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IMPACT OF COVID-19 ON THE RELATIONSHIP BETWEEN LIQUIDITY AND STOCK RETURNS: EVIDENCE FROM FINLAND

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Liquidity is key to the health and fluidity of financial markets. It is the ability to make trade assets in large quantities in a quick fashion without incurring large trading costs or moving the price. Stock market declines, especially during crises, compromise this ability as buyers flee the market. Suddenly, assets cannot be sold without massive unjustified price concessions. A liquidity risk has been realized.

Liquidity is one of the many risk factors that have been studied since Fama (1964), Mossin (1966) and Lintner (1965) laid the groundwork of factor investing by introducing the Capital Asset Pricing Model, which explains stock returns by their sensitivity to market risk. Since then, many factors have been added that have been found to be important determinants of stock returns. Liquidity too has been deemed as such by Amihud & Mendelson (1986), Pastor & Stambaugh (2003) and Acharya & Pedersen (2005) among others, who have all constructed measures to capture varying dimensions of liquidity. Even though some differing opinions have been presented, liquidity has generally been found to be an important state variable that impacts stock returns.

This study seeks to uncover the relationship between liquidity and stock returns in Finland and to reveal a possible liquidity premium. More specifically, we focus on the covariance between stock returns and changes in aggregate liquidity. A stock that is more sensitive to liquidity shocks, and therefore riskier, should provide higher returns. These liquidity shocks have historically been associated with financial crises and other major market downturns. Recently, the COVID-19 crisis shook the world and its financial markets. A deadly disease broke out and spread around the world rapidly. Governments around the world imposed quarantines and shut down businesses, which ground their respective economies to a halt. Stock markets collapsed and so did liquidity. The link between liquidity and crises makes the COVID-19 era an exceptionally interesting area of research. Thus, this study will also reveal the possible effect that the COVID-19 pandemic had on the relationship of stock returns and liquidity.

We adopt the liquidity series of Pastor & Stambaugh (2003) to use as the liquidity factor in our regression analysis. We finalize the model by adding additional control factors that account for risks unrelated to liquidity. The study uses monthly data from 2017-2022 and splits it into two sample periods: one for the pre-COVID period and one for the duration of the pandemic. The data is gathered from OMXH25 companies. The results suggest that there is no significant liquidity effect present. The coefficients of the liquidity factor correspond to prior research, but the results are not statistically significant. Similarly, the COVID-19 pandemic does not seem to influence the relationship between stock returns and liquidity. There are slight changes, but they are not statistically significant. These results may be caused in part by the limitations of this study. Additionally, it could be that the meaningful sources of liquidity risk arise from different liquidity dimensions than the one investigated in this study.

Keywords
Liquidity, Factor investing, COVID-19

Additional information

CONTENTS

FIGURES

TABLES

1 INTRODUCTION

Nowadays, financial markets are more global, interconnected and fluid than ever. As digitalization has taken the world by storm, the stock markets have moved to an online environment where transactions occur between parties that are situated on opposite sides of the world. Finding a suitable counterparty for an exchange has never been easier. Investors can trade their assets in a matter of minutes and switch positions seamlessly as they see fit. Or can they?

Liquidity is what ensures a well-functioning and fluid financial environment. Simply put, it is the ability to trade assets quickly in large quantities without incurring increasing trading costs or moving the price of the asset. In normal times, these conditions are filled relatively well by most assets. Of course, some asset classes like real estate are less liquid than shares of an index fund because finding a suitable counterparty may prove difficult and identical alternative assets are not readily available. The same phenomenon can occur amongst stocks too. At any point in time, someone is always willing to buy Apple at a competitive price. The same cannot be said for smaller stocks.

Unfortunately, liquidity can become compromised on an economy wide level. Financial crises have historically been associated with such occurrences. During crises, the market reacts violently to negative news and the drop in asset prices can be extremely sharp. These drops lead to panic and uncertainty, which leads to further falls in asset prices that are unjustified by any financial metrics. Demand for assets dies down, as investors expect the plunge to continue. Suddenly, assets can no longer be sold swiftly without making extreme price concessions.

The most recent crisis that had a global impact on the financial markets and the world as a whole is the COVID-19 crisis. In late 2019, an acute respiratory coronavirus was identified in the Chinese city of Wuhan. Attempts to contain the virus were unsuccessful and the virus spread around the world like wildfire. Governments around the world responded by closing borders, implementing quarantine measures, and restricting economic activity. the stock markets reacted negatively to these news and stock prices started to drop rapidly. Once again, the disappearance of liquidity had an amplifying effect on other crisis symptoms. The downward slope continued for months until the market started slowly recovering.

Clearly, liquidity, or the lack thereof, poses a great risk for investors. And at the core of finance lies the relationship between risk and return. Additional undiversifiable risk should be compensated for by higher asset returns. Risk is not a simple concept though, as it may arise from several different sources. Sharpe (1964) , Mossin (1966) and Lintner (1965) were the first ones to create a model where stock returns were explained by a risk factor. Their Capital Asset Pricing Model, where market risk exposure explains stock returns, is still the most commonly used factor model and has been built upon by many other researchers. The risk factors can be almost anything, given that they have any attributes that relate to an asset and can explain its returns. Such factors have been created to gauge the effect of liquidity as well. Amihud & Mendelson (1986), Pastor & Stambaugh (2003), and Acharya & Pedersen (2005) have all constructed liquidity measures based on different liquidity dimensions and have found liquidity to be an important determinant of stock returns. Some researchers have disagreed however, and either found the effect to be minimal or even non-existent.

Perhaps the environment in which the research is conducted has an impact on the results. The financial markets of the U.S. and other giants are extremely liquid, which doesn’t reflect the reality of other smaller markets, like Finland. Ahmed et al. (2019) argue that these thinly traded markets, like Finland, would provide an interesting avenue for liquidity effects. There are only a few actively traded stocks, which could reinforce liquidity effects.

This study explores the relationship between liquidity and stock returns in the Finnish market. Additionally, we seek to uncover whether the recent COVID-19 pandemic has an impact on this relationship. The data is gathered from OMXH25 companies from years 2017-2022 and split into two sample periods. A pre-COVID period from 2017 to 2020 and a pandemic period from 2020 to 2022. We conduct multiple regression analyses using a liquidity innovation series developed by Pastor & Stambaugh (2003), which measures liquidity risk as a stocks sensitivity to changes in aggregate liquidity. Intuitively, assets with higher sensitivity to liquidity shocks should yield a higher return. The measure is especially suitable for this study because changes or shocks in aggregate liquidity are often associated with crises. We accompany the liquidity series with other pervasive economic factors to control for risks unrelated to liquidity.

The main research questions for this study are:

- Is there a relationship between liquidity and stock returns in Finland?
- Does the COVID-19 pandemic influence this relationship?
- If a relationship is found, is there premium to liquidity?

We do not find evidence of relationship between liquidity and stock returns in Finland. Regressions produce coefficients that align with prior research, but the results are not statistically significant. As such, the liquidity premium cannot be determined either. Similarly, the effect of COVID-19 cannot be confirmed. There is a small change in the regression results but again, the results are statistically insignificant. The results may be skewed due to limitations in factor and data selection. The data for the liquidity factor and control factors are gathered from outside of Finland and the sample size is quite small, a major difference from the majority of liquidity related studies. Additionally, we merely focus on a single dimension of liquidity. As shown by Ahmed et al. (2019), while a particular liquidity dimension might have an insignificant effect on stock returns, other dimensions may still be impactful.

The paper will continue as follows: Chapter two presents a review of related literature and creates a theoretical framework. Chapter three introduces the data and methodology used in the study. Chapter four presents the results of empirical testing and the discussion of these results. Finally, chapter five concludes the paper and provides ideas for further research.

2 LITERATURE REVIEW

2.1 What is liquidity?

Liquidity is a broad and elusive concept that plays an important role both at the macro and at the micro level. It is essential for achieving a fluid and functioning financial market and economy. This section will form an overview of liquidity by first briefly introducing macro-liquidity and then moving on to micro-liquidity, also known as market liquidity, which is the most often discussed aspect of liquidity in the asset pricing literature. Florackis et. al (2014) characterize macro-liquidity as the money supply provision by central banks and the availability of funds for financial intermediaries and other market participants. Nikolaou (2009) refers to these concepts as central bank liquidity and funding liquidity. Micro-liquidity refers to the trading conditions of assets, such as the costs, speed, volume and price impact of converting cash into assets and vice versa (Florackis et al., 2014).

Central bank liquidity, also known as the supply of base money, is the ability of a central bank to supply the liquidity required by the financial system. Central bank liquidity is a result of the central bank managing its balance sheet in accordance to the current monetary policy stance. The liabilities side of the balance sheet consists of balances of commercial banks that are held by the central bank to meet reserve requirements and other autonomous factors that are not affected by the central bank's monetary policy. These obligations and other factors create an aggregate liquidity deficit in the system, which makes the system reliant on refinancing from the central bank. The deficit must then be balanced by the central bank's "assets" i.e., open market operations that supply commercial banks with liquidity. (Nikolaou, 2009)

Funding liquidity may be viewed from the perspective of both an institution and an investor. It is the ability of financial institutions to meet their liabilities or settle their positions in a timely fashion. From the point of view of an investor, funding liquidity can be understood as the ability of raise capital or cash on a short notice. For both parties, it holds that an entity is liquid when its inflows are at least as large as its outflows. Banks have multiple sources of liquidity. They may enter the asset market and create liquidity through securitization, loan syndication and through the secondary loan market. Additionally, liquidity can be drawn from the interbank loan market, directly from the central bank by bidding on open market operations and from the bank's depositors. (Nikolaou, 2009)

Micro-liquidity or market liquidity, in its simplest terms, is the ease of trading a security. A liquid asset is one that can be traded quickly in large quantities, at low cost and without moving the price (Pástor & Stambaugh, 2003). Based on this, Nikolaou (2009) suggests that the liquidity of a market should be judged on multiple grounds that incorporate the key elements of volume, time and transaction costs. Three dimensions emerge: depth, tightness and resiliency. A market is deep when a high amount of transactions does not affect the price or when the number of available buyers and sellers is large. In a tight market, transaction prices do not diverge from mid-market prices. Market resiliency relies on price fluctuations from trades and order flow imbalances being quickly corrected. When all dimensions are fulfilled, any quantity of assets can be sold quickly at a fair price within market hours.

When one or more of the liquidity dimensions are compromised, the market starts exhibiting illiquidity. Naturally, illiquidity creates uncertainty and risk of not being able to realize assets without making concessions. According to Nikolaou (2009), central bank liquidity risk is widely thought to be non-existent. Central banks, as the originator of the monetary base, are the monopoly provider of liquidity and are always able to supply base money. Because of this, they can never be illiquid. Funding liquidity risk on the other hand is an unsystematic risk that can be diversified away by conscious planning and monitoring. Sharpe (1964) among others established the asset pricing framework, where assets with non-diversifiable systematic risk require a higher return. For liquidity, the systematic, non-diversifiable component of risk is market liquidity risk (Nikolaou, 2009). For this reason, the emphasis of this paper, like most prior studies regarding liquidity and asset pricing, will be on market liquidity.

The sources of market illiquidity are numerous, the most apparent of them being the transaction costs such as brokerage fees, order related costs, transaction taxes and many others. Other, more complex, sources of illiquidity include demand pressure, inventory risk, private information and the difficulty of finding a suitable counterparty for an exchange. All agents are not present in the market at the same time, which creates demand pressure because selling a security quickly might prove difficult if the natural buyers are not immediately available. A market maker may buy the security in anticipation of being able to lay it off in the future. The market maker is exposed to the risk of price changes during the time they hold the asset in their inventory and must be compensated for it, which imposes a cost on the seller of the security. (Amihud et al., 2005)

Private information is a major source of illiquidity. The buyer of a security may think that the seller has private information about an upcoming negative earnings announcement while the seller may think that the buyer knows that the company's share is on the verge of a large of a positive jump in price. In both cases, trading with an informed party will result in losses. Alternatively, agents may have private information about order flow. Knowing a hedge fund is about to liquidate a large position can be exploited by selling securities early and buying them back after the liquidation has depressed prices. (Amihud et al., 2005)

Finding a suitable counterparty for trading a particular asset or a large quantity of a given security may sometimes prove to be difficult. In such cases, the trade must also be negotiated in a non-competitive environment since alternative trading partners are not available on a short notice. These search frictions are especially relevant in over-the-counter markets without a centralized marketplace. The longer the process of finding a suitable counterparty, the larger the financing and opportunity costs. Alternatively, the agent can choose to make price concessions by dealing with a market maker and thus face an illiquidity cost. The whole situation boils down to a trade-off between searching for a suitable counterparty or trading quickly at a discount. (Amihud et al., 2005)

2.2 Factor analysis

Markowitz (1952) laid the groundwork for modern portfolio theory (MPT) and asset pricing by introducing methods of selecting assets in a way that maximizes portfolio returns for a given risk. He formalized the idea of diversification by showing that holding a portfolio of assets that are not perfectly positively correlated reduces risk.

The need for diversification indeed, is the reason for the prevalence of factor investing and risk factor analysis. Standard asset pricing theory assumes that expected stock returns are cross-sectionally related to the return's sensitivities to pervasive economic state variables (Pástor & Stambaugh, 2003) One such variable is the market risk, which was introduced by Sharpe (1964), Lintner (1965) and Mossin (1966) who built upon Markowitz' (1952) work and developed the theory of the Capital Asset Pricing Model (CAPM), which divides risk into two parts: systematic and specific risk. Systematic risk is unavoidable and common across all assets while specific risk is associated with individual assets and can be diversified away. The CAPM assumes that all agents hold the market portfolio in excess of the risk-free rate and the only risk factor is the market risk. No compensation is given for taking on specific risk as it can be eliminated by diversification. The amount of risk a security adds to a portfolio is measured by the beta. If the security is riskier than the market portfolio, its beta is more than one and if the security is exposed to less risk than the market portfolio its beta is lower than one. If this does not hold, the security is mispriced until the prices are balanced by rational investors. The model forms a linear relationship between systematic risk and return but it is unable to capture other important risks that are not explained by the market risk.

The factor analysis framework has since been expanded by multiple authors. Banz (1981) is the first one to discover a size effect, which shows that the stocks of small firms have higher risk-adjusted returns than those of large firms. Fama & French (1993) expand the CAPM by identifying two stock-market factors related to firm size and book-to-market value in addition to the overall market factor. The size factor, also known as Small-Minus-Big (SMB) represents the outperformance of small companies over large companies in the long term. Similarly, the value factor, also known as High-Minus-Low (HML) represents the outperformance of high book-to-market companies in excess of low book-to-market companies. The Fama-French 3-factor model has significantly more explanatory power on diversified portfolio returns than the CAPM.

Jegadeesh & Titman (1993) introduce the momentum effect. They show that a strategy of buying stocks that have performed well in the past and selling stocks that have done poorly in the past generates significant positive returns. Carhart (1997) follows by developing a four-factor model that consists of the three factors of Fama & French (1993) in addition to the momentum factor. Later, Fama & French (2015) create the five-factor model that incorporates the factors from the three-factor model but extends it by adding an investment factor CMA (Conservative Minus Aggressive) and an operating profitability factor RMW (Robust Minus Weak). Fama & French (2018) further add a momentum factor to create a six-factor model due to the former model's inability to explain momentum anomalies. Several other factors have been identified in the literature and that will not stop in the future. As long as there is premium that is unexplained, further research will follow.

2.3 Liquidity as a risk factor

Liquidity has become an increasingly important part of the factor analysis and asset pricing framework. Four different dimensions of liquidity risk have been identified in the literature. The first studies regarding the relationship between liquidity and asset returns focused on the level of liquidity. Amihud & Mendelson (1986) are among the first ones to suggest a link between liquidity and asset returns. In their model, securities are illiquid due to transaction costs. They assume that risk-neutral investors expect to pay a transaction cost when selling an asset and will take that into account when valuing it. As such, the investor must also consider the entire future stream of transaction costs that will be paid on the asset. The price discount due to illiquidity is thus the present value of the expected transaction costs during the asset's lifetime. Amihud & Mendelson (1986) model the effects of the bid-ask spread on asset returns using a CAPM framework. They find that a higher spread, meaning higher transaction costs, is associated with a higher expected return. Additionally, they discover a horizon clientele effect, whereby stocks with higher spreads are held by investors with longer holding periods. Furthermore, smaller traders are more concentrated in illiquid stocks. Due to the clientele effect, the returns on higher-spread stocks are also less spread-sensitive. According to their study, liquidity is clearly a priced variable. Amihud & Mendelson (1986) played a critical role in laying the groundwork for further research on liquidity as an important asset pricing factor.

Brennan & Subrahmanyam (1996) add to the research on the relationship of liquidity level and asset returns. They investigate whether illiquidity costs caused by adverse selection, a situation where buyers and sellers have different amounts of information, are related to higher returns. They use variable and fixed proportional trading costs as a proxy for liquidity instead of the bid-ask spread and adjust for other risks using the three-factor model of Fama & French (1993). They find significant return premiums associated with both variable and fixed trading costs, suggesting that liquidity risk is priced. Additionally, their findings support Amihud & Mendelson's (1986) hypothesis of small traders being more concentrated in smaller stocks, but they cannot find evidence of the horizon clientele effect. Jacoby et al. (2000) follow by creating a liquidity adjusted version of the CAPM in which asset returns are calculated after accounting for the effect of the bid-ask spread. They show that the true measure of systematic risk must incorporate liquidity costs in the form of the bid-ask spread to be accurate. In other words, beta and liquidity are inseparable. Later, Amihud (2002) presents a new measure for the price impact of liquidity and finds more support for the relationship between expected liquidity levels and stock returns.

The second dimension of liquidity, commonality in liquidity, is based on the assumption of investors demanding compensation for stocks that become illiquid when market illiquidity is high. Among the first ones to study this liquidity dimension are Chordia et al. (2000). They show that individual liquidity measures co-move with each other and are more than just attributes of singular assets. Correspondingly, Acharya & Pedersen (2005) build a liquidity adjusted model based on the CAPM, where the required return of a security depends on the covariances of its own liquidity and return with the market liquidity and return, as well as its expected liquidity. By doing so, they show that liquidity affects asset prices through multiple channels. The return premium due to commonality in liquidity, the covariance between a security's liquidity and market liquidity is small but significant. Intuitively, this means that investors require a small premium for holding illiquid stocks when the market as a whole is illiquid. Therefore, the effect of this dimension on stock returns is positive.

The third dimension of liquidity is referred to as the flight-to-liquidity phenomenon. Flight-to-liquidity may be understood as the covariance between asset returns and market liquidity. The effect occurs when investors seek to switch their positions in illiquid assets like certain stocks, to more liquid assets like government bonds, which then leads to uncertainty in the market, the decline of implied asset values and finally, negative stock returns. Logically, investors should demand more compensation for holding stocks with high sensitivities to market liquidity. Acharya & Pedersen (2005) note that flight-to-liquidity affects required returns negatively because investors accept lower returns on assets that exhibit high returns in times of market illiquidity. Simply put, investors are willing to pay to avoid the risk associated with illiquidity.

Pastor & Stambaugh (2003) are among the first ones to investigate this dimension of liquidity risk. They test whether market-wide liquidity is a priced variable by following a portfolio-based approach to create an asset universe with disperse liquidity betas. Stocks are sorted based on their predicted liquidity betas and ten portfolios are formed. A single return series for each decile portfolio is created by linking the 12-month post formation returns across years on these portfolios. The excess returns on these portfolios are then regressed while accounting for exposures to common asset pricing factors, namely the market return, size and value factors. The liquidity beta explains a portion of returns that is not captured by the other factors to the extent that the intercept of the regression differs from zero. They find that a stock's sensitivity to innovations in aggregate liquidity plays a major role in asset pricing. Expected stock returns are cross-sectionally related to these innovations. Stocks with higher sensitivity to aggregate liquidity produce substantially higher expected returns and liquidity seems to be an important state variable. Pastor & Stambaugh's (2003) liquidity measure captures liquidity risk that arises from the flight-to-liquidity effect. Acharya & Pedersen (2005) find further evidence for the effect of flight-to-liquidity. They discover that there is return premium that stems from the covariance between stock returns and market liquidity, also known as the stock's sensitivity to changes in aggregate liquidity. They report that the impact of flight-to-liquidity is slightly larger than that of commonality in liquidity.

The last and fourth dimension of liquidity risk that has been identified in the literature is related to the relationship between stock illiquidity and market returns. Acharya & Pedersen (2005) are among the first ones to study this dimension and they do it in the context a of liquidity adjusted CAPM. They find that the return premium due to the covariance between stock illiquidity and market returns is the most significant source of liquidity risk, which intuitively implies that investors are willing to pay a premium for securities that are liquid when the market return is low. Kim & Lee (2013) find additional support for the importance of this dimension of liquidity risk using a similar LCAPM framework. They report significant premiums arising from the relationship between stock illiquidity and market returns, even in the excess of Acharya and Pedersen (2005) and conclude that this dimension of liquidity seems to be the most important source of liquidity risk in the U.S. market. Intuitively, the relationship between stock illiquidity and market return affects stock returns negatively as investors accept lower returns on stocks with smaller illiquidity costs during poor market conditions. Again, investors are willing to pay to avoid the risk of illiquidity.

Naturally, some studies have come to differing conclusions regarding the role of liquidity in asset pricing. Momani (2018) re-tests Pastor & Stambaugh's (2003) model in the U.S. market and finds differing evidence from the original study. According to him, the liquidity factor is not priced. Similarly, Both Ma et al. (2021) and Li et al. (2019) find only modest support for liquidity as a priced variable using the P&S liquidity measure. Nguyen & Lo (2012) add to the contradicting evidence regarding the pricing of liquidity risk. They use a wide variety of liquidity measures based on both high-frequency and low-frequency data for examining the relationship between liquidity risk and returns in New Zealand. Instead of an illiquidity premium, they find an illiquidity discount which implies that less liquid stocks earn lower returns than liquid stocks. Additionally, they couldn't find evidence for the effect of liquidity on asset returns using any liquidity measures. Pastor & Stambaugh's (2003) liquidity factor seems to predict stock returns, but the evidence disappears in a risk adjusted framework. Moreover, Pontiff & Singla (2019) struggle to find any evidence that common liquidity variables capture priced risk. Li et al. (2019) remark that it may simply be that there is no large illiquidity premium to find. Indeed, a significant portion of the related literature argues that liquidity should only affect asset prices slightly. As the dimensions of liquidity are numerous, the selection of a measure or model is crucial in capturing priced risk. This is shown by Ma et al. (2021) who find that a liquidity adjusted CAPM performs well in explaining expected stocks returns despite the modest performance of the P&S liquidity measure.

2.4 Liquidity risk in the Finnish context

The pricing of liquidity risk has also been studied in the Finnish market. Ahmed et al. (2019) note that the markets of large, developed countries such as the U.S. are the most liquid markets in the world, which might make them insufficient for testing illiquidity effects empirically. They argue that the Finnish market provides a particularly interesting avenue for studying liquidity as it is a thinly traded market with only a few actively traded stocks, which could serve to amplify liquidity related effects. Additionally, smaller markets tend to exhibit larger variation in liquidity over time. Interestingly enough, Butt & Virk (2015) find that there is a substantial risk premium related to liquidity risks for Finnish stocks. The most significant liquidity risk stems from flight-to-liquidity while the level of illiquidity also has an effect on stock returns. The liquidity risk premium is substantially larger than the reported liquidity risk premium in the U.S. markets. The Finnish market is also relatively illiquid in comparison to the U.S. market and larger European markets. Similarly, Butt (2015) finds that illiquidity risk is an important characteristic of the Finnish market. He tests for the four dimensions of liquidity and confirms the importance of flight-to-liquidity as the most important liquidity dimension in the Finnish market. Unlike Butt & Virk (2015) however, he struggles to find any evidence of the pricing of other liquidity dimensions.

Vaihekoski (2009) tests a two-factor asset pricing model with factors for liquidity and market risk using data from the Finnish stock market from 1987-2004. He uses a value-weighted market-wide bid-ask spread as a measure of systematic liquidity risk. The measure is based on the flight-to-liquidity phenomenon. Corresponding to previous studies, he finds strong support for the pricing of liquidity risk. Liquidity appears to be negatively priced, which is in line with previous research by Acharya & Pedersen (2005) and others. The negative pricing of flight-to-liquidity related liquidity risks in the Finnish market is also confirmed by Butt (2015). Intuitively, investors require less compensation for stocks that show higher returns in times of illiquidity and are thus more favorable to hold during times when selling assets causes unprecedented financial losses. Moreover, Vaihekoski (2009) investigates whether a market-wide liquidity measure is enough to capture liquidity related risk or if additional asset specific related characteristics are priced separately. The results suggest that a market-wide liquidity measure is enough to capture all liquidity-related risks.

Ahmed et al. (2019) provide additional evidence of liquidity being a priced variable in the Finnish market. They use two liquidity measures to gauge whether different dimensions of liquidity are priced and estimate the conditional version of the liquidity adjusted CAPM introduced by Acharya & Pedersen (2005). They find that both expected illiquidity and liquidity risk are priced and have a significant effect on the cross-section of stock returns. The results hold when controlling for size and value factors. However, they find no evidence of the flight-to-liquidity related liquidity dimensions being priced in the Finnish stock market. This result is in contradiction with previous studies on the Finnish market, which have found liquidity risks related to the flight-to-liquidity phenomenon to be the most significant dimension of liquidity risk.

2.5 Liquidity during past crises

The subprime crisis of 2007-2008 emphasized the importance of liquidity for the fluidity of financial markets. It is well known that the drastic decline of market liquidity was at least partially responsible for the downfall of the financial system. The decrease in liquidity caused unjustified falls in asset prices that spiralled out of control fuelled by forced fire sales and deleveraging (Florackis et al., 2014). Brunnermeier & Pedersen (2009) explain such liquidity spirals by linking the market liquidity of an asset with the funding liquidity of traders. They show how the lack of funding liquidity leads to liquidity commonality, the degree to which the liquidity of individual securities co-moves with market-wide liquidity, and eventually the deterioration of market liquidity.

According to Brunnermeier & Pedersen (2009), when the market declines for whatever reason, the trader's assets are negatively affected, which increases the probability of margin calls and induces panic selling. The trader is forced to liquidate a portion of their portfolio, which adds further negative price pressure to the already declined markets. Margins soar even further, and a self-induced liquidity spiral is born. As the spiral impacts many securities at the same time, liquidity commonality increases and the liquidity of the market collapses. They also note that the liquidity spiral causes flight-to-liquidity. The decline in market liquidity and an increase in liquidity commonality during crises is also reported by Hameed et al. (2010).

Rösch & Kaserer (2014) find further empirical evidence for the theories proposed by Brunnermeier & Pedersen (2009). They confirm that liquidity spirals played a crucial role in the financial crisis. They note that despite being a crisis symptom, the drying-up of market liquidity also made the consequences of the crisis far worse. Due to the link between funding liquidity and market liquidity, an initial exogenous market shock in the form of a sharp decline may lead to a full-blown financial contagion.

Nagel (2012) inspects the change in expected returns from liquidity provision during the financial crisis. He notes that the definition of a liquidity provider is broad in this context and that liquidity provision can be performed by market participants such as algorithmic traders or even individual investors that may assume a market-making role without being officially designated as one. He proxies for liquidity provision by employing reversal strategies, i.e., selling stocks that went up during the prior days and buying ones that went down. The strategy imitates the trading of market makers who sell when the public is buying and vice versa. He finds that the expected returns of such reversal strategies rise predictably and dramatically in times of financial turmoil. Return reversal strategies formed with individual stocks during the financial crisis of 2007-2009 produce returns that are almost ten times higher than they were in 2006. His findings suggest that the liquidity risk premium earned by liquidity providers is highly time-varying and it increases during times of market turmoil. Hameed et al. (2010) present further support for these findings in the context of other crises and market downturns. They find that the cost of providing liquidity is highest in periods with large market declines and that reversal strategies produce significant returns. Nagel (2012) concludes that this increase in expected returns from liquidity provision is, at least partially, a reason for the evaporation of market liquidity during crises.

Lou & Sadka (2011) show that illiquid stocks outperformed liquid stocks during the financial crisis. They argue that the performance of stocks during the crisis is explained by both historical liquidity risk, a stock's sensitivity to aggregate liquidity and historical liquidity level, the ability to trade large amounts quickly without moving the price. The measures capture different dimensions of a stock's liquidity profile, but liquidity risk can better explain the cross-section of returns during the crisis. They note that the overperformance of illiquid stocks over liquid stocks is not particularly surprising. The liquidity of liquid stocks is likely to dry up during a crisis, which causes a large shock, while illiquid stocks will continue to be illiquid. They conclude that the real danger lies in stocks that are liquid and also exhibit high liquidity risk.

Although the subprime crisis has garnered much of the attention, liquidity has been studied in the context of other crises as well. Liu (2006) identifies multiple large declines in the U.S. market liquidity that respond to major economic events. He finds that market experiences the sharpest and largest tightening of liquidity over the recession of 1972-1974. The second significant event is the crash of 1987, which caused a large and continuing decrease in liquidity that was later amplified in 1990 by the Iraqi invasion on Kuwait and the ensuing Gulf war. Furthermore, he finds that the market experienced a gradual decline in liquidity during the Asian financial crisis of 1997-2001. He notes that the decline coincided with other crises, such as the 1998 Russian default, the collapse of the U.S. Hedge fund Long Term Capital management, the burst of the early 2000s tech bubble and the terrorist attacks of September 2001. Lesmond (2005) provides additional evidence of deteriorating liquidity during the Asian and Russian crises. He finds that bid-ask spreads increase sharply and significantly.

Similarly, Yeyati al. (2008) detect an increase in trading costs during crises. They focus on various crisis episodes in the emerging markets over the period of 1994-2004. They find that emerging markets react differently to asset price fluctuations than developed markets. Instead of shutting down during market downturns, financial markets continue to operate with higher trading volume and costs. The increase in trading volume is associated with portfolio reallocation performed by agents that had not anticipated a crisis and fire sales by liquidity constrained investors. They note that trading activity starts declining only later as crises progress. Their findings indicate an interesting quirk in the relation between trading volume and costs. Although they are negatively related in normal times, the relation seems to break down during crises.

In general, the impact of crises on liquidity is apparent. Every major crisis comes with a sharp downward liquidity shock and heavily increasing liquidity costs. As liquidity deteriorates, market makers demand a larger compensation for providing liquidity to the starved market. Logically, it could be assumed that crises would also influence the liquidity risk premiums required by investors. As assets become increasingly difficult to liquidate, investors are hesitant to hold them due to the uncertainty of being able to get rid of them in the event of a margin call or other constraints. As a result, investors could demand higher liquidity risk premiums across the board. Indeed, Anderson (2011) among others has shown that evolutions in capital markets cause agents to change their attitudes towards risk, which results in the time variation of risk premia. He shows that the sharp decline in stock prices during the subprime crisis is consistent with an increase in risk premia while the subsequent recovery in prices is consistent with stable or falling risk premia, indicating clear time variation. Likewise, Muir (2017) reports that the substantial increase in expected returns (or risk premia) is a common trait across most financial crises.

2.6 The COVID-19 crisis

The COVID-19 pandemic was a global pandemic caused by an acute respiratory syndrome coronavirus that was first identified in the Chinese city of Wuhan in December of 2019. The symptoms of the disease vary between undetectable to deadly and include fever, fatigue, soreness and dry cough. Attempts to contain the disease failed and it spread rapidly worldwide. As reported by Salo (2020a, 2020b), The World Health Organisation declared the virus outbreak a public health emergency of international concern on January 30th of 2020 and later began referring to it as a pandemic on the 11th of March in 2020. Governments around the world countered by closing borders and implementing quarantine measures that restricted economic activity. Restaurants were closed, density levels in public spaces were limited and wearing a surgical mask was close to mandatory. Unsurprisingly, these countermeasures had an immense impact on economic activity, especially in sectors involving social interaction. As of May 2023, there have been nearly 800 million confirmed cases of the virus and the disease has claimed approximately 7 million lives (Our World in Data, 2023). After three gruelling years, the World Health Organization ended the global emergency status for the COVID-19 on May 5th of 2023 (Rigby & Satija, 2023).

The pandemic caused large economic disruptions all over the world. The shock was not felt simultaneously across the globe and mitigation policies were different across countries. Nonetheless, there were some significant similarities in outcomes during the pandemic period. The COVID-19 shock had a severe negative impact on output growth and employment in 2020, especially in middle-income countries. Employment levels fell across the board and GDP growth declined significantly all around the world. Countermeasures employed by governments, mainly increased expenditure, resulted in a rise in debt levels. In addition to fiscal policy measures, many countries used monetary policy to respond to the crisis, which lead to a sharp rise in the growth of the monetary base. Additionally, the shock hurt international trade tremendously in 2020 as the growth rate of real imports and exports fell. Economies around the world began to slowly recover in 2021. Nonetheless, all regions were still lagging in terms of output relative to their pre-pandemic standards. Additionally, price inflation was higher than forecasted before the pandemic. (Martin et al., 2023)

To market participants, the virus outbreak came as a major shock. In 2020, infectious diseases were ranked as only the 10th risk in terms of impact in the World Economic Forum's Global Risk Report (2020), way behind multiple environmental and technological risks. Ramelli et al. (2020) examine the market's response to the spread of the disease. They find that when China was initially shut down, investors avoided stocks with exposure to China and internationally oriented stocks and as the situation in China improved in comparison to the rest of the world, investors began to treat those stocks more favourably again. When the virus spread to Europe and the Unites States, their respective stock markets moved drastically. In the U.S. for example, four major stock indexes (Wilshire 5000 Total Market Index, S&P 500, S&P Mid Cap 400, Russell 2000) lost more than a third of their value within 5 weeks with middle and small capitalization stocks suffering particularly great losses (Shu et al., 2021). Furthermore, Chaudhary et al. (2020) find that the indices of the top 10 countries sorted by GDP exhibit negative mean returns during the crisis period from January 2020 to June 2020, while the pre-COVID period from January 2019 to December 2019 shows positive mean returns.

Despite the initial shock, the markets started showing signs of recovery rather quickly. Chaudhary et al. (2020) show that the minimum value of all indices was in the month of March 2020, at the time of the COVID-19 crash. They find that already during the second quarter of the crisis, mean returns for the indexes were once again positive, albeit with higher volatility.

In terms of liquidity, the COVID-19 crisis demonstrates similar trends as its predecessors. Gofran et al. (2022) study the liquidity impact of COVID-19 on the equity markets of the U.S., UK, Brazil, China, Germany, and Spain. They discover that the pandemic causes significant increases in bid-ask spreads, indicating a short-term loss in liquidity. The impact is greatest for Europe and Latin America and the least significant in China where the liquidity effect disappears shortly after the announcement of the pandemic. Similarly, Jawadi et al. (2021) detect a decrease in liquidity in both the U.S. and Islamic markets during the COVID-19 period, as evidenced by an increase in spreads. Even the liquidity effect of government policy responses to COVID-19 has been noted. Kassamany & Zgheib (2023) find that out of seven Australian stringency policies, including school and workplace closing, cancellation of public events and public transportation, public information campaigns and restrictions on internal and international travel, all but public information campaigns reveal a negative impact on the liquidity of the Australian equity market.

Due to the COVID-19 pandemic being a very recent event, fairly little research has been conducted on its possible impact on risk premiums. Núñez-Mora et al. (2022) explore the impact of COVID-19 on the stock market risk premium in developed and emerging countries. They include stock indexes from nine different countries in three different regions including North America (USA, Mexico, Canada), South America (Brazil and Argentina), and Asia (Japan, South Korea, Singapore, Hong Kong) and inspect them over a pre-COVID period from January 2015 to December 2019 and during the COVID pandemic from January 2020 to December 2021. They find that developed stock markets experienced a significant increase in their risk premium during the COVID period and attribute it to the anticyclical policies implemented by governments. On the other hand, they discover that developing countries particularly in South America experienced a reduction or even a total loss of risk premium in their respective market indexes, possibly due to the disproportional increase in volatility caused by the crisis that could not be matched with the recovery of stock prices. For developed countries, the results align with Muir's (2017) findings regarding risk premia during financial crises. The findings of Núñez-Mora et al. (2022) support the hypothesis of a change in risk premiums during the COVID-19 crisis. Their focus, however, is on the market risk premium, which may not be indicative of changes in the premia of other types of risks.

3 DATA AND METHODOLOGY

3.1 Sample description

The data used in this study is collected from three different sources. The monthly return data for Finnish stocks is retrieved from Refinitiv Datastream, the data for the Pastor & Stambaugh liquidity factor is acquired from Robert Stambaugh's homepage and the data for the Fama & French three factor model is collected from Kenneth R. French data library. The study will use two sample periods to gauge the possible differences in liquidity premiums. One pre-COVID-19 period from the 1st of January 2017 to the 30th of December 2019 and one pandemic period from January 1st 2020 to December 30th 2022.

As previously mentioned, the stock market data for this study is retrieved from Refinitiv Datastream. The goal of this study is to test whether liquidity, measured by the P&S liquidity series, is a priced variable in the Finnish stock market and further uncover if the recent COVID-19 crisis influences the liquidity exposure of Finnish stocks. Additionally, this study seeks to determine the liquidity risk premium for Finnish stocks and whether the premiums change due to the COVID-19 crisis. The stocks included in the OMX Helsinki 25 index are suitable for this task. The index consists of the 25 most traded stocks on the Helsinki Stock Exchange and the stocks that are included in the index as of June 2023 will be used in this study.

While this study chooses to use the OMXH 25 stocks for empirical research, the other viable option would be the OMXH, which includes every stock listed on the Helsinki Stock Exchange. However, the Finnish market is often characterized as fairly thin and only a handful of stocks are actively traded. Even though Ahmed et al. (2019) argue that this may be seen as a positive thing for gauging liquidity effects, it makes sense to limit the data to only the OMXH 25. The smallest stocks listed in the Helsinki Stock Exchange trade with extremely low volumes and their liquidity may easily be affected by the actions of singular traders. Likewise, innovations in aggregate liquidity may have little to no effect on them. Luckily, the stocks included in OMXH25 still retain the advantage of a thinly traded market in terms of observing liquidity. Even the most traded Finnish stocks are a lot less liquid than the American stocks that most liquidity studies have been conducted on.

Monthly total stock returns are utilized for conducting this study. Total returns are used to account for dividends while the usage of monthly return data is motivated by the utilization of the Pastor and Stambaugh (2003) liquidity measure, for which the innovations in aggregate liquidity are reported monthly. Both the pre-COVID-19 period starting in January 2017 and ending in December 2019 and the pandemic period starting in January of 2020 and ending in December of 2022 span across three years. As such, both sample periods have 36 data points for each stock. While the amount of data points is relatively small, it still fulfils the minimum sample size requirement of 30 for the distribution of the sample to approximate a normal distribution and should thus be sufficient. Stocks that are not listed on the Helsinki Stock Exchange for the whole duration of the sample periods will be eliminated from the dataset to ensure the comparability of the produced regressions. Only one such stock exists, Kojamo, for which the first observation appears in July 2018. This leaves us with 24 stocks for the final sample.

The sample data is not subject to selection bias, as the Finnish stock market is well regulated and the data regarding stock performance is publicly available for all listed companies. However, the data might exhibit slight survivorship bias. Multiple companies have been removed and added to the index during the sample period due to the semi-annual reviews performed by Nasdaq. As a result, all of the companies involved in this study have not been a part of the index or among the 25 most traded stocks in the Helsinki Stock Exchange for the full duration of the sample period. Only those that prevailed through the trials and tribulations of the pandemic are left standing among the 25 most traded stocks get to participate. The worst-case scenario for the selection criteria used in this study would be a stock that was involved in the index for the almost the entire sample period but was removed before the June 2023 cut-off. Luckily, the composition of the index has remained quite stable during the sample period and even the latest stock to be added to the index (Metsä Board B) has been a part of the index earlier during the sample period. Additionally, none of the companies included in the index during the sample period have gone bankrupt, which further decreases survivorship bias in the sample. Ultimately, the companies selected for this study provide a sufficiently accurate representation of the Finnish market during the sample period.

3.2 Factor data

This section will present the liquidity series of Pastor and Stambaugh (2003) and its respective data along with the Fama-French (1993) three-factor model used to control for other significant economic factor that affect stock returns.

3.2.1 P&S Liquidity series

Estimating the impact of liquidity on asset prices is difficult as no measure can truly capture all its aspects. As such, different measures of liquidity have been introduced in the literature. Amihud & Mendelson (1986) use the quoted bid-ask spread as the measure of liquidity and model a world where asset returns, net of trading costs, increase with the spread. Datar et al. (1998) perform an alternative test of Amihud & Mendelson's (1986) model, using turnover rate as a proxy for liquidity. Both models are based on trading costs and the holding periods of the investors. Pastor & Stambaugh (2003) measure liquidity as the return reversal in response to volume shocks, Hasbrouck (2009) uses a Gibbs estimate of effective costs of trading and Amihud (2002) defines illiquidity as the daily ratio of absolute stock return to its dollar volume, averaged across stocks. Despite the apparent differences in the definition of liquidity measures, each study has been able to discover a liquidity effect.

This paper will make use of the liquidity series of Pastor & Stambaugh (2003) in measuring the relationship between liquidity risk and stock returns in the Finnish stock market before and during the Covid-19 crisis. Large liquidity shocks tend to be related to crises. Nagel (2012) shows that liquidity evaporated during the financial crisis of 2007-2009 and Jawadi et al. (2021) find that the liquidity of both US and Islamic stock markets exhibit significant time variation during the COVID-19 pandemic. The P&S liquidity series mainly captures the flight-to-liquidity dimension of liquidity risk. As previously mentioned, flight-to-liquidity rises from situations where investors seek to liquidate their illiquid assets and replace them with liquid assets. Intuitively, crises should be prime candidates for events that would induce flight-to-liquidity. As such, The P&S liquidity series should be well-suited for capturing the relationship between liquidity risk and stock returns, and perhaps even more importantly, the change in this relationship as it measures liquidity risk as the co-movement between stock returns and liquidity shocks.

Pastor & Stambaugh (2003) construct a liquidity measure that defines the liquidity in a certain month as the equally weighted average of the liquidity measures of individual stocks on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). Liquidity has many dimensions, and they focus on temporary price changes that accompany the order flow. The liquidity measure for stock i in month t is the ordinary least squares estimate of $\gamma_{i,t}$ in the following regression:

$$r^e_{i,d+1,t} = \theta_{i,t} + \varphi_{i,t} r_{i,d,t} + \gamma_{i,t} sign\ (r^e_{i,d,t}) \cdot V_{i,d,t} + \varepsilon_{i,d+1,v} \quad d = 1,\ldots \text{D}, \qquad (1)$$

$r_{i,d,t}$ is the return on stock i on day d in month $t;$ $r^e_{i,d,t} = r_{i,d,t} - r_{m,d,t}$ where $r_{m,d,t}$ is the return on the Center for Research in Security Prices (CSRP) value-weighted market return on day d in month t. $V_{i,d,t}$ is the dollar volume for stock i on day d in month t. Stocks with less than 15 observations during a given month are excluded from the data. The observations do not have to be consecutive, but each observation requires data from two successive days. Stocks with prices below $5 or above $1000 at the end of the last month are excluded to limit the effect of a possible size factor. Additionally, stocks are excluded for the first and last partial month that they appear on the CSRP.

The basis of the measure is order flow, illustrated simply as the volume signed by the simultaneous excess return on the stock ($sign\ (r^e_{i,d,t}) \cdot V_{i,d,t}$). According to Pastor & Stambaugh (2003) order flow should be accompanied by a return that can be expected to be partially reversed in the future if the stock is not perfectly liquid. The return reversal is assumed to be negatively correlated with the liquidity of the stock, i.e., the greater the return reversal for a given dollar volume, the lower the liquidity. The assumption of volume-related return reversals being linked to liquidity is motivated by Campbell et al (1993) who show that market-makers are compensated with a higher expected return for alleviating selling or buying pressure by providing liquidity. The greater the order flow, the greater the compensation and as such the effect of liquidity on expected returns in the future is larger when the current trading volume is high.

Pastor & Stambaugh (2003) note that the specification of the measure is slightly arbitrary, like any other liquidity measure. The excess return ($r^e_{i,d,t}$) is used both as the dependent variable and to sign trading volume with the goal of removing the effect of market-wide shocks and to isolate the individual-stock effect of the return reversals. As the direction of the order flow is a key feature of this liquidity measure, it is important to limit the quantity of days with zero returns. For small stocks, total daily returns of zero are somewhat common, while zero returns in excess of the market are not. This is why excess return is used to sign the volume instead of total return. The use of excess return makes it possible to identify the stock's order flow as either seller or buyer initiated on days when the stock price is stagnant, but the market moves in either direction. Additionally, a lagged stock return is used as the second independent variable in the regression to capture lagged-return effects that are not related to volume. As the excess return is used to sign volume, total return $r_{i,d,t}$ is used as the second variable to improve precision by reducing the correlation between the independent variables.

Pastor & Stambaugh (2003) inspect the ability of regression slope $\gamma_{i,t}$ in the first equation to identify a liquidity effect. They construct a model in which the return on day d has an order flow component that is partially reversed on the following day. The return on stock i on day d is given by the following equation:

$$r_{i,d} = f_d + u_{i,d} + \phi_i(q_{i,d-1} - q_{i,d}) + \eta_{i,d} - \eta_{i,d-1} \tag{2}$$

where f_d is a market-wide factor and $u_{i,d}$ is a stock specific factor. ϕ_i represents liquidity and its coefficient is negative while $q_{i,d}$ represents the order flow. $\phi_i(q_{i,d-1} - q_{i,d})$ captures the liquidity-related effect that arises from order flow by allowing both the current and lagged return to enter the return, but in opposite directions. Finally, $+\eta_{i,d} - \eta_{i,d-1}$ represents the tick size and bid-ask bounce effects which are additional reversal effects that are independent from order flow. Pastor & Stambaugh (2003) estimate the regression and find strong cross-sectional correlation between ϕ_i and γ_i, which suggests that the first regression is well-suited for estimating the effect of liquidity.

Pastor & Stambaugh (2003) continue by constructing the scaled market-wide liquidity series $(m_t/m_1)\ \gamma_i$. Each month's observation of aggregate liquidity is given by averaging the monthly measures for individual stocks (γ_i) and multiplying it by m_t/m_1 where m_t is the total dollar value at the end of month $t-1$ of the stocks included in the average in month t. m_1 corresponds to the first month of the data sample. The scaling in the series corrects for the relative changes in dollar values across different time periods.

The main series of Pastor & Stambaugh (2003) focuses on the importance of liquidity risk, which they measure as the co-movement between stock returns and unanticipated innovations in aggregate liquidity, also known as liquidity shocks. The scaled market-wide liquidity measure is not used directly for constructing innovations as the fluctuations in the scaling factor may introduce a return component. The innovation series must also be able to appropriately reflect the growth of the stock market. Therefore, instead of differencing the scaled series, the monthly market-wide liquidity measures are first differenced and then scaled. More specifically, the monthly difference in liquidity measures averaged across N_t stocks with data from both the current and previous month is scaled and then the averaged difference in liquidity measures is regressed on its lag as well as the lagged value of the scaled series. Finally, the innovation in liquidity, also known as the liquidity factor, is the fitted residual divided by 100 which is given as:

$$L_t = \frac{1}{100}\hat{u}_t \tag{3}$$

Scaling by 100 is motivated by the goal of producing more convenient magnitudes of liquidity betas.

The main limitation of the P&S liquidity factor is that it is constructed on stocks listed on the NYSE and AMEX, while this study is conducted on the Finnish stock market. Liquidity, however, has been shown to be largely correlated across different markets. Brockman, Chung & Pérignon (2009) find that movements in aggregate bid-ask spreads on individual exchanges are influenced by movements in spreads at the global scale. Similarly, Karolyi, Lee & Van Dijk (2011) discover cross-country patterns in liquidity, explained mainly by the involvement of institutional and foreign investors and correlated trading activity. This indicates that liquidity is correlated across countries. Furthermore, Amihud et al. (2015) examine markets across 45 countries and find major commonality between illiquidity return premiums. They show that illiquidity premiums co-vary positively and significantly with global and regional illiquidity premium factors. The commonality in illiquidity premiums is stronger in countries that are more open to foreign investments and in markets that are heavily integrated with other markets, consistent with the findings of Karolyi, Lee & Van Dijk (2011). Moreover, Chordia, Sarkar & Subrahmanyam (2005) add to the evidence by showing that liquidity is correlated across different stock markets. These findings suggest that the liquidity factor of Pastor & Stambaugh (2003) is suitable for estimating the liquidity exposure in the Finnish stock market.

The data for the Pastor & Stambaugh liquidity measure (2003) is retrieved from Robert Stambaugh’s liquidity series database on his homepage. The dataset spans from August 1962 to December of 2022 and presents the levels of aggregated liquidity (equation 1) along with the main series of the study, the innovations in aggregate liquidity (equation 3). The observations are reported on a monthly basis. Emulating the work of Pastor & Stambaugh (2003), this study will use the monthly observations of the main series as the liquidity factor in empirical research.

3.2.2 Fama & French 3-factor model

There are numerous risks that have been found to have an enormous effect on stock returns. Most of them, however, have little to no relation to liquidity. In this study, the focus is on the link between liquidity and stock returns, which motivates us to account for other risks that would introduce omitted-variable bias to our model. To control for these risks, this study will follow in the footsteps of Pastor & Stambaugh

(2003) and adopt the Fama & French (1993) three-factor model and its factors as control variables. These factors have been shown to be well-suited for the task as they are able to explain up to 90% of the returns on diversified stock portfolios. Additionally, the model is fairly simple which makes it easier to interpret and use for empirical purposes.

The three factors utilized in the model are market excess return $(R_M - R_f)$, Small-Minus-Big (SMB) and High-Minus-Low (HML). $(R_M - R_f)$ measures the market portfolios return less the risk-free rate. SMB accounts for the difference in returns between small and large companies and HML is the difference in returns between high book-to-market companies and low book-to-market companies.

The data for the control factors is collected from Kenneth R. French data library. Naturally, this study uses European factor data as the study is conducted on the Finnish Stock Market. Monthly factor data is used due to the liquidity factor data being calculated on a monthly basis. In addition to the factor data, the data for monthly risk-free rate is retrieved from the data library, which is used to calculate monthly excess returns for individual stocks.

3.3 Research methodology

This study will utilize the liquidity series of Pastor & Stambaugh (2003) as a proxy for liquidity. The goal is to investigate the relationship between liquidity and stock returns and to uncover whether the COVID-19 crisis affects this relationship. If such relationship is found, we will further investigate the magnitude of the risk premium that arises from liquidity and again, the impact of COVID-19 on this premium. It should be noted again that liquidity is a complex concept with multiple different dimensions. Liquidity measures at their core are slightly arbitrary and struggle to capture all dimensions simultaneously. The P&S liquidity series is based on the flight-to-liquidity phenomenon and will mainly measure liquidity effects arising from that specific liquidity dimension. Thus, the results of this study cannot be generalized for liquidity as a whole. Previous studies have already shown that different markets and time periods exhibit differing types of liquidity exposure.

This study will employ the following methods for empirical research. First, we will provide descriptive statistics of the selected sample of Finnish stocks to showcase the important statistical characteristics and differences of the stocks. After that, multiple different regressions analyses will be conducted. If the regressions confirm a relationship between liquidity and stock returns, we will further investigate the magnitude and significance of the liquidity risk premium. The regressions and their characteristics are described in the following subchapter.

3.3.1 Time series regressions

This study will conduct multiple individual regression analyses for each stock included in the sample to analyse their exposure to liquidity. The first set of regressions will be conducted using only the P&S liquidity factor. The equation for these regressions is specified in the equation below:

$$ER_{i,t} = \beta_i^0 + \beta_i^L L_t + \epsilon_t \tag{4}$$

Where $ER_{i,t}$ is the excess return on stock i, β_i^0 is the regression intercept, $\beta_i^L L_t$ is the liquidity measure of Pastor & Stambaugh (2003) and its corresponding beta estimate and ϵ_t is the error term. Regressions using this equation will be ran for both the pre-COVID-19 period from January 2017 to December 2019 and the COVID-19 period from January 2020 to December 2020. The results will then be compared to determine whether the COVID-19 crisis affects the liquidity exposure of Finnish stocks.

Another set of regressions with additional control factors will be run to control for other major economic factors that could affect returns. These regressions will use the three factors of Fama & French (1993) in addition to the P&S liquidity factor and are constructed as follows:

$$ER_{i,t} = \beta_i^0 + \beta_i^L L_t + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \epsilon_t \tag{5}$$

Where $ER_{i,t}$ represents the excess return on stock i, β_i^0 is the regression intercept and L_t is again the liquidity measure. MKT_t is the excess return on a broad market index over the risk-free rate, or the so-called market risk factor. SMB_t denotes the difference in returns between stocks with small and large market capitalization and HML_t represents the difference in returns between high and low book-to-market stocks. β_i^L, β_i^{MKT}, β_i^{SMB} and β_i^{HML} are the respective beta coefficients of the factors while ϵ_t is the error term. Like the previous model, the regressions will be run for both the pre-COVID-19 and COVID-19 period.

The inclusion of control variables is motivated by the intention of finding a model of the best possible explanatory power that also provides the most accurate representation of the relationship between liquidity and stock returns. Comparisons between the models will be drawn based on the regression coefficients of the independent variables, their significance and the R^2 values of the regressions. The regression results of both models are analysed but final conclusions will be drawn from the model with better performance.

4 EMPIRICAL RESULTS

This chapter states the results of the conducted empirical analysis. First, we present the most important descriptive statistics for the data utilized in this study. Following that, results of the conducted OLS regressions and their respective diagnostic checks are presented. Lastly, the results are examined and analysed in the framework of prior literature.

4.1 Descriptive statistics

Table 1 present essential statistics of the Finnish stocks used in this study. Each sample period has 36 datapoints, one for each month during a 3-year period. MEAN stands for the average total excess return on the stock during that sample period. Similarly, MDN is the median total excess return on the stock during the period. Total excess return is calculated by deducting the monthly risk-free rate from the monthly total return. SD stands for the standard deviation of the excess return for the stock while MIN and MAX are the minimum and maximum values of a stock's respective returns during the sample period. It should be noted that the return data is reported as percentage values i.e., 1,00 stands for 1 percentage.

The mean returns are mostly positive across both periods. During the Pre-COVID period, 7 of the 24 stocks display negative mean returns and the number reduces to 4 during the COVID period. Median returns act similarly with 7 stocks exhibiting negative values before COVID, which reduces to 5 during the pandemic. There is no clear relationship between the mean and median returns and the change in sample periods. For some stocks, mean and median increase during the COVID-period while for others, they decrease. However, the most interesting observable change in the descriptive stock statistics is the widespread increase in volatility. 20 of the 24 stocks have higher standard deviations during the COVID-period than the before the pandemic. The average standard deviation across the stocks rises from 7,58 during the pre-COVID period to 9,82 during the pandemic. Unsurprisingly, the change in minimum and maximum monthly excess returns between the two periods is in line with the notion of increased volatility. All but 4 of the stocks display either a more negative minimum return, a higher maximum return or both during the COVID period than before the pandemic. This increase in volatility is in line with prior literature and is a common characteristic of financial crises. As previously mentioned in the literature review, asset prices experience sharp, fundamentally unjustified declines in the beginning of crises. After the dust settles, asset prices rebound just as aggressively. Thus, the highest of highs and the lowest of lows cause the volatility to be stronger than usual during the crisis period. An increase in volatility during the COVID-19 crisis is also reported by Jawadi et al. (2021) among others.

Table 2 presents the correlation matrix of the P&S liquidity factor and the 3 factors of Fama & French used as the control factors in the study. The table displays the correlation coefficients for the factors from the combined timeframe of the two sample periods used in the study, which span across 72 months in total. We inspect the correlation coefficients to avoid multicollinearity, which diminishes the quality of regressions because independent variables should in fact, be independent. If multicollinearity is present, a change in one independent variable also causes shifts in the others. Thus, estimating the relationship between the dependent variables and each independent variable becomes exceedingly difficult. We first inspect the correlation matrix to detect multicollinearity. A correlation coefficient of 0,7 typically indicates the presence of multicollinearity, while the largest correlation coefficient between the variables used in our regression is 0,323. At a quick glance, there is no significant multicollinearity in the model. However, to gain a more decisive verdict, we will conduct multicollinearity analysis using the Variance Inflation Factor (VIF).

Table 3 presents the results of the multicollinearity tests. A VIF value of higher than 5 with a tolerance value lower than 0,2 typically indicates the presence of multicollinearity. RSQ stands for the respective R^2 values of the factors, TOL stands for the tolerance value and VIF stands for the Variance Inflation Factor. Each of the independent variables has high tolerance values with relatively low VIF values. The results of the multicollinearity tests show that our regression is not subject to multicollinearity.

Table 1. Descriptive statistics of monthly stock return data from both periods

	Pre-COVID					COVID				
STOCK	**MEAN**	**MDN**	**SD**	**MIN**	**MAX**	**MEAN**	**MDN**	**SD**	**MIN**	**MAX**
Cargotec	-0,49	-1,64	8,80	-21,60	17,95	2,10	3,58	13,96	-35,00	37,16
Elisa	1,62	1,24	3,94	-6,46	10,81	0,43	1,08	5,86	-16,00	10,23
Fortum	1,70	1,49	5,02	-14,06	11,91	0,26	1,17	12,33	-30,75	34,22
Huhtamäki	0,66	0,14	5,65	-10,65	13,30	-0,23	-0,13	8,01	-21,89	16,93
Kesko	1,20	2,63	5,64	-12,97	11,91	1,43	-0,08	9,33	-16,00	23,95
Kone	1,13	1,57	3,85	-7,03	9,04	-0,05	0,85	6,52	-13,47	14,33
Konecranes	-0,08	1,02	8,34	-20,95	16,92	1,28	1,46	12,62	-41,52	27,14
Metsä Board	0,32	0,07	10,10	-20,87	23,62	1,72	2,55	9,20	-18,27	28,02
Metso Corporation	1,45	3,24	15,28	-39,47	41,58	2,23	2,94	11,15	-23,86	24,06
Neste	3,08	2,00	8,63	-11,66	29,36	1,52	-0,61	10,21	-16,16	25,73
Nokia	-0,37	-0,57	9,32	-29,32	23,77	1,26	1,25	10,43	-17,75	25,80
Nokian Renkaat	-0,43	-0,35	6,62	-20,62	9,44	-1,72	-1,38	10,79	-42,93	15,02
Nordea Bank	-0,33	0,26	6,75	-18,77	14,43	1,68	1,14	8,33	-27,82	18,97
Orion	0,61	1,13	9,47	-23,63	27,43	1,19	0,74	8,29	-15,87	24,41
Outokumpu	-2,33	-1,37	10,65	-26,93	21,99	2,39	2,83	13,25	-33,67	25,43
Qt Group	4,25	0,07	11,31	-12,21	38,12	3,42	5,25	16,32	-35,55	36,08
Sampo	0,24	0,63	4,14	-9,42	7,95	1,35	1,47	7,07	-27,94	13,60
SSAB	0,64	-0,32	9,12	-17,86	21,06	2,46	2,15	11,70	-24,73	27,20
Stora Enso	1,17	2,65	8,36	-19,43	15,75	0,56	0,21	8,67	-16,99	16,81
Telia	0,67	-0,32	4,16	-6,40	13,36	-0,50	-2,15	6,02	-14,96	11,21
Tietoevry	0,66	0,43	5,91	-11,63	12,80	0,54	1,04	8,38	-22,97	24,20
UPM-Kymmene	1,27	2,38	7,27	-17,36	13,83	0,90	0,51	6,87	-12,12	13,84
Valmet	1,59	3,41	7,57	-19,85	14,77	1,11	2,27	9,31	-17,86	16,96
Wärtsilä	-0,72	-1,80	6,01	-10,93	11,42	0,26	0,89	11,17	-26,98	20,16

Descriptive statistics are reported for the total excess returns, calculated by deducting the monthly risk-free rate from the monthly total return. Return data is reported as percentage values, i.e., 1,00 stands for 1 percentage.

Table 2. Correlation matrix of the P&S liquidity factor and control factors

	L	MKT	SMB	HML
N	72	72	72	72
L	1			
MKT	0,203	1		
SMB	0,181	0,323	1	
HML	0,034	0,158	-0,209	1

Table 3. Multicollinearity statistics for the factors used in the model

	L	MKT	SMB	HML
RSQ	0,057	0,174	0,188	0,102
TOL	0,943	0,826	0,812	0,898
VIF	1,061	1,211	1,231	1,113

VIF values of >5 with a TOL value of <0,2 indicate the presence of multicollinearity.

4.2 Diagnostic checks

As this study utilizes the Ordinary Least Squares (OLS) regression technique for analysis, we must test for stationarity of the investigated time series. OLS regressions are based on the assumption of stationarity, which implies that the mean and variance of the time series does not change over time. Fluctuations in the series occur around the mean. OLS regressions conducted on non-stationary data yield inaccurate estimates because the results are time specific and thus cannot be used to draw meaningful conclusions.

We will first graphically inspect the factor time series for trends and irregular fluctuations that could imply non-stationarity. Although graphical inspection may sometimes be enough, sources of non-stationarity may prove difficult to identify. Seasonality, trends, increasing variance and changes in levels may seem easy to detect visually in theory, but in practice visual inspections are far from dependable and are better used to form an initial idea of the time series' properties. Because of this, we will also conduct the Augmented Dickey-Fuller (ADF) (1979), the Phillips-Perron (PP) (1988) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (1992) tests to gauge stationarity. Just like the multicollinearity tests, the stationarity tests and graphical inspection are conducted using a 72-month period that spans both sample periods used in the study.

The ADF test tests the null hypothesis of a unit root being present in the time series model. The test checks whether the average value of data points remains consistent over time. If it does not, the series is non-stationary. The PP test is similar to the ADF test. Instead of checking for the consistency of data point averages however, it checks if the change in data points is predictable. If the data points change in a predictable way, the series is deemed stationary. Intuitively, the ADF test checks if the mean of the time series remains constant over time, while the PP test examines whether the variance of the series stays constant over time. Both tests have the null hypothesis of non-stationarity. The KPSS test differs from these two in that sense. Its null hypothesis is that the observed time series is stationary. Additionally, in the KPSS test the absence of a unit root doesn’t indicate stationarity, but trend-stationarity. It is used to complement unit root tests, like the two previously mentioned. Running the KPSS test in addition to unit root tests, helps in identifying whether a series with unconclusive unit root test results is stationary or not.

4.2.1 Graphical inspection

Starting from the most basic method of stationarity detection, we plot the data of our risk factors and determine visually whether they display known properties of stationarity or non-stationarity. Typical properties of non-stationarity series include time trends, unit roots or random walks and seasonality. Time trends shift the mean of the time series either linearly or non-linearly, which violates the basic assumption of a constant mean associated with stationarity. Likewise, random walks, time series in which the value of the series in one period is the value of the previous period plus random error, are non-stationary due to their changing standard deviation. Lastly, seasonality implies that the data is prone to predictable changes that regularly occur at certain points of time during a year.

Figures 1, 2, 3 and 4 showcase the graphs of our risk factors. Based on graphical inspection, no significant time trends seem to be present in the data of any of the factors. The means of the series stay consistent and visually, the data doesn't seem to trend in any direction. There are slight changes in the standard deviations, which might indicate the presence of unit roots or random walks, but proper testing is required to confirm. Finally, based on a graphical inspection there is no seasonality present in the data.

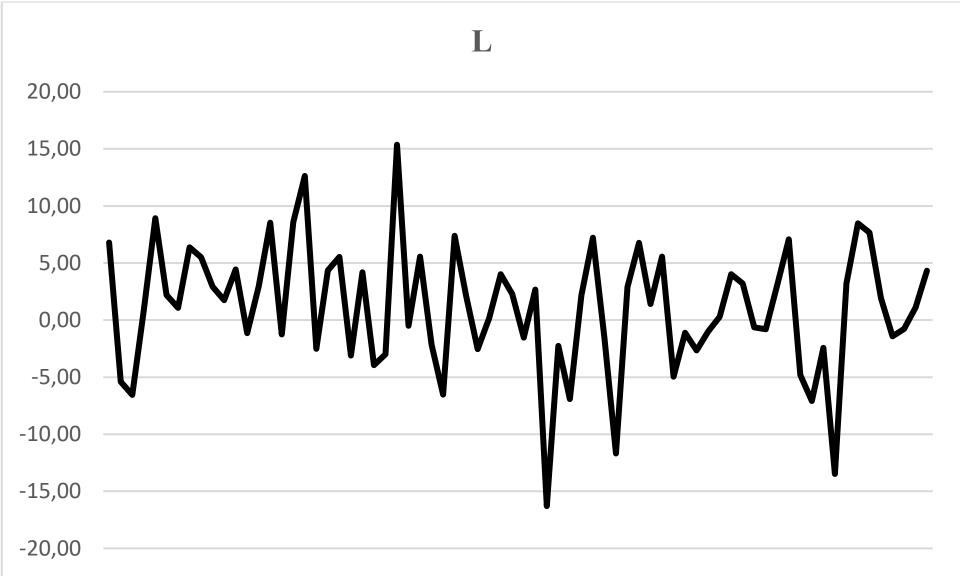

Figure 1. Graph of the P&S liquidity factor

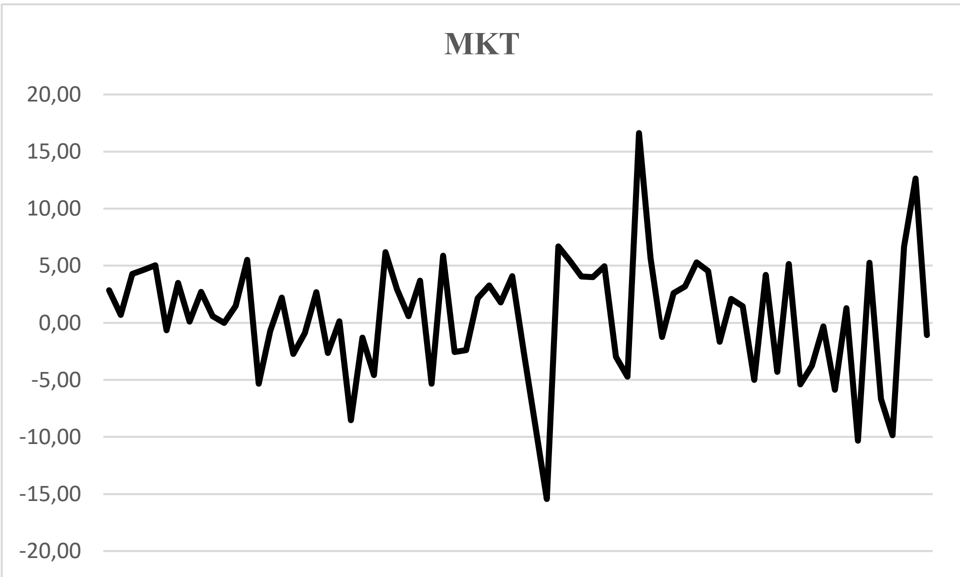

Figure 2. Graph of the market risk factor

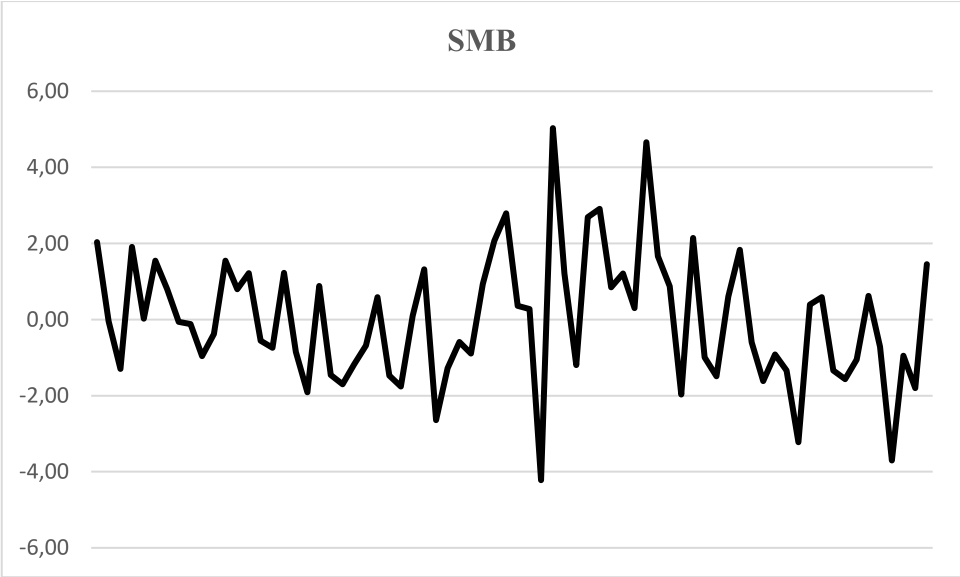

Figure 3. Graph of the size factor

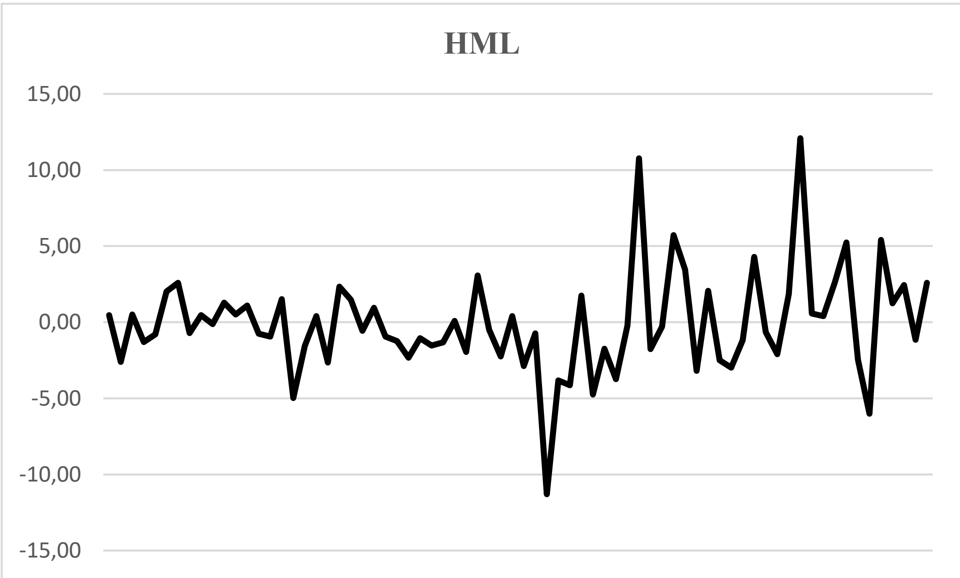

Figure 4. Graph of the value factor

4.2.2 Stationarity tests

We proceed to conduct stationarity tests to obtain conclusive results. Table 4 presents the outcomes of the conducted stationarity tests. The specific results of all three stationarity tests for each factor can be found in appendix 1. For the liquidity and market risk factors, all stationarity tests unanimously deem the factors stationary. For the size and value factors however, the results are inconclusive. According to the

ADF test, the factors are non-stationary while the other two disagree. Despite the results of the ADF tests, the factors will be accepted for use in the regressions due to multiple reasons. Firstly, two of three tests support the stationarity of these factors. Additionally, the PP test, which is somewhat like the ADF test, produces incredibly strong support for the stationarity of the factors with very significant confidence levels while the KPSS test supports these results. Lastly, it should be noted that the size and value factor are in widespread use in all finance literature and generally seen as stationary, which promotes their use as regression variables despite the surprising result of these particular ADF tests.

Table 4. Stationarity tests for regression variables

	ADF	PP	KPSS
L	Stationary	Stationary	Stationary
MKT	Stationary	Stationary	Stationary
SMB	Non-stationary	Stationary	Stationary
HML	Non-stationary	Stationary	Stationary

4.3 Results of time series regression

This section presents the results of time series regressions. First, we will go through the model including only the liquidity factor and after that, the model with additional control factors.

4.3.1 Stock exposure to liquidity factor

Table 5 presents the results of the time series regression using a model with only the liquidity factor as an explanatory variable. Separate regressions are run for each sample period spanning three years. Table 5 shows the intercept and liquidity factor with their respective p-values as well as the R^2 value of the regression. During the pre-COVID period, only 2 out of 24 stocks have statistically significant exposure to the liquidity factor and for most of the stocks, their exposure is negative. The average coefficient for the liquidity factor across the sample is -0,117. The R^2 values of the regressions are remarkably low and range from near zero to a modest 0,129, indicating that the model does a poor job at explaining the returns to these stocks.

Table 5. Stock exposure to liquidity factor

	Pre-COVID					COVID				
STOCK	ALPHA	P-VALUE	L	P-VALUE	RSQ	ALPHA	P-VALUE	L	P-VALUE	RSQ
Cargotec	-0,210	0,899	-0,115	0,696	0,005	2,263	0,324	0,700	0,088	0,083
Elisa	**1,692**	0,028	-0,028	0,830	0,001	0,396	0,688	-0,165	0,344	0,026
Fortum	1,469	0,124	0,099	0,556	0,010	0,351	0,865	0,384	0,295	0,032
Huhtamäki	0,736	0,490	-0,033	0,860	0,001	-0,192	0,887	0,164	0,495	0,014
Kesko	0,902	0,395	0,126	0,504	0,013	1,497	0,342	0,294	0,290	0,033
Kone	0,996	0,174	0,058	0,653	0,006	-0,038	0,973	0,044	0,824	0,001
Konecranes	-0,091	0,954	0,004	0,987	0,000	1,398	0,506	0,494	0,187	0,051
Metsä Board	0,574	0,763	-0,107	0,753	0,003	1,696	0,282	-0,119	0,666	0,006
Metso Corporation	2,471	0,388	-0,429	0,400	0,021	2,328	0,214	0,434	0,189	0,050
Neste	**4,520**	0,005	**-0,602**	0,031	0,129	1,627	0,337	0,447	0,138	0,064
Nokia	0,191	0,913	-0,233	0,454	0,017	1,459	0,358	**0,837**	0,005	0,213
Nokian Renkaat	-0,398	0,750	-0,012	0,957	0,000	-1,612	0,370	0,443	0,166	0,056
Nordea Bank	-0,476	0,708	0,063	0,782	0,002	1,787	0,192	0,442	0,070	0,093
Orion	1,891	0,271	-0,539	0,083	0,086	1,175	0,407	-0,079	0,752	0,003
Outokumpu	-1,779	0,375	-0,230	0,518	0,012	2,520	0,255	0,554	0,158	0,058
Qt Group	4,108	0,060	0,061	0,872	0,001	3,600	0,184	0,784	0,103	0,076
Sampo	0,411	0,597	-0,072	0,606	0,008	1,422	0,227	0,314	0,132	0,065
SSAB	1,292	0,448	-0,275	0,367	0,024	2,496	0,215	0,133	0,704	0,004
Stora Enso	0,856	0,586	0,134	0,633	0,007	0,536	0,717	-0,088	0,734	0,003
Telia	0,975	0,213	-0,126	0,363	0,024	-0,524	0,609	-0,105	0,560	0,010
Tietoevry	1,605	0,131	**-0,395**	0,040	0,119	0,694	0,586	**0,661**	0,005	0,206
UPM-Kymmene	1,201	0,382	0,031	0,900	0,000	0,898	0,445	-0,028	0,894	0,001
Valmet	1,600	0,266	-0,003	0,990	0,000	1,243	0,407	**0,555**	0,041	0,117
Wärtsilä	-0,299	0,789	-0,178	0,376	0,023	0,392	0,829	0,584	0,075	0,091

Bolded values are statistically significant at a 5% confidence level or higher.

The COVID-19 pandemic has an impact on the liquidity exposure of the stocks and the significance of that exposure. Interestingly, the exposures of the stocks change drastically in comparison to the pre-COVID period. Most of the exposures are now positive instead of negative, which goes against the findings of Acharya & Pedersen (2005) and many others, that have found the relationship between flight-to-liquidity, which our liquidity factor is based on, and stock returns to be negative. The average coefficient of the liquidity factor across the sample is 0,32 during the COVID period, a drastic increase from the average of -0,117 before the crisis. While 18 of 24 observations have more significant P-values during the pandemic than before it, only three of the observations are significant at a 5% confidence level. Thus, it cannot be said with certainty that the relationship between stock returns and liquidity experiences a change during the COVID pandemic. What can be said, however, is that the model does a better job at explaining stock returns during the pandemic than before it. 18 of 24 stocks have higher R^2 values during the pandemic period than before it, which could imply that liquidity becomes a more important predictor of stock returns during the crisis. Intuitively, this would make sense as liquidity is often only brought to discussion when it becomes a problem, like it often does during crises. Nonetheless, the R^2 values are still quite poor despite their improvement, which suggests that the model is of poor fit and likely missing some components that are prominent predictors of stock returns. Indeed, Li et al. (2019) among others have argued that liquidity should only affect stock returns slightly, so it is unsurprising that a model with only the liquidity factor runs into struggles. Based on the regression results of this model, the only conclusion that can be drawn is that liquidity does not affect stock returns in a significant manner during either sample period.

4.3.2 Stock exposure to liquidity and control factors

The analysis of the simple model shows that adjustments are required to improve the fit of the model. The low R^2 values indicate that it is highly likely that there are some important omitted variables that have a profound impact on stock returns. We add the market-risk, value, and size factors to control for risks unrelated to liquidity, which allows us to better examine the impact of liquidity itself. While the additional factors are included mostly for the purpose of controlling for unrelated risks, we will also briefly analyse their respective coefficients and significance.

Table 6 presents the results of the time series regression for the pre-COVID period using a model with the liquidity factor and three additional control factors. The table shows the coefficients of the intercept, liquidity factor, market risk factor, size factor and the value factor, in addition to their respective p-values and the R^2 value of the regression. The change in the coefficients of the liquidity factor in comparison to the simple model is explained by the addition of the control factors. Surprisingly, the change in the coefficients is relatively small. As previously mentioned, the simple model exhibits an average coefficient of -0,117 for the liquidity factor during the pre-COVID period. For the model with additional factors, the average liquidity factor coefficient is slightly more negative at -0,135. However, the significance of these results remains very questionable. Just as it was for the simple model, only 2 of 24 stocks have statistically significant exposure to the liquidity factor. Ultimately, the introduction of the control factors does not seem to be able to reveal a meaningful relationship between liquidity and stock returns, at least during the pre-COVID period.

While liquidity doesn't seem to impact stock returns during the pre-COVID period, the most important determinant of stock returns looks to be the market risk factor. 16 of 24 stocks have positive and significant exposure to the market risk factor. The other two control factors perform far worse in terms of explaining stock returns. Only 2 stocks have statistically significant exposure to the size factor. The value factor doesn't do much better with only 4 stocks having significant exposure to it. The results are slightly surprising regarding the control factors, because they have been shown to be important determinants of stock returns time and time again. Regardless, there is a simple reason that could lead to these insignificant results. This study uses European data for the three control factors, gathered from the Kenneth R. French data library. While Finland is obviously a European country, the financial markets vary heavily across different countries in size, trading activity and their composition. Even the largest of Finnish companies pale in comparison to other European giants, and on average the market is quite small and thinly traded. Therefore, data based on the whole of Europe might not be the best fit for analysing

Finnish companies. Using data specifically collected from Finland would likely produce more meaningful results but as of now, such data is not readily available.

Despite the struggles, the addition of control factors greatly improves the fitness of the regression. For each of the stocks included in the sample, the R^2 value increases with the addition of the control factors. Much of this increase can likely be attributed to the addition of the market risk factor as the only factor with generally significant coefficients. The results show that the poor R^2 values of the simple model were due to an array of missing variables.

The results of the time series regression from the COVID period using the liquidity factor and control factors are presented on table 7. Unlike the simple model, this time the coefficients of the liquidity factor do not experience as much of a change compared to the pre-COVID period. The average coefficient is still negative at -0,017, which conforms to much of the earlier research. However, the effect is much smaller than before the pandemic. Unfortunately, the significance of these findings leaves much to be desired just as it did for the other regressions. Once again, only 2 of 24 stocks have significant exposure to the liquidity factor. The significance levels of specific stocks do not exhibit any profound changes either. For some stocks, the p-values improve during the pandemic while for some, they get worse. As for the other factors, the market risk factor again seems like the most important predictor of stock returns. It has a positive and significant effect for all but three stocks. The size and value factor struggle just as they did before the crisis, with 5 and 1 significant regression coefficients respectively. Again, like during the pre-COVID period, the R^2 values are much improved in comparison to the simple model, indicating that the control factors indeed improve the regressions drastically. Additionally, the model performs better for 17 of 24 stocks during the pandemic as opposed to before it. This increased fitness is likely driven by the market risk factor performing better during the pandemic. Overall, it is quite clear that the adjusted model with the control factors is the superior model of the two and the one that analysis should be based on.

Ultimately, it is hard to argue that the COVID pandemic influences the relationship between liquidity and stock returns. In fact, it is hard to argue that liquidity has an effect in general. The liquidity factor produces insignificant coefficients for both periods and even both models. It seems that liquidity is not an important determinant of stock returns. Instead, most of the returns seem to be explained by the market risk factor. As such, it would be pointless to try to determine a liquidity premium, often done by using the Fama-McBeth (1973) two-stage regression, where asset returns are regressed on the beta exposures of a given factor. However, as the liquidity exposures are insignificant, they would not produce meaningful estimations of the liquidity risk premium. Nonetheless, it should be noted that this study has some limitations that could affect the results. The next subsection will focus on discussing these limitations and comparing the results with prior research.

Table 6. Pre-COVID stock exposures to liquidity factor and control factors

	Pre-COVID										
STOCK	ALPHA	P-VALUE	L	P-VALUE	MKT	P-VALUE	SMB	P-VALUE	HML	P-VALUE	RSQ
Cargotec	-1,783	0,205	-0,131	0,598	**1,572**	0,000	0,029	0,975	-1,119	0,146	0,408
Elisa	1,371	0,076	-0,065	0,628	0,207	0,290	-0,406	0,428	-0,771	0,068	0,130
Fortum	0,995	0,305	0,139	0,420	0,482	0,058	-0,348	0,593	0,061	0,907	0,126
Huhtamäki	0,070	0,945	-0,105	0,562	**0,559**	0,039	-0,058	0,933	**-1,271**	0,028	0,227
Kesko	0,897	0,434	0,098	0,629	-0,051	0,862	-0,099	0,898	-0,365	0,558	0,026
Kone	0,203	0,720	0,038	0,705	**0,694**	0,000	-0,495	0,202	**-0,886**	0,007	0,486
Konecranes	-1,466	0,287	-0,013	0,958	**1,404**	0,000	0,242	0,793	-0,945	0,210	0,363
Metsä Board	-0,813	0,651	-0,095	0,768	**1,427**	0,004	0,041	0,973	-0,678	0,491	0,246
Metso Corporation	0,085	0,974	-0,477	0,307	**2,259**	0,002	-0,530	0,763	-2,188	0,130	0,311
Neste	4,181	0,014	-0,557	0,062	0,291	0,488	-0,742	0,501	0,071	0,936	0,154
Nokia	0,653	0,726	-0,278	0,403	-0,500	0,299	0,209	0,868	-0,180	0,859	0,054
Nokian Renkaat	-1,840	0,052	0,027	0,871	**1,405**	0,000	-0,686	0,274	-0,655	0,198	0,541
Nordea Bank	-1,582	0,120	0,121	0,498	**1,290**	0,000	0,543	0,423	0,210	0,700	0,480
Orion	0,641	0,690	**-0,609**	0,039	**0,940**	0,028	-1,394	0,204	**-2,069**	0,023	0,318
Outokumpu	-3,372	0,070	-0,288	0,375	**1,569**	0,002	0,259	0,832	-1,541	0,126	0,313
Qt Group	3,231	0,110	-0,185	0,600	0,789	0,128	1,652	0,222	**-2,849**	0,012	0,272
Sampo	-0,390	0,458	-0,024	0,796	**0,911**	0,000	0,201	0,570	0,148	0,605	0,621
SSAB	0,126	0,919	-0,214	0,333	**1,608**	0,000	**2,140**	0,014	0,767	0,258	0,566
Stora Enso	-0,220	0,876	0,119	0,635	**1,244**	0,002	1,114	0,246	-0,426	0,579	0,326
Telia	0,651	0,361	-0,036	0,778	0,216	0,240	**-1,534**	0,003	0,329	0,397	0,311
Tietoevry	1,185	0,254	**-0,460**	0,017	0,469	0,083	0,872	0,215	-0,709	0,211	0,279
UPM-Kymmene	0,185	0,884	-0,020	0,931	**0,984**	0,005	0,192	0,823	-1,136	0,109	0,270
Valmet	0,407	0,751	0,005	0,984	**1,220**	0,001	0,016	0,985	-0,620	0,378	0,317
Wärtsilä	-0,844	0,410	-0,222	0,227	**0,705**	0,011	1,379	0,052	-0,362	0,517	0,316

Table 7. Stock exposures to liquidity and control factors in the COVID period

	COVID										
STOCK	ALPHA	P-VALUE	L	P-VALUE	MKT	P-VALUE	SMB	P-VALUE	HML	P-VALUE	RSQ
Cargotec	1,651	0,348	0,089	0,787	**1,243**	0,000	1,343	0,191	0,248	0,566	0,512
Elisa	0,348	0,726	-0,203	0,284	0,266	0,145	-0,408	0,480	-0,257	0,299	0,105
Fortum	-0,085	0,964	-0,014	0,968	**0,737**	0,037	0,451	0,681	0,685	0,149	0,268
Huhtamäki	-0,366	0,764	-0,046	0,841	0,419	0,064	1,042	0,146	-0,274	0,365	0,280
Kesko	1,322	0,362	0,103	0,705	**0,598**	0,027	0,308	0,712	-0,516	0,153	0,258
Kone	-0,207	0,798	-0,092	0,550	**0,791**	0,000	**-1,117**	0,023	**-0,638**	0,003	0,519
Konecranes	0,789	0,591	-0,136	0,626	**1,059**	0,000	**2,129**	0,017	0,471	0,199	0,580
Metsä Board	1,379	0,280	-0,482	0,051	**0,550**	0,021	**1,858**	0,016	0,046	0,884	0,413
Metso Corporation	1,704	0,131	-0,148	0,482	**1,357**	0,000	0,343	0,593	0,314	0,255	0,693
Neste	1,310	0,353	0,112	0,673	**0,833**	0,002	0,765	0,349	-0,360	0,301	0,415
Nokia	1,215	0,383	**0,608**	0,026	**0,835**	0,002	-0,365	0,650	-0,501	0,150	0,450
Nokian Renkaat	-1,802	0,297	0,282	0,388	**0,745**	0,021	-0,811	0,416	-0,479	0,262	0,216
Nordea Bank	1,422	0,200	0,091	0,662	**0,586**	0,005	0,810	0,207	0,528	0,058	0,463
Orion	1,056	0,442	-0,192	0,459	**0,503**	0,049	-0,302	0,703	-0,447	0,191	0,154
Outokumpu	1,949	0,284	0,006	0,986	**1,075**	0,002	0,950	0,366	0,523	0,245	0,423
Qt Group	3,076	0,116	0,164	0,652	**1,172**	0,002	**3,026**	0,010	-0,566	0,237	0,570
Sampo	1,068	0,208	-0,033	0,834	**0,534**	0,001	0,981	0,050	0,550	0,012	0,562
SSAB	2,097	0,258	-0,230	0,509	**0,842**	0,016	0,096	0,928	0,296	0,515	0,234
Stora Enso	0,123	0,911	**-0,510**	0,020	**0,699**	0,001	**1,350**	0,041	0,397	0,152	0,495
Telia	-0,630	0,540	-0,186	0,342	0,180	0,336	-0,240	0,687	0,263	0,303	0,095
Tietoevry	0,325	0,708	0,310	0,066	**0,893**	0,000	0,204	0,684	-0,045	0,834	0,667
UPM-Kymmene	0,603	0,539	-0,317	0,094	**0,519**	0,006	0,690	0,228	0,310	0,204	0,370
Valmet	0,933	0,430	0,234	0,297	**0,830**	0,000	0,577	0,400	-0,348	0,236	0,504
Wärtsilä	-0,057	0,966	0,174	0,501	**1,261**	0,000	-0,431	0,586	-0,300	0,377	0,536

4.4 Discussion on results

The regressions reveal a negative flight-to-liquidity effect, consistent with prior literature. However, the results are not statistically significant, which indicates that there is no relationship between liquidity and stock returns in the Finnish market. Consequently, there should be no liquidity premium to find either. Furthermore, the COVID-19 pandemic doesn't influence this relationship in a meaningful way. Truthfully, the results are quite surprising. After all, the general consensus in related research has been that liquidity is a pervasive and important factor for asset pricing. Pastor & Stambaugh (2003) for example deem liquidity an important state variable and Acharya & Pedersen (2005) showcase the economic importance of liquidity. As such, further discussion is required on the various factors that could influence the results. However, it should be emphasized that the absence of a liquidity effect is not unheard of. Some researchers like Ma et al. (2021) find supporting evidence for some liquidity measures or dimensions and insignificant proof for others. A handful of studies, like Pontiff & Singla (2019) struggle to find any supporting evidence whatsoever.

Indeed, the choice of a liquidity measure is an extremely important part of any liquidity study. Liquidity measures are arbitrary and designed to capture a certain dimension of liquidity, all of which function at least somewhat independently. The failure to capture a liquidity effect with a certain measure does not indicate the absence of a liquidity effect in general, but that a certain liquidity dimension might not be influential. The choice of measure for this study is the liquidity series of Pastor & Stambaugh (2003), which is based on the flight-to-liquidity phenomenon, where investors swap their positions from illiquid to liquid assets, thus creating uncertainty and falling stock prices and returns in the market. Assets with high sensitivities to liquidity should receive more compensation for the risk they bear. Conversely, investors are willing to accept lower returns on assets that maintain high returns during times of market illiquidity and thus don't have to be swapped out for more liquid assets.

Specifically, the results of this study indicate that the flight-to-liquidity dimension of liquidity is not an important factor for asset pricing in Finland. Similar results have been reported by Momani (2018) among others. More importantly though, Ahmed et al. (2019) note the absence of a flight-to-liquidity based liquidity effect in the Finnish context. Still, such results are quite rare, as most studies conducted in the Finnish market deem flight-to-liquidity the most important liquidity dimension (Butt, 2015; Butt & Virk, 2015; Vaihekoski, 2009). Nevertheless, even if this liquidity dimension has no relation to stock returns, it is entirely possible that one of the other dimensions is important.

The explanation for the varying results on the effect of flight-to-liquidity may lie in the data. For this study particularly, the selection of factors and the sample may influence the results. As discussed before, the control factors used in the regressions are calculated using European companies, which make them a decent, but not perfect, fit for this study. Incompatible control factors may influence the accuracy of the regression and either exaggerate or downplay the liquidity effect. Still, the inclusion of the value and size factors do improve the fit of the regression compared to just using a model with the liquidity factor and the market risk factor. Additionally, the P&S liquidity series is constructed using American stocks from the AMEX and NYSE, which consist of stocks far larger and more actively traded than Finnish stocks. Even though financial markets are more interconnected than ever in every sense, this may cause some complications. Furthermore, the sample periods used in this study are quite small in the context of liquidity studies. Typically, data is gathered from multiple decades, which makes it easier to establish a pattern and improves the accuracy of the regression. In this case however, no such luxury was afforded as the goal was to gauge the effect of the COVID-19 pandemic on the relationship between liquidity and stock returns, which motivated this study to use periods of three years to ensure comparability between the two periods. Finally, quite a few prior studies have followed a portfolio-based approach in estimating the liquidity effect instead of using individual stocks. For example, Pastor & Stambaugh (2003) form portfolios based on predicted liquidity betas and create a single return series for each portfolio, which are then regressed on the same factors as the ones used in this study. The use of individual stocks likely has an impact on our findings.

This study also struggled to find any evidence of the COVID-19 pandemic affecting the relationship of returns and liquidity. It is possible, that the means of accounting for this effect was not the most optimal. This study chose to compare two sample periods, but it is possible that the changes, or the lack thereof, in the liquidity exposures are also caused by other events during the sample period. Perhaps a different method would have been more suitable. Jawadi et. al (2021) used COVID-19 cases and deaths to explain changes in liquidity and they found a significant negative effect. However, a similar method could not have been adapted due to this study’s focus on liquidity and stock returns, and not just liquidity itself.

5 CONCLUSION

Factor investing has been at the core of finance research ever since the foundation was laid in the form of the Capital Asset Pricing Model by Sharpe (1964), Lintner (1965) and Mossin (1966). Additional risk factors have been proposed through the years, ranging from the size and value factors of Fama & French (1993) to volatility, interest rate and momentum among others. The most basic principle of investing is that additional risk should be compensated for with a higher return. As such, holding assets with exposure to different risk factors should yield premium.

One of the most interesting economic factors is liquidity, the ease of trading assets quickly in large quantities without incurring unusual trading costs or affecting the market price. Liquidity is often taken for granted and noticed only when it disappears. Such occurrences are often associated with financial crises and other drastic market declines. A decline in asset prices creates uncertainty and panic selling, which leads to additional unjustified falls in asset prices. Suddenly, assets can no longer be moved fluidly without incurring major trading costs. This makes crisis periods especially interesting for studying liquidity's relation to asset returns.

The COVID-19 virus took the world by storm in early 2020 and continued to do so all the way up until 2023. Society shut down as extreme measures were taken to avert a health crisis of unseen proportions. While these measures were successful, they had an immense impact on the economy. The stock markets declined rapidly as businesses had to shut down some of their functions either temporarily or for good. Liquidity levels followed suit, as shown by Karolyi et al. (2011).

Majority of the liquidity related literature has deemed it an important determinant of asset returns. Amihud & Mendelson (1986), Pastor & Stambaugh and Acharya & Pedersen among others used unique liquidity measures that focus on different dimensions of liquidity, but all came to similar conclusions. Liquidity is an important state variable for asset pricing and should be accounted for when making investment decisions.

This study, however, did not manage to uncover a liquidity effect in the Finnish market. Specifically, a liquidity effect based on the flight-to-liquidity could not be found. As a result, no liquidity risk premium could be determined either. These are hardly groundbreaking findings, as some researchers have come to similar conclusions. Liquidity is a complex phenomenon with many different dimensions and a single liquidity measure is unable capture them all. Despite the results of this study, it is very much possible, or even likely, that liquidity does affect stock returns, just in a different way. Furthermore, the characteristics of this study could have skewed the results. The selection of variables, measures and samples can all influence our findings. Finally, it cannot be said for sure that the COVID-19 pandemic influences the relationship between liquidity and stock returns. The relationship does experience some slight changes, but the findings are not statistically significant.

These results call for further studies on the matter. Firstly, focusing on a different liquidity dimension provides an interesting avenue for research. For instance, while Ahmed et al. (2019) found no evidence of a flight-to-liquidity based liquidity effect in Finland, they discovered that commonality in liquidity and depressed wealth effect affect stock returns. Additionally, calculating a liquidity measure based on Finnish data and using control factors derived from strictly Finnish data would likely provide more accurate results. Lastly, this study gauged the effect of liquidity by comparing regression results from the pandemic period to a pre-pandemic period. Perhaps a different proxy could have been used to account for the effect of COVID-19, as the sample period may include other important events that could have influenced the results.

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APPENDICES

Appendix 1

RESULTS OF STATIONARITY TESTS

L

	ADF	PP	KPSS
Observed value	-3,894	-7,698	0,293
Critical value	-3,425	-1,945	0,450
P-value	0,015	<0,0001	0,141

MKT

	ADF	PP	KPSS
Observed value	-3,549	-8,158	0,092
Critical value	-3,425	-1,945	0,450
P-value	0,037	<0,0001	0,653

SMB

	ADF	PP	KPSS
Observed value	-2,284	-7,624	0,237
Critical value	-3,425	-1,945	0,450
P-value	0,418	<0,0001	0,209

HML

	ADF	PP	KPSS
Observed value	-2,901	-7,773	0,302
Critical value	-3,425	-1,945	0,450
P-value	0,155	<0,0001	0,134