbalanced, the increasing number of stocks per year implies that greater magnitude per observation will be placed on observations in the earlier periods. This can be adjusted for, but such an adjustment would instead imply that that the statistical importance of one particular year would increase as the number of stocks grow and we therefore make no such adjustments.

5.2 Data

As stated above, all stock data of our study has been gathered from the DataStream service. In addition to this information we have manually gathered data regarding the risk-free rates and the reason for the delisting of companies that are no longer operating. We have also manually adjusted the DataStream data for errors caused by the delisting of companies, as described below.

The risk-free return rate used is based on the historical 1-month Treasury bill rates provided by Sveriges Riksbank (2012) (The Swedish Central Bank). Short-term Treasury bills are commonly expected to closely mimic the expected risk-free return rate for that particular period. This rate is used for all variable estimations that require an approximation of the risk-free rate.

DataStream tends to erroneously repeat the last available price after the delisting date for stocks that have been delisted (Ince & Porter, 2006). To avoid a series of zero returns after the delisting date, we manually remove these returns. Another problem is that DataStream tend to overstate the delisting return of defaulted companies (Ince & Porter, 2006). To avoid bias, we have used the Swedish stock guide Börsguiden to document the time and reason for the delisting of the stocks in our sample. We were able to identify the delisting reason for 330 of the 707 delisted companies. The 23 Companies that were delisted due to default were assigned a delisting return of -100% whereas all other delisted stocks were assigned a delisting return of 0%.

Below we provide statistics regarding the sample. Descriptive statistics is presented in Table 5 and a matrix of the correlation between the independent variables is presented in Table 6.

	Max.	Mean	Median	Min.	Stdev
Rel. Spread	2.342	0.041	0.019	0.001	0.079
ILLIQMA	62.815	0.712	0.016	0.000	4.029
Market Beta	2.210	1.032	1.015	0.469	0.219
LRET100	11.025	0.127	0.027	-0.976	0.716
LRET100R	10.434	0.025	-0.036	-0.960	0.541
LNSize	13.796	6.607	6.488	-0.994	2.146
FF-Market	1.907	0.984	1.016	0.066	0.272
FF-SMB	1.472	0.446	0.417	-0.656	0.464
FF-HML	1.003	0.078	0.141	-0.937	0.398
STDEV	9153.824	34.540	2.861	0.295	221.04

Table 5: Descriptive statistics, independent variables

	Spread	ILLIQMA	Beta	LRET100	LRET100R	LNSize	FF-M	SMB	HML	STDEV
Spread										
ILLIQMA	0.295									
Beta	0.206	0.088								
LRET100	-0.063	0.035	0.092							
LRET100R	-0.165	-0.069	-0.099	-0.075						
LNSize	-0.487	-0.22	-0.118	-0.045	0.209					
FF-M	-0.039	-0.018	-0.079	0.03	0.094	-0.025				
FF-SMB	0.376	0.183	0.103	0.06	-0.123	-0.769	0.204			
FF-HML	0.006	0.031	-0.004	-0.023	-0.086	-0.096	0.017	0.109		
STDEV	-0.052	0.072	0.017	0.006	-0.021	0.076	0.029	-0.043	-0.023	

Table 6: pairwise correlations between the independent variables

Most of the variables are either uncorrelated or only weakly correlated. The primary exceptions are the relative bid-ask spreads and ILLIQMA, which is expected since both variables represent illiquidity; and LNSize and SMB, which is also expected because both variables are intended to represent the return premium based on size. The third exception is the correlation between both of the illiquidity proxies to both of the size variables, which is expected because smaller company stocks tend to be less liquid (Demsetz, 1968) (Amihud, 2002).

Stocks that have missing data in the dependent variable in month *m* of year *y* and/or one of the independent variables in *y*-1 are excluded from the regression of month *m*, year *y*. Values that were invalid/non-numeric or missing in the dataset extracted from DataStream were considered missing data. We were not able to locate any patterns in the missing data except for the following: The firms that are removed due to lack of data tended to have higher illiquidity as expressed through price impact than the average firm, and there is greater a lack of data regarding book-to-market-value ratios in the years 1990-1992 compared to other years. The first pattern implies that our results are unlikely to be generalizable to highly illiquid stock, and the second pattern implies lower sample sizes for the first three years in the regressions where the Fama and French three-factor model is used for risk-adjustments.

5.3 Variable estimation

In this section we describe how we estimate the dependent and independent variables that are used in our regressions. The dependent variable, monthly excess return, is estimated on a monthly basis whereas the illiquidity and risk measures are estimated on a yearly basis. The risk-adjustment variables are only used in the regression that tests the cross-sectional relationship between illiquidity and stock returns.

5.3.1 Return measure

The monthly return of a stock is defined as the percentage change in stock price over one calendar month minus the risk-free interest rate during the month. Stock prices that were adjusted for capital actions such as splits and dividends were collected from DataStream. Monthly stock returns are calculated for each stock and each month by dividing the closing price at the end of the month with the closing price at the end of the previous month and subtracting one plus the risk free rate:

$$R_{iym} = \frac{P_{iym}}{P_{iy,m-1}} - (1 + Rf_{ym}) \quad (1)$$

Where R_{iym} is the return of stock *i* in month *m* in year *y*.

5.3.2 Relative bid-ask spreads

Relative bid-ask spreads are calculated for each stock as the yearly average of the daily ask price minus the daily bid price divided by the daily bid price (Loderer & Roth, 2005). As data on bid-ask spreads is not available in DataStream for periods prior to the year 2002, relative bid-ask spreads are only calculated for the period 2002-2010 and estimations that require the measure are restricted to this period.

$$Spread_{iy} = \frac{1}{D_{iy}} \sum_{t=1}^{Diy} \frac{Ask_{iyd} - Bid_{iyd}}{Bid_{iyd}} \tag{2}$$

Where Ask_{iyd} is the closing ask price of stock *i* in year *y* on day *d* and Bid_{iyd} is the closing bid price of stock *i* in year *y* on day *d*.

5.3.3 ILLIQ

We estimate the illiquidity proxy ILLIQ in line with the estimation procedure of Amihud (2002). ILLIQ is calculated for each stock as the yearly average of the daily percentage change in the stock's price divided by its trading volume denominated in SEK:

$$ILLIQ_{iy} = 10^6 * \frac{1}{D_{iy}} \sum_{t=1}^{Diy} \frac{|R_{iyd}|}{VOL_{iyd}} \tag{3a}$$

Where D_{iy} is the number of days for which data are available for stock *i* in year *y*. R_{iyd} is the return of stock *i* on day *d* of year y and VOL_{iyd} is the daily volume in SEK based on unadjusted prices. We compute daily stock returns from data on daily stock prices adjusted for new issues, splits, delisting and dividends. As in Amihud (2002), ILLIQ is multiplied by 10 to the power of 6 because of the potential problems of working with extremely small variables. This adjustment does not affect the inference of the cross-sectional model, which uses mean-adjusted ILLIQ as described below, but does affect the scale of the coefficients of the time-series model. We also remove extreme outliers by taking away the highest 2% and the lowest 2% of all observations of ILLIQ in each year.

In the estimation of the cross-sectional relationship between illiquidity and stock returns we adjust ILLIQ for variations in ILLIQ over time by replacing ILLIQ with ILLIQMA, which is mean-adjusted. Thus, ILLIQMA is a measure of the illiquidity of each stock relative to the average illiquidity during the period rather than a measure of the stock's absolute illiquidity. To calculate ILLIQMA, we first calculate the average ILLIQ (AILLIQ), of all companies that are admitted to the sample in year y:

$$AILLIQ_y = \frac{1}{N_y} \sum_{t=1}^{Ny} ILLIQ_{iy} \tag{3b}$$

Where Ny is the number of stocks in year *y*.

AILLIQ is then used to calculate a measure of mean-adjusted ILLIQ (ILLIQMA) for each stock in each year. ILLIQMA is defined as the ILLIQ in year y of each stock divided by the average ILLIQ of the sample (AILLIQ) in year y. ILLIQMA is calculated as:

$$ILLIQMA_{iy} = \frac{ILLIQ_{iy}}{AILLIQ_y} \tag{3c}$$

5.3.4 Fama & French factors

The factors of the Fama and French three factor model are estimated in line with Fama and French (1993). For each year we form three equally sized portfolios sorted by the market value of equity: Small, Medium and Big. We also form three portfolios sorted by the book to market value ratio: High, Medium and Low. This is a smaller amount of portfolios than used by Fama-French (1993), and this adjustment has been made because our sample contains a significantly lower amount of stocks. The portfolio categories overlap, which means that there are a total of nine portfolios:

	Small	**Medium**	**Big**
High	Small-High	Medium-High	Big-High
Medium	Small-Medium	Medium-Medium	Big-Medium
Low	Small-Low	Medium-Low	Big-Low

Table 7: SMB and HML Portfolios

To determine the size of each portfolio we divide the total amount of stocks by three. If the number of stocks in an estimation period is not evenly divisible by three, the portfolios corresponding to big/high have priority over the medium portfolios which in turn have priority over the small/low portfolios.

The Fama-French (1993) proposition is:

$$E(R_i) - R_f = a_i + b_i\left[E(R_m) - R_f\right] + s_i E[SMB] + h_i E[HML] \tag{4a}$$

Where R_i is the stock return, R_f is the required risk-free rate and R_m is the market return. SMB is the return premium of small stocks compared to large stocks, and HML is the return premium of high-MTBV stocks versus low-MTBV stocks. We calculate SMB as:

$$SMB_y = \left(\frac{1}{3}\right)\sum Return(S{:}H + S{:}M + S,L)_y - \left(\frac{1}{3}\right)\sum Return(B{:}H + B{:}M + B{:}L)_y \tag{4b}$$

Where *Return(S:H+S:M+S:L)*$_y$ is the sum of the value-weighted portfolio average return of each of the three Small portfolios and *Return(B:H+B:M+B:L)*$_y$ is the sum of the value-weighted portfolio average return of each of the three Big portfolios. HML is calculated as:

$$HML_y = \left(\frac{1}{2}\right) Return(H{:}\,S + H{:}\,B)_y - \left(\frac{1}{2}\right) Return(L{:}\,S + L{:}\,B)_y \qquad (4c)$$

Where *Return(H:S + H:B)*$_y$ is the sum of the value-weighted portfolio average return of each of the two High portfolios corresponding to Big and Small, and *Return(L:S + L:B)*$_y$ is the sum of the value-weighted portfolio average return of each of the two Low portfolios corresponding to Big and Small. When calculating HML, the medium size portfolios are excluded. This is because Fama & French (1993) find that these portfolios do not improve the explanatory power of the model.

To generate portfolio coefficients, we run OLS regressions for each portfolio and each year using monthly data:

$$E(R_{p,my}) - R_{f,my} = a_i + b_{p,my}\left[E\left(Rm_{my}\right) - R_{f,my}\right] + s_{p,my}E[SMB] + h_{p,my}E[HML] \qquad (4d)$$

One regression is performed for each portfolio and year of estimation, for the three factors (*SMB*, *HML* and *Market*), resulting in 567 coefficients. Each stock is then assigned the coefficient of the portfolio it belongs to in year y.

5.3.5 Market model beta

In addition to the market coefficient provided by the three-factor model we estimate the market beta for each stock in accordance with the market model. Daniel & Titman (1997) find that returns adjusted for size and book-to-market values are not strongly correlated with the overall market factor provided by the three-factor model, further supporting the need to incorporate another measure of systematic risk. The market model is defined as:

$$R_{iy} = a_y + \beta_{iy} * RM_y + e_{iy} \qquad (5a)$$

Where R_{iy} is the return of stock *i* in year *y*, RM_y is the equally-weighted market return, β_{iy} is the coefficient that represents the sensitivity of the return of stock *i* to the return of the market portfolio in year *y*, a_y is the intercept and e_{iy} is the residual.

Rather than estimating individual betas for each stock, we follow the methodology of Scholes & Williams (1977) and form ten portfolios based on market capitalization and estimate portfolio betas based on the relationship between the equally weighted returns of each portfolio and that of the market. Equally weighted portfolios differ from value weighted portfolios as each stock has the same weight, and thus the weight of the respective stock is not proportional to its size. We adjust the coefficients in order to mitigate econometric problems emanating from the fact that not all stocks are traded near continuously as assumed by the market model, resulting in biased and inconsistent estimators (Scholes & Williams, 1977). We use the following estimation procedure to alleviate this issue:

$$\hat{\beta}_{py} = \frac{\beta_{py}^{-} + \beta_{py} + \beta_{py}^{+}}{1 + 2\hat{\rho}_{My}} \tag{5b}$$

Where $\hat{\beta}_{py}$ is our adjusted estimated beta for portfolio *p* in year *y*, β_{py}^{-} is analogous to the lagged beta; $\beta_{py}$to the current beta; β_{py}^{+} to the lead beta; and $\hat{\rho}_{My}$ serves as a market autocorrelation coefficient.

$$\beta_{py} = \frac{COV(R_{pdy}, R_{Mdy})}{Var(R_{Md}y)} \tag{5c}$$

$$\beta_{py}^{-} = \frac{COV(R_{pdy}, R_{Mdy-1})}{Var(R_{Mdy-1})} \tag{5d}$$

$$\beta_{py}^{+} = \frac{COV(R_{pdy}, R_{Mdy+1})}{Var(R_{Mdy+1})} \tag{5e}$$

$$\rho_{M}^{s} = \frac{COV(R_{Mdy}, R_{Mdy-1})}{SD(R_{Mdy})SD(R_{Mdy-1})} \tag{5f}$$

Where R_{pdy} is the equally weighted return of each portfolio *p* on day *d* in year *y* and R_{Mdy} is the return of the market portfolio on day *d* in year *Y*. COV is the covariance and SD is the standard deviation.

For the estimation of the cross-sectional model, each stock is assigned the beta of the portfolio in which it is included.

5.3.6 Momentum and stock price volatility

We use two measures of lagged stock returns, LRET100 and LRET100R, to control for momentum effects. LRET100 is defined as the total return over the last 100 days of the year, while LRET100R is defined as the total return over the previous year not including the last 100 days (Amihud, 2002).

$$LRET100_{iy} = \frac{P_{iy,dlast}}{P_{iy,d100}} - 1 \tag{6a}$$

$$LRET100R_{iy} = \frac{P_{iy,d100}}{P_{iy,dfirst}} - 1 \tag{6b}$$

Where *P* is the closing price of stock *i* in year *y*, *dlast* is the last day of trading in a given year, *d100* is the day one hundred days prior to the last day of trading, and *dfirst* is the first day of trading in a given year.

We use the STDEV measure to adjust for differences in volatility between instruments. The measure is defined as:

$$STDEV_{iy} = \sqrt{\frac{1}{N}\sum_{d=1}^{N}(R_{idy} - \bar{R}_{iy})^2} \tag{7}$$

Where R_{idy} is the daily return of instrument *i* on day *d* in year *y*.

5.4 Statistical models

The statistical models used in this study are based on the Fama & MacBeth (1973) and French, Schwert, & Stambaugh (1987) methods. The first model uses panel data to study the relationship between illiquidity and risk-adjusted returns across stocks and the second model uses time series data to study the effect of illiquidity on excess stock market returns. This section presents the specification of each model together with tests of autocorrelation and heteroscedasticity.

5.4.1 Cross-sectional model

We use the cross-sectional model developed by Fama & MacBeth (1973) to test the hypothesis that illiquidity has a positive effect on risk-adjusted excess stock returns. Our model is based on the model used by Amihud (2002) to study illiquidity and stock returns on the NYSE.

The Fama & Macbeth method is a common approach to study cross-sectional relationships between stocks over time. Cross-sectional OLS regressions are performed on the dimensions stock *i* and stock characteristic *k* in order to generate *n* sets of regression coefficients. The coefficients of each firm characteristic *j* are averaged over the estimation period n to obtain the average coefficient for the whole period. A key strength of this method is that it compensates for differences in market-wide returns over time by allowing the intercept of the model to vary between periods (Eleswarapu & Reinganum, 1993).

We estimate a cross-sectional model for each month m=1, 2,…, 12 in year *y* (each year starting April 1) where stock returns are a function of the illiquidity and risk characteristics of the stock. R_{imy} is the return of stock *i* in month *m* and year *y* minus the risk-free interest rate in month *m* year *y*; the coefficients *K* estimate the effect of stock characteristics on stock returns; $X_{ji,y-1}$ represents characteristic *j* of stock *i* in year y-1; and U_{imy}represents the residuals. K_{omy} represents the intercept. We obtain monthly coefficients for each firm characteristic by running the following regression:

$$R_{imy} = K_{omy} + \sum_{j=1}^{J} K_{jmy} X_{ji,y-1} + U_{imy} \quad (8)$$

The coefficients of the whole sample period are computed as the average estimated coefficients, K_{jmy} for each stock characteristic, j, over the sample period. Tests of statistical significance are performed on the standard errors of the estimated coefficients, K_{jmy}, for each stock characteristic, j, over the sample period.

The consistency, unbiasedness and efficiency of the OLS estimator are dependent on a number of assumptions. As we have reason to believe that the assumptions of zero autocorrelation and homoscedasticity might be violated in our model, we adjust for these effects. This is important since violation of these assumptions might cause the standard errors of our estimated coefficients to be overstated or understated. If for example the standard errors of the coefficients of our illiquidity measures are understated, the significance the coefficients will in turn be overstated, which might lead us to wrongly conclude that illiquidity affects stock returns. Note that the adjustments for autocorrelation and heteroscedasticity only apply to the standard errors of the coefficients. The estimated sign and magnitude of the coefficients are unaffected by autocorrelation and heteroscedasticity.

Autocorrelation is present if the error terms are correlated across time and/or firms. Correlations in the error term between observations of the same firm across different time periods are referred to as firm effects. Time effects, on the other hand, refer to correlations between residuals across different firms within the same time period. If these effects are present, the average coefficients remain unbiased, but the standard errors do not, and are likely to be significantly understated (Thompson, 2011). For example, Firm A may be a particularly strong fit to an estimated linear function due to reasons specific for Firm A. The standard error of the regression function will then decrease as additional observations of Firm A are added, even though this effect is specific to the firm and is not related to the estimated function. Petersen (2009) suggests that firm effects are likely to be present in models where monthly stock returns are regressed on annual lagged explanatory variables such as book-to-market ratios. We therefore follow the recommendation of Petersen (2009) and use two-way clustered standard errors to adjust for firm effects and time effects.

The assumption of homoscedasticity refers to zero variance in the error terms across observations (Brooks, 2002). This assumption is violated if for example the variance of the error terms increase with the value of ILLIQMA. If this is the case, the prediction accuracy of the model is lower for higher values of ILLIQMA. We use White's standard errors which are robust to heteroscedasticity. In the presence of heteroscedasticity, White's standard errors account for this effect by adjusting the standard errors upward or downward depending on the form of heteroscedasticity (Brooks, 2002).

In sum, we perform tests of statistical significance on standard errors that are robust to time and firm effects and heteroscedasticity. The standard errors of the coefficients are estimated using the algorithm by Hoechle (2006) and are clustered along the dimensions *firm* and *time*. The test statistic follows a t-distribution with two degrees of freedom.

An additional assumption is that the independent variables are not highly correlated. High correlation between independent variables is referred to as near multicollinearity. In the presence of near multicollinearity, it is difficult to determine to which of the variables the effect on the dependent variable refer (Brooks, 2002). As theory and previous empirical research suggests that the size of the company is highly correlated with different measures of illiquidity (Amihud, 2002), the coefficients and standard errors of these variables might be underestimated or overestimated. We study pair-wise correlations between our independent variables to investigate if we have problems with multicollinearity. One draw-back of this approach is that we will not detect if the two variables are correlated with a third variable. Multicollinearity between multiple variables is however difficult to detect (Brooks, 2002).

5.4.2 Time-series model

We perform a time series regression to study whether stock excess returns are affected by expected and unexpected market illiquidity over time. The method is based on the time series models developed by French et al. (1987), which was used by Amihud (2002). We perform regressions on measures of expected and unexpected illiquidity on monthly excess stock market returns. The return measure is specified as the equally-weighted average return of all stocks in the sample. Our measures of illiquidity are average relative bid-ask spreads and the natural logarithm of average illiquidity of the stocks in the sample, AILLIQ. We use the logarithmic transformation of the latter as in Amihud (2002), who bases it on the assumption that the relationship between the variable and market returns is concave rather than linear.

In line with Amihud (2002), we regress the excess return of the market on measures of expected and unexpected illiquidity, in accordance with equation (9a). As we study both average spreads and average price impact costs, we use the notation Average Market Illiquidity (AMI) in the formulas we present. e_y is used as the residual term in all equations.

$$(RM - Rf)_{my} = c_0 + c_1 AMI_y^E + c_2 AMI_y^U + e_y \tag{9a}$$

As we cannot observe investors' expectations of AMI, we need to estimate the expected and unexpected AMI. Market illiquidity is assumed to follow the autoregressive model:

$$AMI_y = c_0 + c_1 AMI_{y-1} + e_y \tag{9b}$$

This means that we expect the Average Market Illiquidity (AMI) in year y to be equal to a constant (c_0) that represents a "normal" level of market illiquidity, plus a portion (c_1) of the illiquidity level of the previous period (*$lnAMI_{y-1}$*), plus a residual. Thus, if the year y-1 was a year of much higher than average illiquidity, year y would also be expected to experience high illiquidity, but lower than that of the previous year. Similarly, if year y-1 was a year with exceptionally low illiquidity, year y would be expected to continue this pattern but with an increase in illiquidity. We thus assume illiquidity to have an autoregressive relationship, with a tendency to return to a normal level over time. This assumption is based on previous research (Amihud, 2002), and means that increasing illiquidity in one year means increasing expectations of illiquidity in the following year. The residual of this model, v_y, represents the change in illiquidity over the year that was observed ex-post but was not expected by the model.

We assume that investors use information available at the end of y-1 to form expectations about the AMI in period y. Investors' expected AMI (denoted AMI^E) is assumed to follow the autoregressive model:

$$AMI_y^E = c_0 + c_1 AMI_{y-1} \tag{9c}$$

The unexpected average illiquidity (denoted AMI^U) is the residual, or the change in illiquidity that was observed ex-post but which the autoregressive model failed to predict. The unexpected average illiquidity is thus:

$$AMI_y^U = AMI_y - AMI_y^E \tag{9d}$$

We apply this model to the two illiquidity proxies defined above, average relative bid-ask spreads and the natural logarithm of the average price impact, lnAILLIQ. The spread variables are notated ABA^E and ABA^U, and the AILLIQ variables are notated LN($AILLIQ^E$) and LN($AILLIQ^U$).

In the first step we estimate the autoregressive relationship. The regression results of equation (9b) estimated using average relative bid-ask spreads are presented in Table 8 below:

$$ABA_y = c_0 + c_1 ABA_{y-1} + e_y$$

ABA_Y	R^2: 0.311 – F: 2.71
Constant	0.0175 (0.275)
	1.20
ABA_{Y-1}	0.548 (0.150)
	1.64

Table 8: Results of autoregressive function for prediction of ABA_y. p-values in brackets; t-statistics in italics.

The autoregressive coefficient (c_1) in the calculation of expected ABA is estimated to be 0.548 and the constant (c_0) is estimated to be 0.0175.

The regression results of equation (9b) estimated using AILLIQ are presented in Table 9 below:

$$LN(AILLIQ)_y = c_0 + c_1 LN(AILLIQ)_{y-1} + e_y$$

$LN(AILLIQ_Y)$	R^2: 0.665 – F: 37.64
Constant	0.146 (0.493)
	0.70
$LN(AILLIQ_{Y-1})$	0.829 (0.000)
	6.14

Table 9: Results of autoregressive function for prediction of $lnAILLIQ_y$. p-values in brackets; t-statistics in italics.

The autoregressive coefficient (c_1) in the calculation of expected AILLIQ is estimated to be 0.829 and the constant (c_0) is estimated to be 0.146.

In the second step we use equation (9c) to estimate expected illiquidity for each year for both illiquidity proxies. This is done by taking the observed illiquidity for each year, and estimating expected illiquidity for the following year using the model estimated by equation (9b). We then use the expected illiquidity estimates from (9c) to calculate unexpected illiquidity for each year using equation (9d). Unexpected illiquidity is thus the difference between expected illiquidity based on the observed illiquidity of the previous year, and observed liquidity at the end of the current year.

In the third step we then perform the time-series regression to test the relationship between these variables and market returns using equation (9a). The output of equation (9a) is provided in the results chapter. The standard errors of the estimated coefficients in regression (9a) are robust to first-order autocorrelation and heteroscedasticity in regressions where these effects are present.

We use the Breusch-Pagan test for heteroscedasticity. This test is based on the assumption that the error terms are normally distributed which is approximately true for large sample sizes. The null hypothesis of the test is that the residuals are constant across observations (Wooldridge, 2009). If we fail to reject the null hypothesis at the 5% significance level we assume homoscedasticity. The test uses the error terms of our estimated regressions. The square of the error terms are then regressed on the independent variable. The larger the explanatory power of the regression, the larger is the probability that the hypothesis of homoscedasticity is rejected. Note that large explanatory power indicates that the variance of the error term is related to the independent variables. This is an indication of heteroscedasticity, since it implies that the variance of the error term is not constant across observations (Wooldridge, 2009). We fail to reject the hypothesis of homoscedasticity in the time-series model where we measure illiquidity as AILLIQ. The results of the regression are therefore reported with the OLS standard errors. We reject the hypothesis of homoscedasticity for the model where illiquidity is measured as the relative bid-ask spread. Thus the result of this regression is reported with White's standard errors.

Autocorrelation occurs if, for example, the error term in year y exhibits a large correlation with the error term in year y-1. This could be the case if the returns of these years are affected by a factor that is not included in our model (Brooks, 2002). We use the Durbin-Watson test to test for first-order autocorrelation. First-order autocorrelation refers to high correlation between the error terms of two successive observations e.g. y and y-1. The null hypothesis of the test is that the error terms are uncorrelated. The test is performed by computing the difference between the error terms of successive observations. In the absence of autocorrelation, the absolute differences will be large for some observations and small for some observations. If autocorrelation is present, the absolute differences will be small. Thus, the larger the sum of the absolute differences across observations, the larger is the probability that the null hypothesis is rejected. The null hypothesis of zero autocorrelation is rejected at the 1% significance level for the model where illiquidity is measured as

AILLIQ but not for the model where illiquidity is measured as relative bid-ask spreads. We use the Cochrane-Orcutt estimation procedure to obtain standard errors that are robust to first-order autocorrelation for the model with AILLIQ. The degree of autocorrelation is measured from a regression where the error term of observation t is regressed on the error term of observation t-1. The higher the correlation between the residuals of successive observations, the larger is the adjustment to the OLS standard errors (Brooks, 2002).

Detailed test statistics are presented in Appendix 1. Note that the consistency, unbiasedness and efficiency of the OLS estimator are dependent on a number of assumptions which we have not tested. We have restricted ourselves to test the assumptions which we have reason to believe might be violated given previous empirical research. This applies to our cross-sectional model as well as our time-series model.

6 Results

Our results give weak support for a positive cross-sectional relationship between relative bid-ask spreads and excess stock returns after adjusting for other risk factors. However, we find no support for a positive cross-sectional relationship between price impact costs, measured as ILLIQMA, and excess stock returns. The results of the time-series regression suggest that expected relative spreads have a positive effect on stock market returns and that unexpected relative spreads has a negative effect on contemporaneous stock market returns. Our regression results do not support the proposed relationship between expected AILLIQ and expected market returns. The effect of unexpected AILLIQ on market returns is however significant and negative as expected. These results are discussed in more detail in the following sections.

6.1 Cross-sectional stock returns: Relative bid-ask spread

The results of our regressions provide some indication that risk-adjusted stock returns increase with relative bid-ask spreads. The relative bid-ask spread is statistically significant in the first risk specification but not in the second one. However, the coefficient of the relative bid-ask spread is similar in both specifications which indicates that the coefficient is robust to different risk-adjustments. We find that the majority of the risk adjustment variables are statistically insignificant, as would be expected from previous research on the Stockholm Stock Exchange, for example Asgharian & Hansson (2002).

In the first specification we include the market model beta, the momentum factors and LNSize to adjust for risk. The relative bid-ask spread is positive and statistically significant at the 10% significance level. In line with the previous research on the Swedish market which we discussed in the fourth chapter, the risk factors market beta and LNSize are not statistically significant, and neither are LRET100 or LRET100R. Contrary to expectations, LNSize has a positive sign which would suggest that stocks of large companies yield higher returns, but the statistical significance of the coefficient is very low. One possible explanation for the positive sign of LNSize is that the relative bid-ask spread might capture some of the size effect, and we find that LNSize and the bid-ask spread have a correlation of approximately -0.49. To test whether the positive sign of LNSize is attributable to its correlation with relative bid-ask spreads we perform the regression without the spread, and the coefficient of LNSize remains positive and insignificant.

Table 10:
Cross-sectional regression using relative bid-ask spreads.

$$R_{imy} = K_{omy} + \sum_{j=1}^{J} K_{jmy} X_{ji,y-1} + U_{imy}$$

R_{imy}	Specification 1	Specification 2	Expected sign
Constant	**-0.0103**	**0.0070**	
p-value (t-value)	0.552 (-0.60)	0.307 (1.03)	
Relative spread	**0.1478**	**0.1482**	**+**
p-value (t-value)	0.083 (1.75)	0.105 (1.63)	
Market model beta	**0.0024**		**+**
p-value (t-value)	0.807 (0.25)		
LRET100 (momentum)	**0.0067**	**0.0066**	**+**
p-value (t-value)	0.683 (0.41)	0.687 (0.40)	
LRET100R (momentum)	**-0.0052**	**-0.0038**	**+**
p-value (t-value)	0.548 (-0.60)	0.641 (-0.47)	
LNSize	**0.0009**		**-**
p-value (t-value)	0.470 (0.72)		
FF beta		**-0.0078**	**+**
p-value (t-value)		0.218 (-1.24)	
FF SMB		**-0.0045**	**+**
p-value (t-value)		0.468 (-0.73)	
FF HML		**0.0081**	**+**
p-value		0.023 (2.31)	
Average R^2	0.0652	0.0717	
Number of obs.	33,483	33,483	
Number of periods	108	108	

In each month year y = 2002, 2003…,2010, excess stock returns are regressed cross-sectionally on stock characteristics that are estimated from data in year y-1. The year begins at the 1 April and ends at 31 March. The Market Model Beta is estimated on 10 size-based portfolios and the beta of each stock corresponds to the beta of the portfolio to which it belongs. The relative bid-ask spread is the yearly average of the daily bid-ask spread in SEK divided by the daily bid price. LNSize is the natural logarithm of the market capitalization of the stock at the end of March each year. LRET100 is the stock return over the last 100 days before the year end and LRET100R is the stock return over the beginning of the year and 100 days before the year end. FF:beta, FF:SMB and FF:HML are estimated for portfolios sorted by market capitalization and book-to-market value. Each stock is assigned the HML and SMB coefficients of the portfolio to which it belongs. Stocks with missing values on one or more of the variables are excluded from the sample, and so are stocks with less than 100 trading days during the year. Tests on statistical significance are performed on two-way clustered White's standard errors to adjust for heteroscedasticity, firm and time effects.

The R-squared of the specification without the bid-ask spread is 0.047, compared to 0.0652 with the spreads included. This indicates that the spread has explanatory power that is not related to multicollinearity with size. Although the R-squared of the models may seem low, they are within the normal range for models of this type.

As a further robustness check we perform separate regressions for each size portfolio. The regressions include the relative bid-ask spread, LRET100, LRET100R, market model beta and LNSize. As opposed to the regression with the full sample, LNSize has a negative coefficient in the regressions divided into large, medium and small companies. The coefficient of the relative bid-ask spread is however only statistically significant in the regression with small firms. This could indicate that the coefficient of relative bid-ask spread captures risks related to size in the regressions with the full sample. Furthermore, the explanatory power of the relative bid-ask spread seems to be constrained to small firms although more research is needed to understand the effect of size. The size-segmented regression results are presented in Appendix 3.

We also divide our sample into two time periods, 2002-2006 and 2006-2010, to investigate if the illiquidity effect is robust over time. The regression results indicate that the illiquidity effect is constrained to the first sub-period where the magnitude and significance of the coefficient of relative bid-ask spreads is higher than for the whole study period. The coefficient of the relative bid-ask spread is not statistically significant during the second sub-period although the coefficient is of similar magnitude as for the whole study period. The results of our regression in the period 2002-2006 are similar to those of Westerholm (2002). Further results from these regressions are presented in Appendix 5.

In the second specification we use the Fama & French three factor model and the momentum factors to adjust for risk. The relative bid-ask spread has a positive sign as expected and the coefficient is highly similar to the coefficient of the previous specification, but is not significant at the 10% level. HML has a positive sign as expected and is statistically significant at 5% significance level. The three-factor model market coefficient however does not have the expected sign and is not significant. SMB, the size-related variable of the three-factor model, is statistically insignificant and has a negative rather than positive sign. As we exclude the bid-ask spreads from the regression, the market coefficient remains negative whereas SMB turns positive, indicating that SMB might be multicollinear with the relative bid-ask spread. However, SMB remains statistically insignificant. The correlation between the relative bid-ask spread and SMB is 0.38 which is a relatively low correlation in the context of multicollinearity. A correlation matrix was presented in Section 5.2 and the results of the regressions that exclude relative bid-ask spreads can be seen in Appendix 4. When removing the bid-ask spread from the model the R-squared decreases to 0.0524, from 0.0717 with the spreads included.

6.2 Cross-sectional stock returns: Price impact

The results of our regressions indicate that illiquidity measured as mean-adjusted price impact (ILLIQMA) does not contribute to explain cross-sectional variations in stock returns. As can be seen in Table 11, the coefficient of ILLIQMA in the first specification is statistically significant but not economically significant since the coefficient has the opposite sign compared to what would be suggested by economic theory. The coefficient changes sign and loses its significance in the second specification.

In the first specification, we regress excess monthly stock returns on ILLIQMA, the market model beta, the momentum variables, LNSize and STDEV. ILLIQMA is significant at the 10% level but has a negative sign which contradicts our hypothesis. If ILLIQMA is a proxy for illiquidity costs and investors require compensation for these costs, the relationship between ILLIQMA and risk-adjusted stock returns should be positive. In the second specification we regress excess monthly stock returns on ILLIQMA, SMB, HML, beta, LRET100 and LRET100R. The coefficient of ILLIQMA is positive as expected but is not significant. As the coefficient of ILLIQMA varies between models with different risk-adjustment, our results indicate that ILLQMA does not contribute to explaining cross-sectional variations in stock returns. Furthermore, the fact that ILLIQMA is statistically significant but has the opposite sign compared to what is suggested by theory might indicate that ILLIQMA captures cross-sectional differences between stocks which are not related to illiquidity. For example, ILLIQMA contains information about past stock returns in the numerator and information about trading volume in the denominator.

Alternatively, our model might not be correctly specified. Nevertheless, the first model corresponds to the model used by Amihud (2002) to study the illiquidity-return relationship on NYSE. Furthermore, all of the control variables have the expected signs in the first model. The second model includes momentum proxies as well as the Fama & French risk proxies which are commonly used in asset pricing research. All of the variables except for the Fama & French beta have the expected signs.

Table 11:
Cross-sectional regression using ILLIQMA.

$$R_{imy} = K_{omy} + \sum_{j=1}^{J} K_{jmy} X_{ji,y-1} + U_{imy}$$

Rm-Rf	Specification 1	Specification 2	Expected sign
Intercept	**-0.0124**	**0.0080**	
p-value (t-value)	0.315 (-1.01)	0.153 (1.43)	
ILLIQMA	**-0.0053**	**0.0013**	**+**
p-value (t-value)	0.052 (-1.95)	0.616 (0.50)	
LRET100 (momentum)	**0.0027**	**0.0025**	**+**
p-value (t-value)	0.583 (0.55)	0.652 (0.45)	
LRET100R (momentum)	**0.0056**	**0.0018**	**+**
p-value (t-value)	0.350 (0.94)	0.786 (0.27)	
Market Model Beta	**0.0105**		**+**
p-value (t-value)	0.136 (1.49)		
LNSize	**-0.0001**		**-**
p-value (t-value)	0.941 (-0.07)		
STDEV	**0.0033**		**+**
p-value (t-value)	0.106 (1.62)		
FF: Beta		**-0.0054**	**+**
p-value (t-value)		0.366 (-0.90)	
FF: SMB		**0.0009**	**+**
p-value (t-value)		0.795 (0.26)	
FF: HML		**0.0020**	**+**
p-value (t-value)		0.582 (0.55)	
Average R^2	0.1259	0.1225	
Number of obs.	46,578	46,572	
Number of periods	252	252	

In each month year y = 1990, 1991…,2010, excess stock returns are regressed cross-sectionally on stock characteristics that are estimated from data in year y-1. The year begins at the 1 April and ends at 31 March. The Market Model Beta is estimated on 10 size-based portfolios and the beta of each stock correspond to the beta of the portfolio to which it belongs. ILLIQ is calculated as the yearly average of the daily absolute stock return divided by the daily SEK trading volume of each stock. ILLIQMA is calculated as ILLIQ divided by the average value of ILLIQ across stocks in each year. LNSize is the natural logarithm of the market capitalization of the stock at the end of March each year. STDEV is the standard deviation of the stock daily return during the year. LRET100 is the stock return over the last 100 days before the year end and LRET100R is the stock return over the beginning of the year and 100 days before the year end. FF:beta, FF:SMB and FF:HML are estimated for portfolios sorted by market capitalization and book-to-market value. Each stock is assigned the HML and SMB coefficients of the portfolio to which it belongs. Stocks with missing values on one or more of the variables are excluded from the sample, and so are stocks with less than 100 trading days during the year. Tests on statistical significance are performed on two-way clustered White's standard errors to adjust for heteroscedasticity, firm and time effects.

6.3 Time-series stock market returns

The results of our time-series models are presented in Table 12 and Table 13. In the first model, excess monthly stock market returns are regressed on expected and unexpected average relative bid-ask spread. Tests of statistical significance are performed on White's standard errors to adjust for heteroscedasticity. In the second model, excess monthly stock market returns are regressed on expected and unexpected AILLIQ. Each independent variable is found to have its expected sign, and each variable except the expected AILLIQ is found to be statistically significant. Tests of statistical significance are performed using the Cochrane-Orcutt method to adjust for first-order autocorrelation. Additional information regarding robustness checks and alternative estimation models are available in Appendix 1 and 2.

In line with our hypothesis, the regression results indicate that the expected illiquidity of the market as measured by the relative bid-ask spread has a positive effect on the market excess return. The expected relative bid-ask spread coefficient is significant at the 1% level, but the expected AILLIQ coefficient falls just short of statistical significance when adjusted for autocorrelation. The two results are not directly comparable because of the difference in time period of measurement, but performing the regression using AILLIQ on the same time-period as the relative spreads yields highly similar results. The regressions indicate that unexpected illiquidity, measured as the difference between the expected and the realized illiquidity of the market, has a negative effect on market excess returns. Both the coefficient of unexpected AILLIQ and the coefficient of unexpected average spreads are negative and statistically significant.

The results of the bid-ask spread model are consistent with the results of the cross-sectional model discussed in the previous section. The implication is that just as an investor expecting a high bid-ask spread in one particular instrument will demand a premium for holding that instrument, so will an investor require a premium for holding equity instruments over risk-free alternatives in times of high market illiquidity. The bid-ask spread model is however limited by an estimation period of only eight years due to lack of additional spread data, which limits the generalizability of the results.

Table 12:
Time-series regression using relative bid-ask spread

$$(RM - Rf)_{my} = c_0 + c_1 ABA_y^E + c_2 ABA_y^U + e_y$$

(RM-Rf)	Average Spread	Expected sign
Intercept	**-0,035**	
p-value (t-value)	0,030 (-2,20)	
ABA^E	**1,277**	**+**
p-value (t-value)	0,007 (2,77)	
ABA^U	**-2,1202**	**-**
p-value (t-value)	0,000 (-3,82)	
Average R^2	0,258	
Number of obs.	96	
Number of periods	96	

Excess market returns are regressed on market illiquidity proxies representing expected and unexpected illiquidity that are estimated using an autoregressive model. ABA^E is the expected average bid-ask spread of the market estimated end of year y-1 (ex ante) while ABA^U is the unexpected average bid-ask spread of the market estimated end of year y (ex post). Estimated using white's standard errors that are robust to heteroscedasticity.

Although we do not find support for a cross-sectional relationship between ILLIQ and risk-adjusted stock returns, our time-series regression indicates that AILLIQ contributes to explaining time-series variations in excess stock market returns. The results of our time-series regression are similar to those of Amihud (2002) when tests of statistical significance are computed on the OLS standard errors. However, the coefficient of the expected AILLIQ falls just short of being significant at a level of 10% when the Cochrane-Orcutt estimation used to adjust for first-order autocorrelation. The coefficient of unexpected AILLIQ is however strongly significant.

In line with our hypothesis, the results of our time-series regressions indicate that the expected illiquidity has a positive effect on stock market excess returns and that unexpected illiquidity has negative effect on contemporaneous stock returns. These findings indicate that the market risk premium might include compensation for illiquidity costs. However, we have not controlled for other factors that affect the market risk premium. Thus we cannot rule out that our illiquidity measures are correlated with other factors that cause the market risk premium to vary over time.

Table 13:
Time-series regression using AILLIQ

$$(RM - Rf)_{my} = c_0 + c_1 \ln(AILLIQ)_y^E + c_2 \ln(AILLIQ)_y^U + e$$

(RM-Rf)	AILLIQ	Expected sign
Intercept	**0,009**	
p-value (t-value)	0.121 (1,55)	
AilliqE	**0,0072**	**+**
p-value (t-value)	0.119 (1.57)	
AilliqU	**-0,0284**	**-**
p-value (t-value)	0.000 (-4.25)	
Average R^2	0,076	
Number of obs.	251	
Number of periods	251	

Excess market returns are regressed on market illiquidity proxies representing expected and unexpected illiquidity that are estimated using an autoregressive model. $AILLIQ^E$ is the expected average ILLIQ estimated end of year y-1 while $AILLIQ^U$ is the unexpected average ILLIQ estimated end of year y. Estimated using the Cochrane-Orcutt method to adjust for first-oder autocorrelation.

In addition, AILLIQ appears to rise sharply in periods of poor economic performance of the overall market. Given this tendency, it is possible that market illiquidity is affected by market return rather than vice versa. Investors might for example reduce their trading frequency and require higher stock returns if they expect that the stock market performance of future periods will be poor. However, it seems unlikely that investors would be able to accurately predict periods of poor performance. Figure 3 plots variations in AILLIQ over time. The shaded area beginning in 1990 represents the Swedish banking crisis, the area beginning in the year 2000 represents the collapse of the Dotcom bubble and the shaded area beginning in 2008 represents the financial crisis.

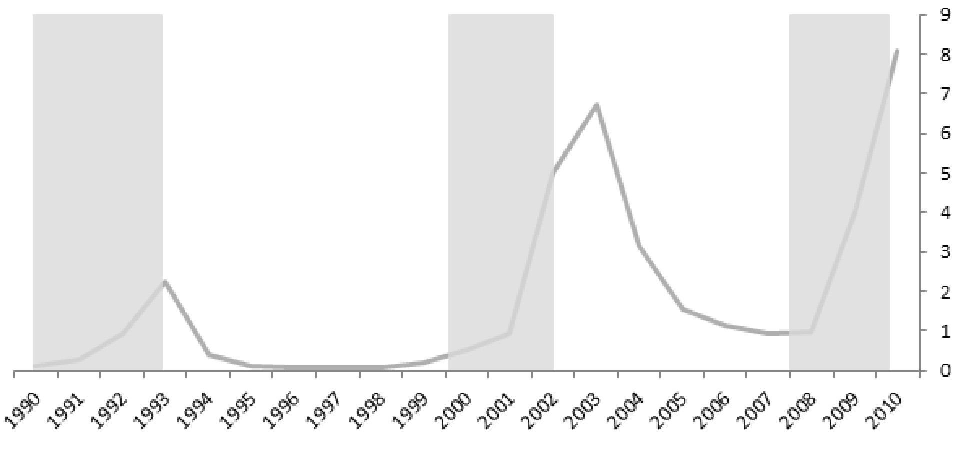

Figure 3: AILLIQ plotted over time with shaded areas representing significant events described below

7 Conclusion

In this paper we study if illiquidity costs estimated as relative bid-ask spreads and the price impact measure ILLIQ contribute to explain variations in stock returns on the Stockholm Stock Exchange. We use a sample consisting of all Swedish stocks which are listed in Thomson Reuters DataStream over the period 1990-2010, but the lack of data on quoted bid and ask prices restricts the sample for the estimations that contain the relative bid-ask spreads to the period 2002-2010. In each year, stocks that were traded during less than 100 days during the previous year and stocks with missing values on data that were required to calculate one or more of the explanatory variables are excluded. The results of the study are therefore not generalizable for stocks with less than 100 trading days. Our economic models are based on the assumption that investors form portfolios at the beginning of April each year based on the illiquidity and risk characteristics of the previous year. Our risk adjustment methods are based on the CAPM augmented with size and momentum factors, and the Fama-French three factor model augmented with momentum factors.

We find no support for a cross-sectional relationship between the price impact measure ILLIQ and risk-adjusted stock returns, but do find limited support for a positive relationship between relative bid-ask spreads and risk-adjusted stock returns. The significance of this relationship is dependent on the risk-adjustment model used, but the regression coefficients appear to be robust. As we divide the sample into sub-periods, we find that the effect of the relative spread seems to be constrained to the period 2002-2006. We also divide the sample into three sub-samples based on the market capitalization of the companies and find that the illiquidity effect seems constrained to companies of low market capitalization. We conclude that although we find indications that a relationship between the relative bid ask-spread and risk-adjusted stock returns does exist; it appears to have declined in strength over the estimation period and primarily affects small firms.

We find support for a positive time-series relationship between expected average relative bid-ask spreads and market returns, but not for a similar relationship between average ILLIQ and market stock returns. However, we find support for a negative relationship between both unexpected average relative bid-ask spreads and market returns, and unexpected average AILLIQ and market returns. We thus conclude that expected and unexpected market illiquidity appears to affect excess stock market returns over time on the Stockholm Stock Exchange. These findings indicate that excess stock returns include compensation for illiquidity costs.

Our regressions indicate that the effect of illiquidity on excess stock returns is weaker on the Stockholm Stock Exchange compared to, for example, results documented on the NYSE by Amihud (2002). A potential explanation for our results is that the performance of foreign stock exchanges might have a large impact on the performance of the Stockholm Stock Exchange, in particular since the market capitalization of the Stockholm Stock Exchange is relatively small compared to stock exchanges such as NYSE, Amex, Nasdaq and the London Stock Exchange. Furthermore, the presence of a large amount of foreign investors on the Stockholm Stock Exchange could have implications on the relationship. These investors might not be so much concerned about the differences in illiquidity across the stocks traded on the Stockholm Stock Exchange but rather cross-sectional differences in stocks traded on all of the stock exchanges on which they hold stocks.

The potential influence of foreign stock exchanges on the Stockholm Stock Exchange could also have implications for other risk factors. The risk factors we use to control for risk have low explanatory power in our regressions which is in line with previous research on the Stockholm Stock Exchange. Although our control variables are motivated by previous research, one could question whether we appropriately account for differences in riskiness across stocks. For example, it might be more appropriate to estimate systematic risk as the co-variation of the stock returns to the excess stock returns of an international stock index.

Finally, our sample selection criteria might be overly encompassing. For example, Amihud (2002) excluded firms with stock prices below $5 to remove differences in tick sizes across stocks. We do not employ such a criterion since it would reduce the generalizability of our results. Our estimated regressions differ between sub-samples sorted by size, which might indicate that the stocks belong to different sub-populations.

Potential avenues for future research within illiquidity on the Stockholm Stock Exchange could involve using more restrictive sample selection criteria to remove potential differences between sub-populations of stocks or to study the differences in the relationship between subpopulations. The size of stocks in particular appears to be a factor that affects the strength of the relationship between illiquidity and excess stock returns. Based on the performance of our risk adjustment variables, there is also a need for further research into risk and asset pricing on the Stockholm Stock Exchange.

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Appendix

Appendix 1: Time-series robustness – Heteroscedasticity and autocorrelation

Results of Breusch-Pagan / Cook-Weisberg test for heteroscedasticity:

Heteroscedasticity	**Chi2**	**P**
Av. Bid-Ask Spread	5.15	0.02
AILLIQ	0.13	0.72

Table A-1: Breusch-Pagan / Cook-Weisberg test

Null hypothesis of homoscedasticity is therefore rejected in the average bid-ask spread model at the 0.95 significance level.

Durbin-Watson statistics to test for the presence of autocorrelation:

Autocorrelation	**Chi2**	**Lower Bound**	**Upper Bound**
Av. Bid-Ask Spread	1.723	1.502	1.582
AILLIQ	1.563	1.653	1.693

Table A-2: Durbin-Watson statistics

The lower and upper bounds are different because of the difference in length of the sample periods (Bid-ask spread based models are restricted to 2002-2010). Null hypothesis of first-order autocorrelation is rejected in the average bid-ask spread model at the 0.99 significance level, but is not rejected in the AILLIQ model.

Appendix 2: Time-series Robustness - Alternative Estimations

The aim of our time-series methodology is to use the best linnear unbiased estimator in each model. This means that we test each model separately for heteroscedasticity and autocorrelation, and only make the adjustments that are neccesary to correct detected issues. In this appendix we provide alternative estimations models, which are the models that would have been estimated had bias not been detected. We also provide the test statistics that were using to disqualify them.

Below we provide the results of the OLS regressions using white's standard errors. The results of the average spread model are found to be unbiased, but the AILLIQ model is biased by first order autocorrelation and is provided below primarily for comparative purposes. The primary difference from the estimations used in the main body of the report is that the expected AILLIQ is found to be significant at the 10% level, while it was insigificant using the unbiased estimator.

Table A-3:

Time-series OLS estimations with white's standard errors

$$(RM - Rf)_{my} = c_0 + c_1 AMI_y^E + c_2 AMI_y^U + w_y$$

$(RM\text{-}Rf)_{my}$	Average Spread	AILLIQ	Expected sign
Intercept	**-0,035**	**0,009**	
p-value (t-value)	0,030 (-2,20)	0,0054 (1,94)	
AspreadE	**1,277**		**+**
p-value (t-value)	0,007 (2,77)		
AspreadU	**-2,1202**		**-**
p-value (t-value)	0,000 (-3,82)		
AilliqE		**0,0072**	**+**
p-value (t-value)		0,054 (1,95)	
AilliqU		**-0,0284**	**-**
p-value (t-value)		0,000 (-5,47)	
Average R^2	0,258	0,112	
Number of obs.	96	252	
Number of periods	96	252	

This table contains estimators that may be biased, and which should only be used for comparative purposes. AMI refers to the Average Market Illiquidity, measured either through the average relative bid-ask spread or AILLIQ depending on the model specification.

Below we also provide time series models estimated through the Cochrane-Orcutt regression process with one lag. The AILLIQ model is found to be autocorrelated in its original form, but the transformed model is not found to contain autocorrelation.

Table A-4:
Time-series Cochrane-Orcutt estimation

$$(RM - Rf)_{my} = c_0 + c_1 AMI_y^E + c_2 AMI_y^U + w_y$$

$(RM\text{-}Rf)_{my}$	Average Spread	AILLIQ	Expected sign
Intercept	**-0.035**	**0.009**	
p-value (t-value)	0.030 (-1.85)	0.121 (1.55)	
AspreadE	**1.2648**		**+**
p-value (t-value)	0.004 (2.91)		
AspreadU	**-2,1761**		**-**
p-value (t-value)	0.000 (-4.05)		
AilliqE		**0.0072**	**+**
p-value (t-value)		0.119 (1.57)	
AilliqU		**-0,0272**	**-**
p-value (t-value)		0.000 (-4.25)	
Average R^2	0.217	0.076	
Number of obs.	95	251	
Number of periods	95	251	
D-W Stat. (original)	1.723	1.563	
D-W Stat. (new)	1.935	1.987	

This table contains estimators that may be biased, and which should only be used for comparative purposes. D-W Stat. (original) refers to the Durbin-Watson statistic of the original OLS model, while D-W Stat. (new) refers to the Durbin-Watson statistic of the transformed model that was estimated using the Cochrane-Orcutt method.

Appendix 3: Size-segmented cross-sectional regressions

The results of the regressions of each size portfolio are provided below. Estimations are conducted using relative bid-ask spreads, and risk-adjustments are made according to specification 1. In each year the sample for that year was divided into three equally large portfolios. The discrepancy in terms of amount of observations is caused by a lack of data within smaller companies.

Table A-5:
Size-segmented cross-sectional regressions

$$R_{imy} = K_{omy} + \sum_{j=1}^{J} K_{jmy} X_{ji,y-1} + U_{imy}$$

Ri-Rf	Small	Medium	Big	Expected sign
Constant	**0.0526**	**0.0426**	**0.0242**	
p-value (t-value)	0.495 (0.69)	0.212 (1.26)	0.261 (1.13)	
Relative spread	**0.1271**	**-0.1979**	**0.1792**	**+**
p-value (t-value)	0.091 (1.71)	0.169 (-1.39)	0.406 (0.83)	
Market Model Beta	**-0.0480**	**-0.0300**	**-0.0102**	**+**
p-value (t-value)	0.209 (-1.26)	0.254 (-1.15)	0.534 (-0.62)	
LRET100 (momentum)	**0.0174**	**0.0070**	**-0.0050**	**+**
p-value (t-value)	0.547 (0.60)	0.320 (1.00)	0.607 (-0.52)	
LRET100R (momentum)	**-0.0030**	**-0.0079**	**-0.0054**	**+**
p-value (t-value)	0.766 (-0.30)	0.280 (-1.09)	0.565 (-0.58)	
LNSize	**-0.0037**	**-0.0013**	**-0.0017**	**-**
p-value (t-value)	0.707 (-0.38)	0.687 (-0.40)	0.221 (-1.23)	
Average R^2	0.1000	0.0788	0.0973	
Number of obs.	9,688	11,537	12,258	
Number of periods	108	108	108	

In each month year y = 2002, 2003…,2010, excess stock returns are regressed cross-sectionally on stock characteristics that are estimated from data in year y-1. The year begins at the 1 April and ends at 31 March. The Market Model Beta is estimated on 10 size-based portfolios and the beta of each stock corresponds to the beta of the portfolio to which it belongs. The relative bid-ask spread is the yearly average of the daily bid-ask spread in SEK divided by the daily bid price. LNSize is the natural logarithm of the market capitalization of the stock at the end of March each year. LRET100 is the stock return over the last 100 days before the year end and LRET100R is the stock return over the beginning of the year and 100 days before the year end. FF:beta, FF:SMB and FF:HML are estimated for portfolios sorted by market capitalization and book-to-market value. Each stock is assigned the HML and SMB coefficients of the portfolio to which it belongs. Tests on statistical significance are performed on two-way clustered White's standard errors to adjust for heteroscedasticity, firm and time effects.

Appendix 4: Cross-sectional regressions without illiquidity proxies

The results of the regressions where the illiquidity proxies are excluded are provided below.

Table A-6:

Cross-sectional regression without illiquidity proxies, full sample (1990-2010)

$$R_{imy} = K_{omy} + \sum_{j=1}^{J} K_{jmy} X_{ji,y-1} + U_{imy}$$

Ri-Rf	Specification 1	Specification 2	Expected sign
Constant	**-0.0155**	**0.0059**	
p-value (t-value)	0.189 (-1.32)	0.553 (-0.59)	
Market model beta	**0.0085**		**+**
p-value (t-value)	0.212 (1.25)		
LRET100 (momentum)	**0.0080**	**0.0079**	**+**
p-value (t-value)	0.292 (1.06)	0.322 (0.99)	
LRET100R (momentum)	**0.0048**	**-0.0006**	**+**
p-value (t-value)	0.435 (0.78)	0,927 (-0.09)	
LNSize	**0.0007**		**-**
p-value (t-value)	0.483 (0.70)		
STDEV	**0.0027**		**+**
p-value (t-value)	0.135 (1.50)		
FF beta		**-0.0035**	**+**
p-value (t-value)		0.553 (-0.59)	
FF SMB		**0.0021**	**+**
p-value (t-value)		0.579 (0.56)	
FF HML		**0.0015**	**+**
p-value		0.677 (0.42)	
Average R^2	0.1056	0.1019	
Number of obs.	252	252	
Number of periods	48,211	48,217	

In each month year y = 2002, 2003…,2010, excess stock returns are regressed cross-sectionally on stock characteristics that are estimated from data in year y-1. The year begins at the 1 April and ends at 31 March. Tests on statistical significance are performed on two-way clustered White's standard errors to adjust for heteroscedasticity, firm and time effects.

Table A-7:

Cross-sectional regression without illiquidity proxies, bid-ask period sample (2002-2010)

$$R_{imy} = K_{omy} + \sum_{j=1}^{J} K_{jmy} X_{ji,y-1} + U_{imy}$$

Ri-Rf	Specification 1	Specification 2	Expected sign
Constant	**-0.0002**	**0.0122**	
p-value (t-value)	0.989 (-0.01)	0.04 (2.08)	
Market model beta	**0.011**		**+**
p-value (t-value)	0.412 (0.82)		
LRET100 (momentum)	**0.010**	**0.010**	**+**
p-value (t-value)	0.520 (0.64)	0.516 (0.65)	
LRET100R (momentum)	**-0.007**	**-0.007**	**+**
p-value (t-value)	0.423 (-0.80)	0.464 (-0.73)	
LNSize	**-0.001**		**-**
p-value (t-value)	0.424 (-0.80)		
FF beta		**-0.012**	**+**
p-value (t-value)		0.09 (-1.71)	
FF SMB		**0.005**	**+**
p-value (t-value)		0.441 (0.77)	
FF HML		**0.005**	**+**
p-value		0.211 (1.26)	
Average R^2	0.0470	0.0524	
Number of obs.	108	108	
Number of periods	33,483	33,483	

In each month year y = 2002, 2003…,2010, excess stock returns are regressed cross-sectionally on stock characteristics that are estimated from data in year y-1. The year begins at the 1 April and ends at 31 March. Tests on statistical significance are performed on two-way clustered White’s standard errors to adjust for heteroscedasticity, firm and time effects.

Appendix 5: Cross-sectional estimation using bid-ask spread divided into two periods

The results of the regression with relative bid-ask spreads over sub-periods are presented in the table below.

Table A-8:
Cross-sectional regression using bid-ask spread, divided into subperiods

$$R_{imy} = K_{omy} + \sum_{j=1}^{J} K_{jmy} X_{ji,y-1} + U_{imy}$$

	Specification 1		Specification 2	
R_{imy}	*2002-2006*	*2006-2010*	*2002-2006*	*2006-2010*
Constant	**0.0020**	**-0.0226**	**0.0220**	**-0.0080**
p-value (t-value)	0.942 (0.07)	0.266 (-1.13)	0.009 (2.73)	0.458 (-0.75)
Relative spread	**0.1647**	**0.1310**	**0.1762**	**0.1203**
p-value (t-value)	0.063 (1.90)	0.374 (0.90)	0.039 (2.12)	0.462 (0.74)
Market model beta	**0.0017**	**0.0032**		
p-value (t-value)	0.899 (0.13)	0.831 (0.21)		
LRET100 (momentum)	**0.0211**	**-0.0077**	**0.0213**	**-0.0081**
p-value (t-value)	0.482 (0.71)	0.572 (-0.57)	0.477 (0.72)	0.566 (-0.58)
LRET100R (momentum)	**-0.0013**	**-0.0091**	**0.0004**	**-0.0080**
p-value (t-value)	0.933 (-0.08)	0.258 (-1.14)	0.975 (0.03)	0.301 (-1.04)
LNSize	**0.0001**	**0.0018**		
p-value (t-value)	0.977 (0.03)	0.140 (1.50)		
FF beta			**-0.01850**	**0.0030**
p-value (t-value)			0.063 (-1.90)	0.701 (0.39)
FF SMB			**0.0001**	**-0.0092**
p-value (t-value)			0.990 (0.01)	0.211 (-1.27)
FF HML			**0.0143**	**0.0019**
p-value			0.012 (2.60)	0.657 (0.45)
Average R^2	0.0814	0.0490	0.0902	0.0532
Number of obs.	14,363	19,120	14,363	19,120
Number of periods	54	54	54	54

In each month year y = 2002, 2003…,2010, excess stock returns are regressed cross-sectionally on stock characteristics that are estimated from data in year y-1. The year begins at the 1 April and ends at 31 March. Tests on statistical significance are performed on two-way clustered White's standard errors to adjust for heteroscedasticity, firm and time effects.

Appendix 6: Data processing

Data collection was conducted through the use of the DataStream plugin for Microsoft Excel. The process was automatically performed by specifying the sample of companies, the variables to download and the relevant time period. The resulting output was then automatically downloaded into the spread sheet document. The following data requests were made, covering the entire time period (time period defined relative to the year being studied using that particular data):

Variable	**Period**
Daily Adjusted Prices (P)	Year t-2 to Year t
Daily Unadjusted Prices (UP)	Year t-1 to Year t
Daily Volume Traded (VO)	Year t-1 to Year t
Market Value at Year End (MV)	Yea4r t-1
Market to Book Value at Year End (MTBV)	Year t-1
Monthly Adjusted Prices (P)	Year t
Daily Bid Prices (PB)	Year t-1
Daily Ask Prices (PA)	Year t-1

In order to avoid errors stemming from mistakes in manual data treatment we processed the data automatically by using a pre-programmed spread sheet that converted the information provided above into the variables that were required to test each hypothesis. The data treatment model was specifically designed for the sample and allows data quantities up to 1250 individual stocks and 270 trading days each year, with no lower bound. Errors and missing data were automatically corrected through filters.