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LIQUIDITY RISK AND ASSET PRICING – EVIDENCE FROM NEW ZEALAND

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ABSTRACT

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This thesis studies the existence of systematic liquidity risk and stock returns within New Zealand Stock Exchange by employing LCAPM developed by Acharya & Pedersen (2005). In this thesis we use two proxies for liquidity, Turnover to measure the immediacy and Amihud -measure (ILLIQ) to measure price impact of liquidity dimension. The sample consist of all the New Zealand Stock Exchange shares between January 2000 and December 2020. Regression tests for liquidity risk pricing are run at the portfolio level by using Fama and Macbeth (1973). Two robustness tests are employed: Dividing sample into two different time-periods and ranking shares according to their sizes.

The results imply that there is weak evidence that the time-varying liquidity risk is priced from one risk channel perspective, moreover from the co-movement between stock illiquidity and market returns, when using Amihud -measure. Overall results are incoherent that vary according to a liquidity measure and don't hold up throughout robustness tests. Evidence of liquidity risk disappears when utilizing sub-time period robustness test and the coefficients don't always provide correct signs throughout tests, implying that the liquidity risk is, in accordance with previous evidence, not actually priced within New Zealand Stock Exchange and the results are driven by a low sample size, unfit model, or liquidity measures that does not capture the liquidity risk of New Zealand Stock Exchange.

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Tämä pro gradu -tutkielma tutkii systemaattisen likviditeettiriskin olemassaoloa Uuden-Seelannin osakemarkkinoilla käyttäen Acharya ja Pedersen (2005) likviditeettikorjattua CAPM-mallia. Työssä käytetään kahta tunnettua likviditeettimittaria, osakkeen kiertonopeuden mittaria ja Amihud (ILLIQ)-mittaria. Tutkielman osakedata perustuu Uuden-Seelannin pörssissä noteerattuihin osakkeisiin aikavälillä 1.1.2000-31.12.2020. Likviditeettiriskiä ja osakkeiden hinnoittelua tutkitaan käyttäen Fama & Macbeth (1973) regressiomallia, sekä likvidisyysjärjestyksellä järjestetyillä osakeportfolioilla. Robustisuuden varmentamiseksi aineisto jaetaan yrityksen kokoluokkien mukaisesti, sekä tutkimusperiodi jaetaan kahteen yhtä suureen ajanjaksoon.

Tulokset osoittavat heikkoa olemassaoloa osakkeen epälikvidisyyden ja markkinatuottojen yhteisliikkeen välillä. Löydös rajoittuu vain Amihud (ILLIQ) -mittariin. Yleisesti eri tulosten välillä vallitsee epäyhtenäisyys ja tulokset vaihtelevat likviditeettimittarin mukaan eivätkä ole robusteja vaihtoehtoisilla testeillä suoritettuna. Likviditeettiriskin olemassaolo katoaa aikaperioditestissä ja estimaatit osoittavat odotuksen vastaisia etumerkkejä. Johtopäätöksenä on, että aikaisempien tutkimustulosten mukaisesti likviditeettiriski ei tosiasiassa ole hinnoiteltu Uuden-Seelannin osakemarkkinoilla. Taustasyyt voivat olla osakkeiden absoluuttinen alhainen määrä, huonosti istuva tilastollinen malli tai käytetyt likviditeettimittarit ovat epäsopivia Uuden-Seelannin osakeainestolle.

TABLE OF CONTENTS

1. Introduction

Liquidity can be considered as one of the most ubiquitous and crucial asset pricing factors in financial markets. The existence of liquidity can be observed throughout financial markets, affecting various type of asset classes, instruments extending from microstructure studies to a market wide phenomenon. Its broadness and pervasive nature have made it possible for liquidity to be constantly present in financial discussions. For the past decades liquidity has been studied from various perspectives extending its academic research from stock markets to treasuries and bond markets, and even alternative asset markets. The classical studies such as Amihud and Mendelson (1986a,1986b), Glosten and Harris (1988), Brennan and Subrahmanyam (1996) have provided extensive evidence of the effects of liquidity level on expected share returns and prices.

There is currently a considerable number of research concerning stock and market liquidity and asset pricing, its corporate theory applications, systematic liquidity risk, and its various applicable dimensions. Moreover, classical studies (Demsetz 1968, Kyle 1985, Amihud and Mendelson 1986, 1991 and Grossman & Miller 1988) focusing on markets' microstructure (transaction costs, demand pressure, inventory risk and information asymmetry), liquidity effect and asset returns have created a healthy basis for a future study which have broadened and shifted from simple one-dimensional approaches to more delicate and multidimensional touches throughout years. There is a large number of liquidity studies that focus specifically on United States (US, hereafter) stock markets. This is rather understandable as US equity markets have been and still are the most liquid and largest financial markets in the world with long traditions of finance academia. However, the focus of liquidity studies has lately shifted geographically outside the US and moved towards other developed economies and subsequently emerging countries markets, covering stock exchanges representing even the furthest and most exotic parts of the world. One of those parts is Australasia, a region of Oceania, comprising of Australia, New Zealand, and New Guinea, have been left without considerable attention from liquidity and asset returns perspective in financial literature. The goal of this thesis is to fill this research void.

Australia, being the largest economy in the area, naturally has the largest number of research papers covering asset pricing and liquidity from market microstructure perspective. Yet the major number of studies focusing on Australian stock markets such as Chan and Faff (2003,2005), Marshall (2006), and Limkriangkrai et al. (2008) have each been able to capture merely one dimension of liquidity and provided fragmented evidence of pricing asset returns and liquidity. Next to Australia (AUS, hereafter) is located New Zealand (NZ, hereafter) a small (market capitalization merely over a 179 billion[1] New Zealand dollars in 2021) yet highly developed country with a market-order driven market structure (much like the Nordic countries) making it an intriguing subject of study. To the best of author's knowledge, the amount of previous liquidity research from New Zealand is practically non-existent, and only one paper seems to be concentrating specifically on liquidity, liquidity risk and asset pricing (Nguyen and Lo, 2013).

In this thesis we utilize Liquidity Capital Asset Pricing model (LCAPM, hereafter) developed by Acharya & Pedersen (2005) for the first time on NZ's stock data and conduct a study on the pricing of liquidity and liquidity risk covering (il)liquidity level, three distinctive liquidity risk channels and two widely used (il)liquidity proxies. We use a timeframe covering the years 2000 - 2020, extending the previously known study periods by almost a decade and covering the newest Covid-19 induced market shock of 2020. The use of New Zealand as a test country is interesting from various perspectives. Firstly, NZ is a rather remote developed economy whose equity returns have low correlation to other developed countries (Marshall et al. 2015). Secondly, New Zealand, as its close neighbor Australia,

[1] Data retrieved from https://www.nzx.com/markets/NZSX on 30.11.2021

functions as an order-driven market, which compared to hybrid-driven markets (like US) is less studied and has been an early adopter of automated trading. In addition, the existing number of studies have resulted with contradictive results. New Zealand is known to be small in size with low number of companies, yet it has a modern market system and strong market policies (Cameron, 2007). The economic and financial market integration, (*Trans-Tasman integration*, between Australia and New Zealand) presents an interesting setting when we are looking at the state of NZ stock market.

In this thesis we use two unique liquidity measures, the Amihud measure and the Turnover measure, to study (il)liquidity from level and risk perspective. Each of these measures aim to capture a different dimension of liquidity: Amihud-ratio representing depth and the Turnover measure representing immediacy of liquidity dimension respectively. In this thesis the author uses the Fama & Macbeth (1973) method as their initial method. We test our results with robustness checks, using portfolio construction with size (market capitalization) component, and alternative time sub-samples.

Our aim with focusing on New Zealand is to increase knowledge of the liquidity and liquidity risk research in a less studied country with unique market characteristics, by utilizing a coherent liquidity risk framework (LCAPM) for the first time and extending the research by almost a decade.

This thesis is organized as follows. In section 2 we will discuss the body of work of liquidity and asset pricing research. The literature review presents studies of individual stock and market wide liquidity and provides an insight into the most well-known measures both from US and international markets, with emphasis on Australian and New Zealand studies. In section 3 we will describe the data, statistical properties, present liquidity proxies, present the LCAPM framework which is used in this thesis and calculate pre-requisite calculations required for final regressions. Section 4 comprises of the empirical results, robustness tests and interpretations of the results. Section 5 concludes with summary and remarks on the future implications.

2. Literature review

2.1 Definition of Liquidity

As the name itself, liquidity, expresses the concept of liquid-form which is hard to get a grip on and can be conceptualized in various ways considering from which perspective one looks at the construct. The concept of 'liquidity' or its converse concept 'illiquidity' are not a novelty in financial markets academia, yet they and their features (dimensions) have been associated with various definitions throughout time.

Black (1971) provided an intuitive view on market liquidity and defined liquidity from markets perspective with following statements:

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

1. The difference between the bid and asked prices (*the spread*) is *always small*.
2. An investor who is buying or selling a large amount of stock, in the absence of special information, can expect to do so over a long period of time *at a price not very different*, on average, *from the current market price*.
3. An investor can buy or sell a large block of stock *immediatel*y, but at a *premium or discount* that depends on the *size of the block*. The larger the block the larger the premium of discount''

Kyle (1985) defines liquidity as a ''elusive'' and ''slippery'' construct that includes transactional market properties such as *depth*, *resiliency,* and *tightness*. Demsetz (1968) mentioned *immediacy* to liquidity description and Bernstein (1987) breadth as an additional definition to depth.

Focusing on depth and breadth, the first definition refers to the impact of different sized orders to order flow, moreover that how the market behaves (the size of an impact) on different size of orders and latter definition on how widely there is buyers and sellers available on financial markets all the time [even when there is scarcity of outsider buyers and sellers (Bernstein, 1987)].

Resiliency refers to how easily and fast (the speed of convergence) the prices are to rebound in case of unexpected and random shock to a share In other words, how well a stock price returns to its pre-shock price after a shock induced price deviation. Tightness refers to a cost component (bid-ask spread), moreover how much it would cost for investor to switch from bid to ask and vice versa, this is reflected within share's bid-ask spread.

Huberman and Halka (2001) defines liquidity dimensions as procedure where financial market to be liquid when a market participant can trade a large size of stocks with immediacy with a price that is executed near to an ex-ante price and causing minimum impact on ex-post price. Yet the liquidity is hard to observe directly. Lesmond (2005) defines liquidity from market transaction point of view where direct trading cost represents tightness and is observed via bid-ask spread and indirect cost representing depth and resiliency via price impact proxies.

Under these definitions we can further define academic research when looking at the explanatory factors of equity market liquidity. There is a research branch focusing on a exogenous transaction costs and their effect on shares liquidity (Demsetz, 1968). There is also a branch that focuses on intangible frictions such as private information and information asymmetries (Bagehot 1971, Grossman 1976, Kyle 1985, and Mendelson and Tunca 2004), search related frictions and demand pressure with inventory risk (Amihud and Mendelson (1980), Garman (1976) and Ho and Stoll (1981). A vibrant research area of market microstructure has played a pivotal role when defining the liquidity and its essence. Moreover, there seem to be a awoken interest towards the studies of liquidity effect and liquidity risk from asset pricing and corporate perspective that coincides anecdotally with the global financial (sub-prime) crisis of 2008. The systematic financial crisis that caused constant downward spirals of market prices and liquidity dry ups leading to a substantial market losses and economic distress. Naik and

Reddy (2021) gather with their study all the different themes (stock market liquidity measurement (46 pcs), liquidity effect and asset returns (116 pcs), corporate liquidity and cost of capital (250 pcs) and liquidity risk and required rate of return (26 pcs)) related to liquidity studies and the published papers post-financial crisis and concludes that total number 439 studies were conducted from year 2008 onward. Therefore, there is no doubt about the importance of liquidity and asset pricing research within the finance academia, but more the section of studies on which one should focus. Authors concluded the need for future studies were especially relating to emerging and small but developed markets and liquidity risk, which this thesis's fits perfectly.

Liquidity research is therefore vast and wide area of financial research, which contains never-ending areas of research, in this thesis our focus is within empirical research between asset returns and (il)liquidity and more recent area of study, a pricing and the effect of time-varying liquidity risk on asset returns.

2.2 How to measure different liquidity dimensions?

Due to the illusive nature of liquidity, it cannot be directly measured, but approached indirectly using different liquidity approximations to be able to capture one or more dimensions of liquidity.

Kim and Lee (2014) state following measurement challenges proportional to liquidity; ''Does the pricing of liquidity risk vary from according to measure used, possibly because each measure proxies a different aspect of liquidity? Indeed, it is therefore crucial task to find a measurement that have a best fit from the model and market perspective.''

The effectiveness of liquidity proxy is therefore reciprocally subordinate not only the chosen measurement itself but also to the framework that is used considering different market peculiarities (market sophistication, market capitalization, investor protection and market concentration) and the quality of a data and statistical methodologies used in specific research. There is luckily consensus of bifurcation between the liquidity proxies, moreover high-frequency and low-frequency proxies with additional high-frequency benchmark to utilized as the basis for the effectiveness testing of used proxies. In addition, liquidity, and asset pricing’s academical research studies are rather novel regarding the time periods of the studies. Moreover, as Baradarannia and Peat (2013), Hasbrouck (2009) and Goyenko et al. points out a microstructure studies based on high frequency intraday data have data available at earliest beginning of 1983 and studies utilizing low-frequency measures (daily data) with bid-ask spread and volume observations are easily available starting from 1963, therefore most of the literature can be considered starting from the latter year at earliest. There are though some studies likes of Baradarannia and Peat (2013) and Hagströmer et al. (2013) who uses data predating 1963 More delicate measures such as bid-ask spread and intraday transaction level quotations would possibly offer more breadth and depth to liquidity measurement metrics, but unfortunately due to the unavailability, high cost and lacking in length (Amihud, 2002) of this type of microstructure data on most of the stock markets makes the use of it unattainable.

2.2.1 High Frequency measures

High-frequency measures are the most straightforward proxies as they represent the most visible part of the transaction costs deriving from endogenous factors of equity shares. Intraday bid-ask prices and their different variations and their corresponding quoted depth levels represents the cost impact and transaction costs of a trade and can capture these costs quite well. These measures are considered as the most classical, yet topical high frequency proxies used in the asset pricing, transaction costs and later in liquidity effect and risk studies likes of Glosten and Harris (1988), Hasbrouck (1991), Brennan Subrahmanyam (1996), Chordia et al. (2000, 2001), Hasbrouck and Seppi (2001) Huberman and Halka (2001, 2014) and Marshall et al. (2015) to name a few.

High-frequency liquidity measures have been used mostly within financial asset's microstructure studies, starting from a traditional domain of individual shares and its characteristics (see the 4.2 for further reading of a stock as characteristic) and in the beginning of 2000 shifted from individual stock research towards a co-variation between the market movements and factors and their effect on shares and vice versa (ultimately representing new findings likes the aggregate market risk, commonality of liquidity, flight to liquidity and economic depreciation).

High frequency proxies are rather simple, firstly a bid-ask spread with different variations to it (quoted and effective bid-ask spread) and best bid-ask prices and secondly different depth levels of order book. Quoted spreads and depths are the prices and levels that are announced on a market at a specific time (notice the market structure difference between quoted-, hybrid and order-driven market). Some studies enhance the depth measure by adding a bid or ask price to it, so that a currency denominated depth value is derived. Moreover, as most of the trades happen in between quoted spreads (Chordia et al., 2000), the real measure of actual transaction costs is effective spread. Effective spread is defined as the difference between the execution price and mid-point of quoted bid-ask prices. This way researcher can utilize an actual spread experienced by investor when buying or/and selling shares, and affiliated order flow's impact changes. As Fong et al. (2017) states high frequency measures are also used as high frequency benchmarks, as they represent the real transaction costs of a trade.

2.2.2 Low Frequency measures

Utilizing intraday data can be challenging not only because of the computational encumbrance, but also because from the historical perspective the data itself is notoriously hard to obtain, especially with longer data-periods to be able to run a valid statistical result. In addition, using fine-grinded observation data with minutes or even seconds and milliseconds timespan does not automatically mean better results as the results based on this type of data might be plagued by various statistical challenges

In addition, the most effective regression procedures and frameworks might favor proxies with low frequency time-interval observations instead of a high frequency counterpart Luckily there is a healthy number of studies specialized to provide evidence on this subject, likes Goyenko et al. (2009) and Fong et al. (2017) to name few who provided evidence of the efficacy of low frequency liquidity proxies (see next chapter for further reading). The number of measures is almost as many as there is written on liquidity related research papers. Yet there seems to be so that a certain liquidity measure has become more or less a market standard compared to the others.

Amihud (2002) describes measurement of illiquidity via his ILLIQ measure as the *average across stocks of the daily ratio of absolute stock return to dollar value.* With this Amihud aimed to capture the price impact of trade as the ILLIQ measure portrayed the price sensitivity with absolute volume trading stocks. The theoretical rationale behind this measure is closely tied to Kyle's (1985) seminal work on information asymmetry and Kyle's lambda (λ) measure which refers to the market's capability to absorb trade quantities without any substantial effect on price subsequently portraying a depth liquidity dimension. Due to its nature ILLIQ -measure falls into a cost-per-volume proxy category (Fong et al. 2017). Utilizing ILLIQ throughout 1964-1997 across NYSE stocks Amihud (2002) found that expected stock returns over time had positive linearity with illiquidity. Amihud divided the nature of illiquidity in two pieces according to how the illiquidity presented itself. In cases of expected illiquidity, the expected returns contain positive increasing relationship, but on contrary unexpected, realized liquidity shocks causes stock prices to drop expressing the shifting mechanism of innovation of liquidity.

Trading volume-based measures are one of the oldest used approximations for trading activity and immediacy from liquidity perspective. The seminal work of Datar et al. (1998) and Hu (1997) popularized the use of the volume related measures as a liquidity proxies.

In order replicate the bid ask spread transaction costs an interesting measure called Zero Returns -measure was created by Lesmond et al. (1999) which reflects the effective spread dimension of liquidity. The rationale behind this proxy is twofold. Firstly, stocks that have zero volume days will subsequently have zero return days, which transforms into a lower liquidity level. Secondly due to private information (information asymmetry) the stocks with high transaction costs have a substantially higher threshold for private information value to turn into transaction as the transaction costs will outweigh information signal and market participants will choose not to trade (Bekaert et al., 2007

2.2.3 Liquidity benchmarks

The number of liquidity research papers have rapidly increased in numbers, and simultaneously the number of different liquidity measures have become almost overflowing in numbers as almost every author is providing their own liquidity measure, which usually is a incremental modification of a previous proxies. Due to multidimensional and illusive nature of liquidity [(Acharya & Pedersen (2005), Amihud & Mendelson (1986), Chordia et al. (2001), Amihud (2002)] there is currently no comprehensive proxy that would capture all these dimensions, therefore the demand for new proxies is continuous.

When utilizing different liquidity proxies, it is important to be able to choose a liquidity measure that measure liquidity (Goyenko et al. 2009) or at least a have some objective research on the subject when making enlightened guesses when choosing a proper quality measure to liquidity research.

To answer to this dilemma a few performance studies have been conducted on this subject, such as Lesmond (2005), Goyenko et al. (2009), Kang & Zhang (2014) and Fong et al. (2017). Liquidity proxies can be high-frequency (intraday) or low-frequency (day, week, month)., see 2.2.1 and 2.2.2 for additional information. As a benchmark a high-frequency (intraday) trade data is used, moreover different variations of bid-ask spreads. Goyenko et al. (2009) used as their high frequency benchmarks (effective spread, realized spread) NYSE's Trade and Quote (TAQ) and Rule 605 database data over 1993-2005 and run a number of liquidity proxies (Roll, Effective tick, Holden, Gibbs, LOT, Zeros as spread proxies and Amihud, Extended Amihud, Roll impact, Pastor and Stambaugh, Amivest as price impact proxies. Authors concluded that for monthly and annual effective and realized spreads the best proxy was Holden, yet it was considered as difficult to calculate, therefore, Effective Tick was suggested due to its easiness of calculation. Price impact measures were deemed to be not appropriate to use as proxies for realized and effective spreads, but for price impact Amihud was showed to be the best proxy. Authors notified of the difficultiness of creating a proper price impact benchmark as their data didn't contain block trades which are a crucial part of price impact effect. Moreover Goyenko et al. (2009) notifies that as the results are based on US data and non-thin shares a generalization of the results to international studies cannot be made nor usability of the proxies to a thinly traded shares without caution. Lesmond (2005) uses number of price and volume-based measures (Roll's measure, the LOT model, Amivest, Turnover and Amihud's ILLIQ measure) and runs them against spread-plus-commission-cost high-frequency benchmark through 1987-2000 emerging markets setup. Author notifies that price-based measures (LOT and Roll's measure) fares better over volume proxies defining cross-country differences in liquidity. Overall, the LOT and Amihud are to be considered as the best liquidity proxies within emerging market setup, both cross-country and within-country. Yet according to author Amihud and turnover measures presents downward bias due to low trading volume and zero volume days (especially on Amihud measure, as zero volume days provides undefined value for the measure), which weakens statistical significance of these measures. Turnover is defined as the least suitable liquidity proxy for the emerging market environment as it represents the weakest correlation towards bid-ask spread benchmark. A result in line with Goyenko et al. (2009) finding that volume-based proxies are not valid to explain bid-ask spread cost components but a price impact (Amihud) and possibly trading activity related liquidity dimension (turnover). Kang and Zhang (2014) complement Lesmond's findings on emerging market setting and suggest Adjusted Amihud illiquidity as the best liquidity proxy for emerging markets liquidity and liquidity risk studies.

Fong et al. (2017) studies the efficacy of monthly and daily liquidity proxies with global dataset (based on daily data) and determines Closing Percent Quoted Spread as a best proxy for daily and monthly percent-cost proxy, moreover Amihud, Closing Percent Quoted Spread Impact, LOT Mixed Impact, High-Low Impact and FHT are considered best for cost-per-dollar-volume (lambda) proxies with Amihud being most suitable measure as a daily cost-per-dollar-volume proxy as well. Study is based on 38 countries, both developed (containing New Zealand as one of the constituents and emerging markets) and covering two time periods: 1996—2007 and 2008-2014. Authors employ as proxies Roll's measure, Effective Tick, LOT Mixed, LOT Y, FHT, Zeros, Zeros2, High-Low, Closing Percent Quoted Spread Impact, Amihud, Pastar and Stambaugh and Amivest. Zero's measure fared on average rather well, the measure was correlated with benchmarks, even though never gaining a top score nor a lowest one.

It is also important to notice that due to liquidity multidimensional nature, the use of high frequency proxies should not be considered automatically superior to low-frequency counterparts, as Fong et al. (2017) points out that low frequency proxies may capture some liquidity dimensions which high frequency is not able to do. Moreover, as we move to finer data, the existence of noise becomes more prevalent (Kim 2011, Kim and Lee 2014, Vu et al. 2014)

Based on these research papers and the previous liquidity research paper's results on New Zealand, Australia, and international studies we use in this thesis following two liquidity proxies Turnover measure and Amihud (ILLIQ) measure. The reasoning behind this is that firstly Amihud which is price impact measure have performed well throughout all the tests and have been widely and successfully used on vast amount of empirical research papers. Turnover measure is one of the first liquidity ratios used in the academic research and it contains a logical component (volume and outstanding stocks) which are connected to trading activity, and which analogously have a healthy microstructure related (Amihud and Mendelson 1986) background to it.

2.3 Liquidity as characteristic and market wide feature

Liquidity studies can be divided into two main arrays, moreover studies focusing on shares liquidity as characteristic (level of liquidity) or liquidity effect and furthermore studies on market liquidity or market return as a systematic factor which have transitory function through shocks over individual stock's liquidity(illiquidity) level. In addition, from market wide illiquidity perspective, liquidity (illiquidity) is time-varying and persistent by its nature which have reciprocal variation to market wide liquidity, returns and return premiums. Contemporary liquidity studies combine the classical approach of cross-sectional to time-series and from individual to market wide perspective. The most profound divide is usually when it comes to the data's observation frequency interval, moreover whether to use a high- or low -frequency proxies.

As one of the first modern studies related to liquidity effect is by Amihud and Mendelson (1986) study in which authors present coherent evidence over a positive connection between expected return and transaction costs (bid-ask spread) or more commonly known a liquidity effect. The positive relation of required return and transaction costs is revealed as a concave by a nature, which is explained by a clientele effect, meaning that a risk neutral investors investment horizon defines which type of asset she is holding. Investor with a long period horizon prefers illiquid shares as she can amortize the costs over a longer period (returns nearing a concavity due to marginal increase of returns) in opposite to investor with short investment period, who prefers liquid shares. Authors therefore define the liquidity effect as priced characteristic with shares return being an increasing function of the transaction cost (share's bid-ask spread).

Within this context there is also an expectation component according to which expected cost of illiquidity translates further into illiquidity premium (the difference between illiquid and liquid shares premium), meaning that investor is compensated illiquidity premium beyond merely expected cost of illiquidity (Amihud and Mendelson, 2015).

An interesting branch of liquidity research are the ones that focuses on corporate level implications and resolutions on how to affect the individual stock il(liquidity) level by conducting corporate financial policy actions that leads to liquidity-enhancing. Amihud and Mendelson (1988) noticed the for example that existence of poor financial disclosure, private ownership and incurring trading costs lead to decreased stock prices, wide bid-ask spreads and increased expected returns. As a solution authors provided a corporate level solution of improvement such as going public, increasing uniformity of financial claims, increase the quality and amount of financial disclosures in order to battle against insider -dilemma, participate actively in stock splits, listing on organized exchanges instead of a dealer market to decrease opportunity cost of capital, enhance the stock liquidity bid-ask spread (transaction costs) and enhance the liquidity. Corporate financial policies and institutional level studies are an interesting branch of liquidity-related research which is not in scope of this thesis, but an admittable array of valuable research to mention about which portrays well the wide spectrum of contemporary liquidity studies.

The initial area of a liquidity studies of individual security (or characteristic) within microstructure research started abruptly to shift from a study focusing on a single share attribute towards covariation between market wide factors and shares and common underlaying factors, innovation of movement through time, persistence, and co-movement of a market wide liquidity perspective.

The first studies that turned their focus from classical studies involving individual stock characteristics to a common determinants of liquidity and its innovations were by Chordia and Subrahmanyam (2000) studying the liquidity proxies' co-movement with industry and market level liquidity; Hasbrouck and Seppi (2001) with their intraday data study on common factors of order flows, returns and time-varying effect of trade impact; Huberman and Halka (2001) testing on their behalf a liquidity proxies' and their innovations against different explanatory market variables.

Using different variations of bid-ask spreads and quoted depth as their liquidity measures authors (Chordia and Subrahmanyam, 2000) From co-movement perspective it was found that smaller sized stocks were less sensitive to a market-wide shocks from spreads perspective, the sizes of return β (betas) were found to be bound to a firm size showing an counterintuitive increasing relationship between large corporate firm spread and market-wide changes in spreads even though the average spreads of large firms are considerably smaller compared to a market averages. Authors find a commonality between liquidity proxies and market and industry (data divide of 8 industries) determinants as a source of commonality. When searching for a common influencing factors authors show two possible explanations, moreover inventory risk and asymmetric information, from informed and uninformed traders' point of view. A strong positive commonality connection between stock premiums to the absolute number of transactions and negative relation to market-wide level of trading.

Authors acknowledged the connection to broader set of frameworks of inventory risk (possibly rising from uninformed trader) and asymmetric information (informed traders operating on miniscule trade sizes). In addition, authors notify interesting application of commonality, a timing of performance optima stock buys when spreads are low. This idea in the future will be one of the first starting points for liquidity augmented portfolio timing studies.

Hasbrouck and Seppi (2001) found a relevant proof of commonality between absolute returns and order flows when using high frequency intraday (15 minutes interval) quote data on 30 Dow Jones Stock from 1994. In contrast to Chordia and Subrahmanyam (2000) and Huberman and Halka (2001) authors couldn’t find any significant commonality within liquidity, but a weak evidence of log quote slope that presented 13% of total variation of commonality. Huberman and Halka (2001) uses 60 randomly selected stocks by size and utilizes daily data with spread, spread to price ratio, number of shares and dollar denominated depth. Author finds a commonality between liquidity proxies and positive (negative) correlation to stock returns (volatility). Due to no coherent theoretical explanatory framework which could explain the results authors uses a priori adverse selection and cost of holding inventory as a possible intuitive explanation behind the commonality.

Rösch and Kaserer (2013) extends commonality of liquidity study (Chordia 2000) and conducted a study the relation between commonality of liquidity risk and share returns from market distress (financial crises) and flight to quality view. They adapted on German data a special volume-weighted spread (provided by Deutsche Börs) which measures a roundtrip price impact that takes into consideration specific trade’s round-trip cost against the limit order book’s fair value. Authors show that there is a considerable commonality in liquidity on an individual shares level which peaks during financial crisis and that the commonality is time varying and is induced by a deteriorating funding liquidity of market intermediaries and flight of quality when investors shift to a stock of higher liquidity during a financial turmoil.

Isaenko and Zhong (2014) complement financial distress studies from bond market perspective and finds a strong liquidity premium during financial crises and deduce investor’s overoptimism as a root-cause of historical liquidity premium. In addition, Amihud et al. (2015) found an interesting spill-over effect and additional commonality behavior, as they noticed that there was a cross-country commonality in the illiquidity return premium for illiquid-minus-liquid stocks (see for example as a comparison to Lee (2011) finding of cross-country commonality within just a illiquidity).

2.4 Previous Studies on Liquidity-Adjusted Capital Asset Pricing Model (LCAPM)

Acharya and Pedersen (2005) brought a fresh stream of ideas to a liquidity and liquidity risk in asset pricing academia as they combined the ideas of commonality of liquidity presented by Chordia (2001) Huberman and Halka (2001), Amihud (2002) and Hasbrouck & Seppi (2001) and formed an unified framework which provides researcher a possibility to study the pricing of (il)liquidity and (il)liquidity risk utilizing not only market aggregate risk but different unique risk channels as well and load different liquidity measures in order to capture multiple dimensions of liquidity. Based on classical Capital Asset Pricing model authors combined a unified framework containing co-movements to cover different liquidity channels and providing a test ground for a load of a different illiquidity measures to cover as many liquidity dimensions as needed.

Lee (2011) applied LCAPM model on 50 countries and over a 1988-2007, utilizing Zero Returns liquidity measure using both cross-sectional regressions and factor model. Author finds overall evidence of liquidity risks being priced and persistent, moreover main finding was that each liquidity risks are priced independently from market risk (β^1) and illiquidity level. Author furthermore studies whether there is a global effect of liquidity and risks, focusing both on local and global liquidity risk factors. The strongest effects are shown to derive from commonality liquidity risk (β^2) to local market returns and flight to liquidity risk (β^3) to both local and global market required returns. After conducting a controlling for risk Lee (2011) finds specifically that liquidity risk effect is most pronounced with the covariation between stock illiquidity and locally aggregated liquidity risk (providing premium of (7.8% and 13.6% for developed and emerging markets subsequently) and global market returns. In addition, US market is found to be a significant driving force of liquidity risk and there is evidence of global / local liquidity risk for politically and economically open / closed economies.

Author provides a new insight into liquidity risk persistency as it is found to vary according to geographical, level of political risk, economic stability, and market conditions. Moreover, showing first time that global liquidity risk is more prominent within developed countries whereas the local liquidity risk has a strong foothold on emerging markets with less open market structures and foreign investors. In addition, Lee shows that the individual liquidity risk channels play substantially much more important role than the market risk from asset pricing perspective.

Kim and Lee (2014) extend the US market (NYSE and AMEX) LCAPM research by employing eight different low-frequency liquidity proxies to be able to capture a multiple dimensions of liquidity risk simultaneously. In addition to two-pass cross sectional regression authors follow likes of Pastor and Stambaugh (2003), Korajzyk and Sadka (2004) and Lee (2011) and utilizes factor model regression method. Authors finds a common component across liquidity proxies with principal component analysis, which subsequently extracts the common and systematic component of liquidity proxies to diminish the noisiness, verifies the existence of common and systematic underlying factor that is priced instead of individual proxies and showing it to consist of 33% of whole variation of liquidity proxies.

One feature that is good to acknowledge is that there is alternative or rivaling LCAPM models available likes of Liu (2006) used likes of Nguyen and Lo (2013) The differentiate characteristics between LCAPM models is that each of them address to pricing of single liquidity risk, yet Acharya & Pedersen's model is only one that integrates multiple risk channels into one unified framework.

A thorough discussion on LCAPM is provided In Chapter 4.3 containing a theoretical framework and step-by-step guidelines of the model's implication in scope of this thesis.

2.5 Evidence of Liquidity pricing

2.5.1 Liquidity studies on US and developed countries

USA is the largest equity market in the world by volume and market capitalization and considered as one of the most liquid financial markets in the world. Therefore, it is no surprise that the largest part of liquidity, liquidity risk and asset pricing research is naturally based on this market and a vast number of studies is available beginning from 1980s to this day.

Baradarannia and Peat (2013) studies the role of liquidity level explaining the cross-sectional variation of expected stock returns with EFFT (Effective Tick4) liquidity proxy created to simulate effective spread liquidity benchmark, on shares traded on NYSE (New York Stock Exchange). Authors provide first time a time-series of liquidity research covering extensively long period of time, moreover a 1926-2008. Extending research of liquidity effect (characteristic of a stock) to include a period of pre-1963, on which is widely considered lacking even from USA equity markets. Authors find a liquidity level to be priced confirming the studies of Amihud and Mendelson (1986) and Baradarannia & Subrahmanyam (1998). Authors notes that the effect of liquidity is more prevalent over entire sample and post-1963, assuming as explanatory reason an flight to liquidity effect, as due to an economic state the shift from illiquid to liquid shares have occurred pre-1963 (contractive economy) and opposite for post-1963 (expansive economy). Hagströmer et al. (2013) provides complementary evidence to the previous study using the same EffectiveTick4 liquidity proxy, studying NYSE and Amex throughout 1927-2010. As an addition to the previous study authors utilizes conditional model of LCAPM framework, extending the previous studies towards liquidity risk. Marcelo and Quiros (2006) studies existence of illiquidity risk factor within Spanish stock market (1994-2002) using Amihud ratio as a liquidity proxy within liquidity augmented Fama & French three factor model. Authors shows that their results support the US findings of expected excess asset returns explained by illiquidity risk factor. Results also shows increase of illiquidity risk level on January months, moreover, presenting evidence of existence of January effect in spirit of Reinganum and Eleswerapu (1993). Shortcomings of this study is considered the rather short time-estimation period.

Butt et al. (2014) studied illiquidity risk from Nordic country perspective, and moreover Finland and finds that the markets are illiquid and therefore the liquidity proxies does capture the asset illiquidity, showing an astonishing risk premium of 92% in full periods and 60% in calm periods against 17% in US market (Acharya & Pedersen, 2005). Li et al. (2014) studies Japanese markets from illiquidity and illiquidity risk perspective using Adjusted Amihud suggested by Hasbrouck (2005) measure as their liquidity proxy over a extensive time-period (1975-2006). Authors utilize both cross-sectional and time-series analysis using a LCAPM model for latter. Results provide an interesting insight, as a strong effect is found between illiquidity and return premiums, but only pre-1990 -time sample, furthermore an evidence line with Acharya & Pedersen (2005) a positive connection between average illiquidity and number of company and market related components such as volatility of illiquidity innovation, Book-to-Market, portfolio volatility returns negative to turnover and firm size. Moreover, authors find a of positive expected illiquidity to stock returns and negative of unexpected illiquidity and contemporaneous stock returns. Small evidence of flight of quality is observed but only weak evidence of pricing of liquidity risk from LCAPM perspective.

2.5.2 Liquidity: Australia and New-Zealand

The liquidity risk in asset pricing literature from Australia and New Zealand perspective is scarce for the first and almost nonexistent for the latter. These two countries share an economical and financial market integration (Conway et al. 2013) and therefore it is justified to address the liquidity and asset pricing research of both countries.

Chan & Faff (2003) used Fama-French cross sectional three factor model and stock Turnover by Datar et al. (1998) as their liquidity proxy and found that during 1990-1999 the proxy had a strong negative relation to stock returns. Authors couldn't find any strong seasonality evidence and the results were robust even after including momentum -effect nor there was evidence of a size effect throughout the time sample. Authors provided further evidence for the support of liquidity augmented Fama-French model when using the generalized method of moments (GMM) (Chan and Faff, 2005). Marshall & Young (2003) found similar findings with rate and in addition an evidence of negative size effect. Demir et al. (2004) conducted their study (1999-2001) on the momentum strategies and found excess returns to be significant within Australian market and larger in size than ones found within European and US markets. Demir et al. (2004) used average daily stock volume (Brennan et al. 1998) as one of their robustness checks showing non-conclusive evidence of liquidity proxy but confirming the noteworthiness of the liquidity dimension across different portfolios' momentum returns when ranking portfolios by volume. Fabre and Frino (2004) moved from traditional microstructure stock as characteristic studies and employed a novel commonality in liquidity perspective utilizing a high-frequency liquidity proxies using transaction data throughout year 2000. Authors provided results showing partial evidence of commonality in liquidity within Australian stock markets, but with much less significance and impact, eventually deducting the possible influence as a different markets structure (Fabre and Frino, 2004).

Marshall (2006) argued against the feasibility of liquidity measures that portrayed the past trading habits, such as trading volume and trading turnover ratio, within order-driven stock market and utilized a new high-frequency liquidity proxy which he calls as Weighted Order Value (WOV). The finding of negative relationship provided author additional evidence of existence of the positive liquidity premium within Australian context.

Limkriangkrai et al. (2008) presented results that raised the need to discuss of the validity of used models when comparing both domestic- and US-based Fama & French's three factor model and finds latter model to be able to capture the returns of largest companies yet fails on smallest stock. This leads authors to conclude that Australian markets are internationally segmented but nevertheless the small companies to be domestically segmented (Limgkriangkrai et al. 2008).

Chai et al. (2013) studied a commonality of liquidity utilizing their own low frequency monthly based IM -illiquidity proxy, running regressions via Carhart four factor model with liquidity adjustment covering years 1982-2010. Even using longer time periods and addressing different liquidity measure authors find only partial evidence of liquidity explanatory power within common variation of Australian markets and pinpointing as a conclusion a multifaceted nature of liquidity risk. Further commonality is studied by Vu et al. (2015) where authors utilized Acharaya & Pedersen's (2005) LCAPM model, moreover with emphasis on co-movement of liquidity and the transition effects of liquidity risk in different type of markets states. Authors used Amihud (2002), Zero returns, Stock turnover and -adjusted zero daily volumes as their liquidity measures ran their regressions using panel regressions, a first time used within Australian studies. Main findings were that the pricing of liquidity risk is reliant to the liquidity transmission channel, moreover, emphasizing liquidity risk's fragmentary nature. In accordance with expectation authors showed the negative relationship between stock return sensitivity to market liquidity and with lesser extent a negative covariation between security's liquidity and market return. In addition, authors conduct controlling tests and found a support for size effect and co-variation of liquidity as evidence of aggregate systematic risk effect (β^{net}) to returns in down markets. (Vu et al. 2015)

The studies concerning liquidity risk and liquidity from New Zealand perspective are almost non-existent and to the knowledge of author only a single study exist (Nguyen and Lo 2013) that explicitly focuses on New Zealand from liquidity level and risk perspective. Authors incorporated a cross-sectional data consisting of seven different liquidity measures both high- and low-frequency measures and utilized Carhart four factor model over a period of 1996 -2011. They also used LCAPM model developed by Liu (2006) to address the liquidity risk aspect.

The results of Nguyen and Lo (2013) were contradictory to the theoretical expectations (from traditional stock as characteristic and market-wide commonality perspective) as according to their study low liquidity stocks or high commonality sensitivity stocks didn't produce higher returns in compensation compared to their liquid counterparties, but in contrary there was significant negative returns. In addition, there was evidence that the liquidity risk was not priced within New Zealand even after running regression with different controlling risk factors. This study raises a question of multifaceted nature of a liquidity within a small and developed market which this thesis aims to provide additional evidence. In addition, there exist few studies on NZ from stock market perspective, namely by Bryant and Eleswerapu (1997) who conducted transaction cost study on NZSE 40 index constituents and studied the bid-ask spreads effect on expected returns and almost two decades later Marshall et al. (2015) study that updates the previous study and extends it to cover all shares of New Zealand stock exchange.

Amihud et al. (2015) included New Zealand as one of the constituents of the 45 countries of their research paper which searched for a illiquidity premium and furthermore liquidity commonality from an international perspective. Both Australia and New Zealand defined as developed markets produced average monthly premium of 1.49% (0.63%) for Australia and 0.38% (0.19%) New Zealand on equally return weighted (value weighted) portfolios and subsequently monthly alpha of 1.38% (0.55%) and 0.60% (0.28%).

Respectively the monthly premium for a whole portfolio was 0,77% (0.46%) and for the monthly alpha as 0.79% (0.42%) with high premium defined for emerging markets, the result was contradictive between Australia and New Zealand. This provided additional view of New Zealand stock market and low expected return premium, underlining the peculiar view of New Zealand as small and illiquid yet developed economy with modern market structure (order-driven market) but low expected returns.

Therefore, the question of which are most suitable liquidity proxies and theoretical frameworks in Australian and especially New Zealand stock markets that could capture variation in stock returns and would be best fit is yet found.

2.5.3 International Liquidity studies (emerging markets)

After extensive studies on US equity market throughout 1980-1990s the interest towards liquidity as research subject started to increase outside US, first within other developed countries and from there on emerging and frontier markets. The development of emerging markets' positive financial market development and emergence of a new studies of liquidity risk and asset pricing as market wide characteristic (commonality of liquidity) with spillover effect and co-movement between countries created a fertile ground for a new geographically dispersed studies around the world. Before the 2000's the emerging markets studies have been scarce in numbers and studied on a single emerging market instead of a coherent overview. Studies such as Bailey & Jagtiani (1994) on Thailand Amihud et al. (1997) on Israel, Berkman et al (1998) on India were each pioneering emerging markets microstructure studies focusing on a single emerging market from a cross-sectional stock liquidity risk perspective.

Bekaert and Campbell (1997) studied volatility within emerging markets throughout 1976 – 1992. Even though authors didn't use liquidity proxies but tries to explain cost of capital via volatility as explanatory variable, they utilized liquidity-based stock selection, moreover stock trading days and volume, as a base of their portfolio construction. Absence of liquidity aspect of model leaves authors with partly satisfied results, moreover the acknowledgment of the different level market integration factor within emerging markets, the difficulty of volatility modelling. Openness of economies, credit quality, and market liberalization against the level of volatility, which all of these had a positive impact (lower volatility). Rouwenhorst (1999)

Jun et al. (2003) studies 27 different emerging markets throughout 1992-1999 using turnover ratio, trading value and turnover-volatility multiple as their liquidity measures and finds positive correlation the measures and market wide liquidity. Moreover, they conduct both cross-sectional and time-series analysis with control for world market beta, market capitalization and price-to-book market ratio. This study's main findings are the gradual improvement of liquidity measures over time against aggregate liquidity, but yet from cross-sectional perspective a lower integration towards global markets (Jun et al. 2003). This means that even though emerging markets are not (yet) interconnected to a global market there is evidence of improvement of economic growth and development implying the importance of policy improvements from economical political perspective.

Lesmond (2005) used five different liquidity proxies (bid-ask spread, turnover, Amihud, Roll's measure and The LOT model) to study which would be able to capture firm level liquidity best with broader set of liquidity estimation dimensions of 31 emerging markets throughout 1987-2000. Across countries the best liquidity proxies were price based, moreover LOT and Roll's measures with prior amassing considerable over 80 % correlation against cross-country bid-ask spread. The poor performance of volume-based proxies, Amihud and turnover, were argued to be downward biased implying an incorrect fit as a proxy for a low trading volume emerging country. Within-country results showed LOT and Amihud being the best proxies with 50% of correlation of each country's bid ask spread.

Furthermore, after conducting maximum likelihood factor analysis extending the study to a commonality of liquidity on which LOT and Amihud showed the best fit. The Turnover as a proxy was argued to be poor on both within -and cross-country regressions emphasizing the question of viability of this measure. As an interesting additional find author examines the impact of legal and political institutions to liquidity measures finding that the improvement of country's political institution will increase the liquidity of a market as decease the liquidity costs.

Bekaert et al. (2007) follows Lesmond et al. (1999) and Lesmond (2005) lead, utilizing the proportion of zero daily returns (ZR) liquidity proxy, and studies the liquidity and stock return dynamics of emerging markets using both transaction cost and systematic risk factor perspective. Developing their own take on LCAPM model using vector autoregression model (VAR) authors studies the market wide liquidity risk and provides evidence that within emerging markets the global integration doesn't necessarily hinder the existence of local liquidity factors. In fact authors shows that the local marketwide risk factors have substantial effect even if the country is internationally integrated, providing insight into the power of local segmentation from emerging markets perspective.

Lam and Tam (2011) conducts comprehensive time-series based analysis on the liquidity (illiquidity) pricing within Hong Kong market throughout 1981-2004. Authors use nine (9) different liquidity proxies and runs them through liquidity augmented Fama & French 4-factor model and finds that liquidity is priced and represents an important factor in Hong Kong's market. On contrary authors do not find evidence of momentum factor effect being priced.

Lee (2011) conducted extensive study on 50 countries (including both developed and emerging markets) in order to determine whether market wide liquidity risk is priced from global perspective utilizing LCAPM framework and ZR (Zero Returns) measure as a liquidity proxy. Study was conducted using both cross-sectional regression framework and factor model regressions. Same as author finds a evidence of commonality in liquidity, as an interesting feature the liquidity risks are independent of market risk, meaning that the global market risk effect is emphasized in developed countries with low political risk and better market transparency. Countries with weak institutional factors the local liquidity risk is emphasized over global liquidity risk. Meaning that the commonality liquidity's co-movement with market returns are not dependent on market risk but more like an independent channel. Lee (2011) shows that the US market is driving force of global liquidity risk and that the sample country's' expected returns are affected by their country's liquidity covariance to US market.

Liang and Wei (2012) studies further the existence of local liquidity risk within commonality of liquidity from 21 developed country. Authors find that the local risk is indeed priced in various countries, providing a positive sign both with Pastor and Stambaugh's (2003) measure and Amihud (2002) Illiq measure. Authors also notified that the improvement of level of country's market regulations, transparency and other institutional factors reduce the liquidity risks pricing premium. A liquidity spillage is also observed meaning that the innovation of illiquidity has possibly a cross-border nature.

Amihud et al. (2015) extends previous international studies on liquidity risk and employs an analysis on market risk research by comparing the illiquidity premium spillage or moreover illiquidity commonality across 45 different countries (containing both developed and emerging markets). Using Amihud's (2015) -measure as a liquidity proxy. Using volatility-based portfolios authors calculated average excessive monthly premium, the spread between illiquid and liquid stock portfolios, of 0.77 % or 0.46 % when using equally-return-weighted and value weighted portfolio returns respectively.

Authors present furthermore strong evidence of country's illiquidity premium covariation with global liquidity premium and as in Lee (2011) and Liang Wei (2012) the level of co-movement strength is proportional to the level of country's institutional factors (such as economic development, market openness, investor protections). Study provides additional evidence of the market risk factors transition strength and channel via market integration / local segmentation perspective.

3 Hypotheses

As can be observed from the previous studies, there is a good amount of evidence around the world regarding the liquidity and asset pricing from equity perspective, yet the studies on liquidity risk and moreover aggregate liquidity risk are partly sparse especially on some specific small sized developed and emerging market countries.

This thesis examines whether the liquidity risk is priced within New Zealand, which is considered as developed yet small economy with order-driven market structure that provides an intriguing setting for a liquidity risk studies. Moreover, in this thesis we utilize first time Liquidity Augmented Asset Pricing Model (LCAPM) -framework to New Zealand market using different individual liquidity risk channels and aggregate market risk to find the evidence between shares returns and liquidity risk, moreover whether the liquidity risk is priced. Using innovations of illiquidity and LCAPM framework this study aims to provide complementary results to Nguyen and Lo (2013) previous contradictive findings from New Zealand, moreover that the liquidity effect and risk are not priced and. In contrary opposite to expectations and results from other developed countries, an illiquidity discount seems to exist within this market.

The main hypotheses of this thesis are as following:

H1 There is a positive co-movement between stock illiquidity and market illiquidity.

Also known as commonality in liquidity (Chordia et al. 2000), this form of liquidity risk effect derives from the evidence that the market illiquidity and shares illiquidity co-move in same direction. In other words, the rise in market illiquidity raises the stock illiquidity and which in turn rises the share's expected returns.

H2 There is a negative co-movement relation between stock returns and market illiquidity.

This co-movement is related to the Pastor and Stambaugh (2003) finding that the stronger sensitivity level of stock returns to market wide illiquidity (and liquidity shocks) the greater expected returns should command for these types of shares. In other words, the expected returns are increasing function (negative effect) to the co-variation sensitivity of a stocks to market liquidity, resulting an economic phenomenon called as flight-to-liquidity.

H3 There is a negative co-movement relation between stock illiquidity and market returns.

This liquidity risk channel to the economical depreciation effect of investors, moreover in market downturns, liquidity dry-outs and negative market shocks where investors are willing to pay a premium for a stock that becomes liquid in dire market wide movements. Otherwise, investor will be experiencing an asset liquidation cost through depreciated prices and subsequently negative wealth effect. This liquidity risk channel was first found by Acharya & Pedersen (2005) in their seminal body of work and is represented in LCAPM model as a negative relation to expected returns.

H4 Aggregate (systematic) liquidity risk are priced in New Zealand market

In addition to ´liquidity risk pricing from specific liquidity channel perspective this thesis makes a distinction between market risk and liquidity risks and whether the liquidity risk is priced when all the risk channels dedicated risks are combined (isolated) so that we can observe the effect of liquidity risks with presence of market risk and liquidity level (illiquidity cost).

4. Data and Methodology

4.1 Data

The decision to use data from New Zealand was natural, as it represents small but open developed economy with order-driven market exchange structure. New Zealand pose several characteristics that are aligned to a small developed European developed country likes from Europe's Nordic region (Finland, Denmark, Sweden, Norway).

Our data consist of common shares traded on New Zealand Exchange's Main Board. The study period is set to begin from January 1, 2000 and end to December 31, 2020. We use daily level shares data, obtained from Thomson Reuters's Datastream platform. Data variables that are included are stock's daily close price, trading volume, monthly level number of outstanding shares of a firm and for robustness checking purposes firm's market capitalization (size) at year end. Market capitalization and volume are presented as millions of units and thousands of units of local currency respectively. As risk free rate we use New Zealand's 30-days Treasury Bill. The study comprises of initial number of 267 shares.

In this thesis we conduct multiple cleanups to obtain a robust dataset. Firstly, we remove all shares that are cross listed on other exchanges: Shares that are cross listed on Australia's Stock Exchange (ASX) are removed as well as those shares listed on Berlin's Stock Exchange (Börse Berlin). Secondly, we utilize only common shares, meaning that we exclude financial companies, banks, real estate investment funds and other financial vehicles from the data sample. This is standard procedure as according to Fama and French (1992) financial companies tend to have high leverage which with non-financial firms would be perceived as financial distress. Therefore, only common shares listed on actual New Zealand Stock Exchange's Main Board are included in this thesis.

These shares are furthermore trimmed and filtered with additional procedures to obtain a robust dataset.

To tackle the survivorship bias we include the delisted companies to the sample up until to the year they were delisted. Due to the low number of total shares and to avoid running into low statistical validity of results because of low number sample size, this thesis will not employ any restrictions on the upper and low boundaries of share prices that have been normally employed widely in liquidity and asset pricing research papers (Amihud (2002), Lee (2011), Vu et al. (2014)). We also make comparison test on all the share's variables and remove any shares that had mismatch over between variables or missing values for longer than 3 months. Part of stocks that are delisted during our sample period might contain a static last price and outstanding number of shares value post-delisting day. All these values are corrected as not-available (NA) values. After initial data pre-process the final sample size is 197 shares throughout the sample. In this thesis we focus on monthly figures. Our dataset consists of 5480 (252) and 4,384,000 (199,584) daily and monthly trading days and stock variable observations respectively.

In this thesis we use only for Size for robustness tests as B/M (book-to-market rate) values were not readily available via Datastream and required additional manual assembly from company's book value and share price variables. Book values contained numerous null values and mismatches which would have further decreased sample size. Therefore, we do not utilize B/M as a robustness check variable within this thesis.

Each illiquidity measure requires its own pre-requisite of valid data demands to be able to compute eligible liquidity measure, which will cause the number of eligible observations to vary throughout portfolios and time.

4.2 Liquidity Proxies

4.2.1 Stock Turnover Ratio

In this thesis we use turnover measure to reflect stock's trading activity proxying for liquidity, which is defined as absolute number of shares traded and divided by the number of shares outstanding in that specific stock, averaged over a month (Datar et al. 1998, Hu 1997). Turnover is a volume-based liquidity measure represented by trading speed which subsequently relates to a immediacy -dimension of liquidity. In this thesis we utilize Datastream as a source of daily trading volume and outstanding number of stocks at the beginning of the month. We denote turnover as Turnover.

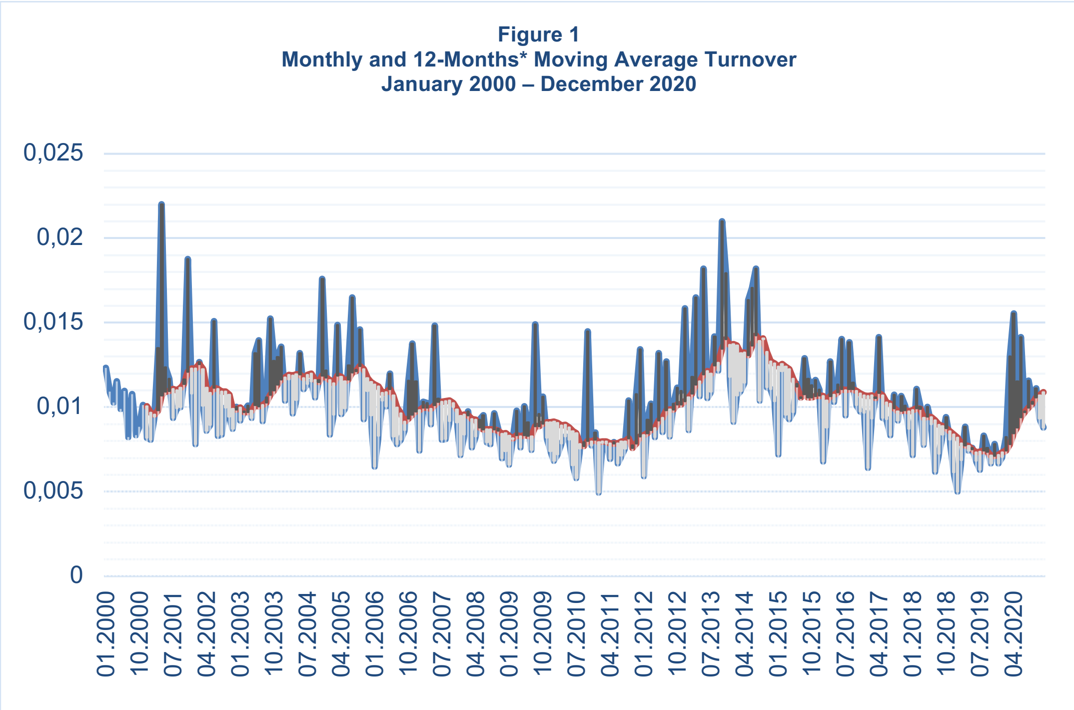
$$Turnover = \sum_{i=1}^{N} \frac{SH,_{i,t}}{SE_{i,t}} \qquad (1)$$

Where $SH_{i,t}$ is a stock's i shares traded during a month t, $SE_{i,t}$ expresses a total number of outstanding shares of stock i in month t. N is the total number of companies during a t month.

Turnover express volume of trading to the total number of shares outstanding. The data for this measure is widely available over a long period of time and therefore a easy to calculate, but does not represent a most simplistic arcane proxy used in early studies like absolute shares volume. The intuition behind this measure is that a liquid shares trade actively compared to illiquid counterparts, but moreover the holding period (Atkins and Dyl, 1997) for liquid stocks is shorter than for the illiquid stocks, complementing the investors' holding period and assets returns theorem (clientele effect) and positive correlation between asset returns and trade activity (Amihud & Mendelson ,1986a; 1986b). Therefore, there should be negative relationship between turnover and expected share returns. Amihud and Mendelson (1986) showed that within their model's equilibrium a stock illiquidity had a negative correlation to stock turnover, with further rationale that investors holding period and bid-ask spreads are proportional to lower turnover rate, which subsequently represents an ''clientele effect'' (Amihud & Mendelson, 2015). In a spirit of a Datar et al. (1998) we trim the outliers by removing the lowest 1% and highest 1% observations out of the turnover data. Our Turnover measure is calculated using a previous month averaged over outstanding shares, individual share and further portfolio level (including market portfolio). Datar et a. (1998) notified that using averaged month values of 1-9 months didn't alter the effectiveness of the measure.

Figure 1 represents the combination of average monthly and 12-months moving average turnover ratio over market portfolio level. This measure, based on the levels, is not the actual illiquidity measure as we focus on illiquidity innovations (discussed and calculated further in Chapter 4.5.). Yet turnover presents an interesting glimpse into the development of NZ market. Figure reveals that instead of an increasing trend turnover have been rather moderate and even stagnating throughout time sample and especially during Financial Crisis of 2008. Both provides additional evidence of the stagnant nature of NZ market. This might be driven by our rigor share selection criteria, which left out financial companies from our data sample. This would explain why example given financial crisis of 2008 doesn't show yet a there is a spike in the begin of 2020 which coincides with Covid-19 pandemic which is not financial markets deriving crises and therefore have straight impact to financial and common shares as well. Trading volume presents similar pattern as Turnover, see Figure 5, Appendix 1.

Figure 1. Monthly and *12- months moving average Turnover ratio representing New Zealand market portfolio over time-period of 2000-2020.



4.2.2 Amihud illiquidity measure

In this study we incorporate a well-known low-frequency liquidity proxy based on a daily data. Amihud -ratio, hereafter Amihud. This measure is an average ratio of a daily absolute stock return to a daily volume of that specific stock. Conceptually ILLIQ ratio provides percentage ratio of the price impact to monetary unit daily volume. As author Amihud (2002) defined, it is a ratio of ''daily price impact of the order flow'', which is analogous to Kyle's (1985) accurate intraday data-based price-to-net order flow concept of price impact -measure also known as Kyle's lambda (λ) relating to depth dimension of liquidity.

Amihud -measure (ILLIQ) as defined by Amihud (2002):

$$ILLIQ_{im} = {}^{1}/_{D_{im}} \sum_{t=1}^{Dim} \frac{|R_{imd}|}{\mathrm{VOLD}_{imd}} \tag{2}$$

Where D_{im} is number of days the stock has been trading in month m. R_{imd} is a stock return i on day d on month m. VOLD_{imd} is respective stock i trading value on day d in month m. The value is denominated in New Zealand dollars (1,000 NZD).

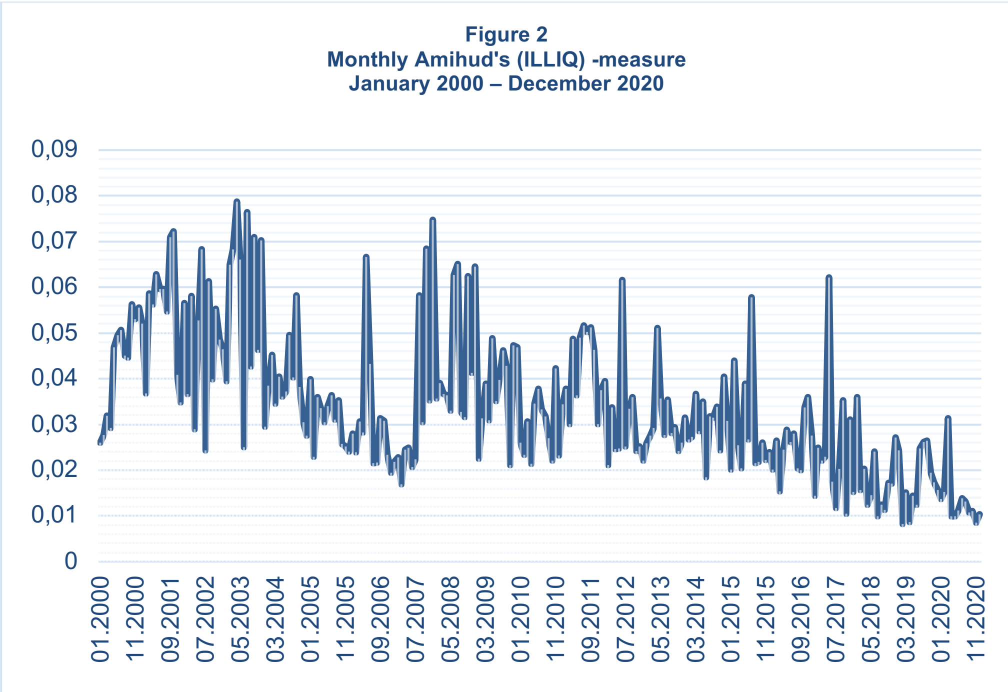
Furthermore, we calculate monthly average $AILLIQ_m$ which provides us with average price impact per traded 1000 NZD volume:

$$AILLIQ_m = {}^{1}/_{N_m} \sum_{t=1}^{N_m} \mathrm{ILLIQ}_{im} \tag{3}$$

Where N_m is the number of sample's shares that are traded during a month.

Due to a small sample size, we omit the exclusion of a price band of maximum and minimum stock price values as was done in prior studies (Acharya & Pedersen, Amihud et al. 2015), yet we maintain the demand of minimum of 15 days of return and volume data per month for each share included in liquidity portfolio. We trim 1% outliers from Amihud -ratio -values to reduce variation of the measure. Figure 2 represents monthly value of Amihud -measure, of our NZ market portfolio sample. As acknowledgment this value represents an illiquidity level, a price impact, and not innovation of illiquidity which is calculated in later chapter. As can be observed from the figure there seems to be higher illiquidity during 2000-2010 over New Zealand stock market, a value close to the one of Nguyen and Lo (2013), and a clear downward trend of illiquidity can be observed beginning from 2010.

Table 2. Monthly Amihud's (ILLIQ) -measure (Amihud -ratio) representing New Zealand market portfolio over time-period of 2000-2020-



Before the portfolio calculation, we must consider a stationarity problem relating to illiquidity estimates. According to Acharya & Pedersen (2005) a stationarity regarding the cost of trade issue persists relating to ILLIQ proxy and its approximation. To fix this issue we will normalize all the illiquidity measures with following adjustment:

$$C_t^i = ILLIQ_t^i P_{t-1}^M \quad (4)$$

$$P_{t-1}^M = \frac{P_{t-1}^M}{P_{December2000}^M} \quad (5)$$

Where C_t^i is normalized measure of illiquidity of stock *i* at month *t* and $ILLIQ_t^i$ is the initial illiquidity proxy value (ILLIQ and TURN) of stock i in month t. Moreover the P_{t-1}^M is the ratio of market portfolio's market capitalization at month $t-1$ and market portfolio's market capitalization at the end of

December 2000. As noted in chapter 4.1 (Data) we do not exclude any price values from the sample to not miniscule the sample size, therefore we do not either present any capped levels to omit above certain level of per trade costs from our sample. Table 7 Appendix 2 presents the summary statistics of data.

4.3 LCAPM Liquidity-Capital-Asset-Pricing Model

As liquidity shifted from first studies beginning in 1980's concentrating on individual stock's liquidity level (Kyle 1985, Amihud and Mendelson 1986, Brennan and Subrahmanyam 1996;) in cross-section towards market-wide and systematic liquidity and liquidity risk in the beginning of 2000's (Huberman and Halka 1999 and Chordia et al 2000; Hasbrouck and Seppi 2001 and Pastor and Stambaugh 2003) an anticipation towards a framework that could capture multiple liquidity dimension intensified.

Acharya and Pedersen took the basic framework of Capital Asset Pricing model (Markowitz, 1952; Sharpe 1964; Lintner 1965; Mossin 1966), CAPM hereafter, and augmented it by combining liquidity level and liquidity risk components under a same framework called Liquidity Capital Asset Pricing Model, LCAPM hereafter. Moreover, according to LCAPM expected net excess return is a function of expected illiquidity measure and four different portfolio Betas each channeling a different type of systematic dimension of liquidity risk. In this thesis we employ LCAPM as our main framework to test whether liquidity level and liquidity risk (innovations of liquidity) are priced and affect the expected net excess returns within New Zealand stock markets.

Based on the assumption of rational (risk averse) agents (investors) maximizing their utility within model where expected net excess return depends on market return, relative illiquidity cost component and relative market illiquidity Acharya and Pedersen (2005) extends the original CAPM model into a frictionless economy that turns into net returns of original economy with illiquidity costs.

The conditional expected net return of share i is therefore:

$$E_t\left(R_{t+1}^i - C_{t+1}^i\right) = R_f + \lambda_t\left(\frac{cov_t\left(R_{t+1}^i - C_{t+1}^i, R_{t+1}^M - C_{t+1}^M\right)}{var_t\left(R_{t+1}^M - C_{t+1}^M\right)}\right) \quad (6)$$

Where $\lambda_t = E_t\left(R_{t+1}^M - C_{t+1}^M - R_f\right)$ is the risk premium, R_{t+1}^i is the gross return of share i at period $t+1$, R_{t+1}^M is the market return at period $t+1$, R_f is the risk free return. The use of short selling is omitted within the model as according to authors; when considering investment equilibrium short position are worse than long position and moreover C (illiquidity cost) can be negative (Acharya & Pedersen 2005).

The conditional expected gross return is

$$E_t\left(R_{t+1}^i\right) = R_f + E_t\left(C_{t+1}^i\right) + \lambda_t \frac{cov_t\left(R_{t+1}^i, r_{t+1}^M\right)}{var_t\left(R_{t+1}^M - C_{t+1}^M\right)} +$$

$$\lambda_t \frac{cov_t\left(R_{t+1}^i, r_{t+1}^M\right)}{var_t\left(R_{t+1}^M - C_{t+1}^M\right)} - \lambda_t \frac{cov_t\left(R_{t+1}^i, r_{t+1}^M\right)}{var_t\left(R_{t+1}^M - C_{t+1}^M\right)}$$

$$- \lambda_t \frac{cov_t\left(R_{t+1}^i, r_{t+1}^M\right)}{var_t\left(R_{t+1}^M - C_{t+1}^M\right)} \quad (7)$$

Where risk premium is $\lambda = E\ (\lambda_t) = E\left(R_t^m - C_t^M - R^f\right)$ (8)

Expected relative illiquidity cost is $E_t(C_{t+1}^i)$, proportional to excess returns, and the rest four covariances are the different betas portraying different channel of liquidity risk (first β represents an ordinary CAPM market risk component and the rest three are each a different variation of liquidity augmented betas representing different forms of liquidity risk). Market risk beta (β^1) is considered as a standard variation of CAPM according to which an asset's return is linear to market beta (that is covariation between shares return and market return).

Authors derive the equation (8) into predictive form by assuming the persistence of illiquidity, moreover commonality, and conditional covariances that also considers constant risk premiums (λ). This respectively leads to unconditional model.

Unconditional model is as following:

$$E\left(R_t^i - R_t^f\right) = E\left(C_t^i\right) + \lambda\beta^{1i} + \lambda\beta^{2i} - \lambda\beta^{3i} - \lambda\beta^{4i} \tag{9}$$

Where four different liquidity innovation betas

$$\beta^{1i} \; \frac{cov\left(R_t^i, R_t^M\right)}{var(R_t^M - [\, C_t^M - E_{t-1}\left(C_t^M\,\right])}, \tag{12}$$

$$\beta^{2i} \; \frac{cov\left(C_t^i - E_{t-1}\left(C_t^i\right), C_t^M - E_{t-1}\left(C_t^M\right)\right)}{var(R_t^M - E_{t-1}\left(R_t^M\right) - [C_t^M - E_{t-1}\left(C_t^M\right)])}, \tag{13}$$

$$\beta^{3i} \; \frac{cov\left(R_t^i, C_t^M - E_{t-1}\left(C_t^M\right)\right)}{var(R_t^M - E_{t-1}\left(R_t^M\right) - [\, C_t^M - E_{t-1}\left(C_t^M\,\right])}, \tag{14}$$

$$\beta^{4i} \; \frac{cov(C_t^i - E_{t-1}(C_t^i), R_t^M - E_{t-1}(R_t^M))}{var(R_t^M - E_{t-1}\left(R_t^M\right) - [\, C_t^M - E_{t-1}\left(C_t^M\,\right)])}, \tag{15}$$

Covariation combinations between illiquidity and returns (represented by market and liquidity risk betas) leads theoretically to set of three distinct liquidity risk betas, also called as illiquidity channels, each containing a separate economic interpretation.

The β^2 liquidity effect is that of return increase with the covariance of asset illiquidity and the market illiquidity. Economical background behind this is that an investor requires additional compensation for holding an illiquid asset in situation of deteriorating market liquidity. Empirical studies by Chordia (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), Sadka (2008) and Karolui and van Dijk (2009) confirmed the economical sense of the beta showing the positive co-movement between stock illiquidity and market illiquidity. As market illiquidity rises so does the illiquidity of most of the stocks, moreover a commonality of liquidity effect is observed, where proportional illiquidity rise is justifiable by a rise in expected rate of return. Therefore, β^2 liquidity is also commonly known as commonality liquidity beta.

β^3 effect relates to a negative covariation between stock's expected return and market liquidity. The decrease of a market liquidity consequently affects rational investors, who experience a negative wealth shock in case they are holding stocks that are illiquid and highly sensitive to market liquidity which consequently shift investors to move from illiquid towards a more liquid stock. This leads to cases of liquidity dry ups where investors are willing to except a lower return for securities that are highly liquid in down turns (Acharya & Pedersen, 2005; Amihud et al. 2005).

Final, liquidity beta (β^4) defines required rate of return as a covariation between share's illiquidity and market returns. Acharya & Pedersen who presented this novel liquidity channel within their seminal paper argues that investors experiences negative wealth shock with market downturns. This leads investors who are holding illiquid shares to, in fear of spiraling impoverishment, shift to ´more liquid shares, preferably towards market downturns resilient shares, and in return accept a lower expected return. This liquidity risk beta can therefore be interpreted as ''wealth shock beta''.

As authors define the liquidity as a persistent implying that liquidity can predict future returns and is time-varying by nature (Chordia et al. 2000, Hasbrouck and Seppi 2001, Pastor Stambaugh 2003, Korajzyk and Sadka 2008) the model therefore assumes that today's high illiquidity will predict the subsequent day's illiquidity, following a high required rate of return (Acharaya and Pedersen 2005). Therefore, the interest lays within the innovations in illiquidity in portfolio sense (as in this thesis) $(C_t^P - E_{t-1}(C_t^P)$.

Net beta, implying an aggregate systematic risk, which is defined as:

$$\beta^{net,p} := \beta^{1p} + \beta^{2p} - \beta^{3p} - \beta^{4p} \tag{16}$$

Following Acharya & Pedersen (2005) we use the net-beta to tackle the possible collinearity problem between different betas. Therefore, a restriction is imposed on model that: $\lambda^1 = \lambda^2 = \lambda -^3 = -\lambda^4$ (17)

Therefore, the net beta adjusted LCAPM can be rewritten as:

$$E\left(r_t^p - r_t^f\right) = \alpha + kE\left(C_t^p\right) + \lambda\beta^{net,p} \tag{18}$$

In addition, we also define an additional combined beta in line with Lee (2011) and Vu et al. (2013), so that we can separate the effect of market risk from the other liquidity risks (β^2-β^4). Net beta is defined as:

$$\beta^{5,p} := \beta^{2p} - \beta^{3p} - \beta^{4p} \tag{19}$$

This will lead to aggregate liquidity risk defined as:

$$E\left(r_t^p - r_t^f\right) = \alpha + kE\left(C_t^p\right) + \lambda^1\beta^{1,p} + \lambda^5\beta^{5,i} \tag{20}$$

Where α is defined as a nonzero intercept in the estimation (expected as non-significant), also in the model k is defined as $k = 1$, meaning that the investor holding period will translate to a single period, a month. As mentioned in Acharya & Pedersen (2005) investors' actual holding period deviates from the assumption, therefore we consider using in this model a holding period calculated of average turnover rate across all viable stocks used in our sample and throughout full period. Following Atkins and Dyl (1994) procedure to recalculate the average turnover and turn it into average holding period ($\frac{1}{Turnover}$) defined in months. The average share's turnover rate of this thesis's sample was 1,01% which translates into a holding period of 99 months (8 years and two months) ($\frac{1}{0{,}0101}$). Naturally this is rather unrealistic average holding period, nor the 1 month of holding period presented by Acharya & Pedersen (2005) sounds logical. Therefore, we run regressions treating k as free parameter, bearing in mind that this might cause further statistical invalidity as the restriction on short selling might be violated (illiquidity level present negative value).

The expected illiquidity $E\left(C_t^p\right)$ is calculated as a portfolio's average monthly illiquidity.

To study the separate effect of different liquidities over market risk $\beta^{1p}$and liquidity level $\left(E(C)\right)$ we can rewrite LCAPM into:

$$E\left(r_t^p - r_t^f\right) = \alpha + kE\left(C_t^p\right) + \lambda\beta^{1,p} + \lambda\beta^{net,p} \tag{21}$$

Our main testable seven regressions are as following:

Regression $\beta^{1,p}$(represents initial CAPM market risk):

$$E\left(r_t^p - r_t^f\right) = \alpha + kE\left(C_t^p\right) + \lambda\beta^{1,p} + u_{pt} \tag{22}$$

Regression $\beta^{2,p}$ represents commonality in liquidity risk:

$$E\left(r_t^p - r_t^f\right) = \alpha + kE\left(C_t^p\right) + \lambda\beta^{2,p} + u_{pt} \tag{23}$$

Regression $\beta^{3,p}$ represents flight-to-liquidity risk:

$$E\left(r_t^p - r_t^f\right) = \alpha + kE\left(C_t^p\right) + \lambda\beta^{3,p} + u_{pt} \tag{24}$$

Regression $\beta^{4,p}$ represents wealth shock risk:

$$E\left(r_t^p - r_t^f\right) = \alpha + kE\left(C_t^p\right) + \lambda\beta^{4,p} + u_{pt} \tag{25}$$

Regression that represents aggregate systematic risk:

$$E\left(r_t^p - r_t^f\right) = \alpha + kE\left(C_t^p\right) + \lambda\beta^{net,p} + u_{pt} \tag{26}$$

Regression that represents aggregate liquidity risk:

$$E\left(r_t^p - r_t^f\right) = \alpha + kE\left(C_t^p\right) + \lambda^1\beta^{1,p} + \lambda^5\beta^{5,i} + u_{pt} \tag{27}$$

Regression that represents joint effect of the liquidity betas:

$$E\left(r_t^p - r_t^f\right) = \alpha + kE\left(C_t^p\right) + \lambda^1\beta^{1,p} + \lambda^2\beta^{2,i}$$
$$-\lambda^3\beta^{3,i} - \lambda^4\beta^{4,i} + u_{pt} \tag{28}$$

Where α is regression's intercept, k is constant representing investor's average holding period and u_{pt} represents regression's residual error.

Line (28) regression represents the generalized relation between betas without model restrictions of $\lambda^1 = \lambda^2 = -\lambda^3 = -\lambda^4$.

We discuss further in Chapter 5 regarding the Fama & Macbeth (1973) regression method and Cochrane's (2005) variation of this pricing model that is utilized in this thesis.

4.4 Portfolio formation

To test the relation between return premiums and liquidity and moreover liquidity risk there can be used two different perspectives on how to address the data, moreover either studying each individual share or forming a specialty constructed portfolios. In this thesis we follow the latter procedure and employ portfolio method to decrease the possible noisiness deriving from individual shares method.

Due to the low size of initial sample of the constituents of New Zealand Stock Exchange's Main Board, utilizing 25 illiquidity portfolios as used in numerous US -studies would result running a statistical analysis with low number of shares per portfolio which respectively could lead to a low results precision and poor statistical validity.

Instead of following the usual procedure of forming 25 portfolios we decrease the portfolios numbers to 3 portfolios ranked by their illiquidity measures (and Size when adjusting for robustness test). When forming portfolios, we follow a combination of Rouwenhorst (1999), Chai et al. (2013) and Nquen & Lo (2013) steps. Firstly, as a basis of our portfolio calculation we use daily return and volume data. Secondly, stocks are grouped on monthly basis at the beginning of each month sorted in ascending order based on each illiquidity measure (Turnover and Amihud). Thirdly, shares are placed into these three portfolios as following: Top 30, middle 40 and down 30. Resulting three balanced portfolios with enough constituents for a valid testing. Portfolios are further rebalanced every month and are calculated as equally weighted portfolios instead of value-weighted portfolios. Number of studies have utilized both calculation methods and found no significant differences in results when using them side by side (Chordia et al. 2001, Amihud 2002, Acharya and Pedersen 2005, Nguen and Lo 2013, Vu et al. 2014 and Kim and Lee 2014). In addition, Limkriangkrai et al (2008) noticed that in Australian context the large number of small stocks required equal weighting method to balance out the disproportion of weights caused by value-weighting method. New

Zealand is even smaller sized market compared to ASX, containing even larger number of small stocks, therefore we employ only equally weighted portfolios in this thesis. In addition, due to a small size of our total sample, which includes shares that are disproportionally large sized compared to others we address the possible issue with portfolio forming resulting skewed portfolio to an over-weighted shares by utilizing equally weighted portfolios.

Market portfolio is formed every month *t* of our sample period comprising of all the valid stock constituents of that month, portfolio is constructed using equally weighted method and includes market portfolio return, volume, and illiquidity measures. Stocks with at least 15 consecutive days of return and volume data during a month, instead as discussed in Data -chapter we do not pose any price level restrictions on the stocks included in the portfolios as was presented in Acharya & Pedersen's (2005) paper. Calculation for each portfolio p follows Acharya & Pedersen (2005) as equal-weighted variation:

$$r_t^p = \frac{1}{N} * \sum_{n,i=1} r_t^i \tag{29}$$

where the summation is a return over all of the stocks included in specific portfolio at month t times equal-weighted multiplier. N represents the number of stocks of specific portfolio

In same vein we calculate the normalize illiquidity of portfolio p as following:

$$c_t^p = \frac{1}{N} * \sum_{n,i=1} c_t^i \tag{30}$$

Where summation is a normalized illiquidity over all stocks in a specific portfolio at month t times equal-weighted multiplier. N represents the number of stocks of specific portfolio.

Table 1 provides an overview of portfolios formed by (il)liquidity level and presents the mean illiquidity value, mean return and their corresponding standard deviations. One can also observe the variability of shares included Amihud ratio and turnover measure are both monotonically decreasing and increasing in values respectively from highly liquid to highly illiquid portfolios.

This in line with the functionality of these measures. Turnover is known to have negative relations to expected returns (Datar et al. 1998) therefore it is logical that the most liquid stocks with highest turnover have the largest returns and the most illiquid stocks with lowest turnover the smallest, as is portrayed in Table 1. Naturally small illiquid stocks are traded less than the larger stocks therefore driving the turnover rate downward with illiquidity level. Worrying knowledge is that the turnover rate itself seems to be rather low, with medium and low portfolios having 0,7% and 0.2% monthly turnover rate respectively. The average turnover rate was only a 1,0% for a market portfolio as well, which is indeed low compared to for example Australia (Chan & Faff, 2003) and possibly characterizes the slow-paced nature of NZ stock markets.

Amihud -ratio tries to capture a depth dimension of liquidity and increases either if the return is larger or traded volume smaller. The mean returns show also positive relationship between level of illiquidity and rate of return, which in line with liquidity theories. It is though considerably lower than what was provided (0.130) by Amihud et al. (2015) on their international liquidity and asset returns study. Naturally the sample period has a substantial effect on the results, which can also be one of the reasons behind these deviations. Our Amihud impact varies from 0.1%-8% indicating the price change impact on 1000 NZD traded. Yet both of (il)liquidity proxies do show similar values than ones provided by Nguyen & Lo (2013) for NZ market.

We have calculated correlations (Pearson model) between each portfolio level (il)liquidity measures. Correlations are negative which is logical as turnover and Amihud ratio as liquidity measure have different, first negative and second positive dependency to expected rate of return respectively. Only lowest turnover portfolio and highest Amihud portfolio have a positive correlation which is possibly an anomaly relating to our initial stock picking criteria. It is also important to acknowledge that our sample size is extremely small and number of shares per portfolio is rather low, which can lead to a low statistical validity. This has been notified by

Table 1. Presents the main characteristics of (il)liquidity portfolios per liquidity proxy used (Amihud and Turnover) and Pearson correlations for liquidity portfolios. Presented numbers are monthly figures.

Portfolio	Mean illiquidity value	Mean return	Mean value standard. Deviation	Mean return standard deviation	Variation of stocks per portfolio
Panel A. Amihud					
Top 30	0,00017	0,0046	0,00027	0,0130	28-36
Middle 40	0,00350	0,0081	0,00338	0,0124	27-49
Down 30	0,08087	0,0106	0,20552	0,0269	28-36
Panel B. Turnover					
Top 30	0,02489	0,0240	0,02518	0,0335	26-36
Middle 40	0,00707	0,0175	0,00214	0,0325	35-48
Down 30	0,00229	0,0092	0,00145	0,0130	26-36
Panel C Pearson correlation between Amihud and Turnover measures					
			Turnover		
		Top 30	Middle 40	Down 30	
Amihud	Top 30	-0.218	-0.500	0.079	
	Middle 40	-0.124	-0.617	-0,525	
	Down 30	-0,190	-0,855	-0,019	

4.5 illiquidity Innovation’s calculations

In this section we will estimate illiquidity innovations on portfolio level according to each liquidity measure. Due to the persistence of a market illiquidity, with evidence provided by Amihud (2002) and Pastor & Stambaugh (2003), and to avoid the autocorrelation of variables, the calculation of illiquidity is obtained by autoregressive model.

Before the calculation of innovations, we un-normalize the illiquidity as in equations (4-5) but this time on portfolio level. We omit the use of 30% cap in our normalization calculations, knowingly that this might lead to a large sized impact value of Amihud measure.

$$ILLIQ_t^p = \frac{C_t^{pM}}{P_{t-1}} \quad (31)$$

Where $C_t^p$is the un-normalized illiquidity of portfolio p at month t .and C_t^p

is equally weighted portfolio p at time t.

We use Autoregressive model with 2 months lag (AR 2) as was used by Acharya and Pedersen (2004) and Vu et al. (2014).

Illiquidity innovations are calculated with AR (2) as following:

$$ILLIQ_t^p P_t^M = a_{0+}a_1(ILLIQ_{t-1}^P P_{t-1}^M) + \ a_2(ILLIQ_{t-2}^P P_{t-1}^M) + u_t \quad (32)$$

Where u_t represents the residual term, moreover an innovation of illiquidity of portfolio p at month t , representing illiquidity innovation of $u_t = c_t^p - E_{t-1}$. The use of P_{t-1}^Mas market index with same date in three terms is to ensure that we are measuring innovations only in illiquidity and not the changes to market index P^M. The innovations of market portfolio are constructed using same autoregressive method. As we use 2 months lag periods this will shorten our data sample by 2 months. In addition, we run successfully Augmented Dickey Fuller stationarity test with 95% confidence level to avoid possible spurious results (Brooks, 2008).

Figures 3 and 4 presents the plots of portfolio level innovations of illiquidity for both liquidity measures. As can be observed both innovations deviate from each other but has some similarities as well.

The first part of 2000 it seems that both innovations have substantial movement in the first part of the sample (2000-2010). Dot-com bubble seems to have much more substantial effect on turnover than on price impact, yet during 2003 and financial crisis of 2008 Amihud shows substantial spikes and turnover measure seems to be stable or even stalling without any considerable movements.

Same thing happens in 2008 with financial crisis where Amihud shows substantial movement and turnover has still movement. This could be explained in two ways. The first is rather simple, turnover is known to have a negative relationship with expected returns and therefore lower or stagnating turnover represents a crisis where investors with long holding periods retains from trading. Secondly the average annual number of companies deviates from 88 to 119, which can have adverse effect on the sample quality.

Also, the 2020 Covid -pandemic presents itself within innovation of liquidity of both measures. The reason behind synchronicity on 2020 pandemic might relate to the issue that 2008 crisis was financial industry induced whereas 2020 was not a financial crisis but crisis deriving from global health pandemic and effecting into real economy instead of financial economy.

Figure 3. presents the innovation of market illiquidity using Amihud illiquidity measure throughout March 2000 December 2020.

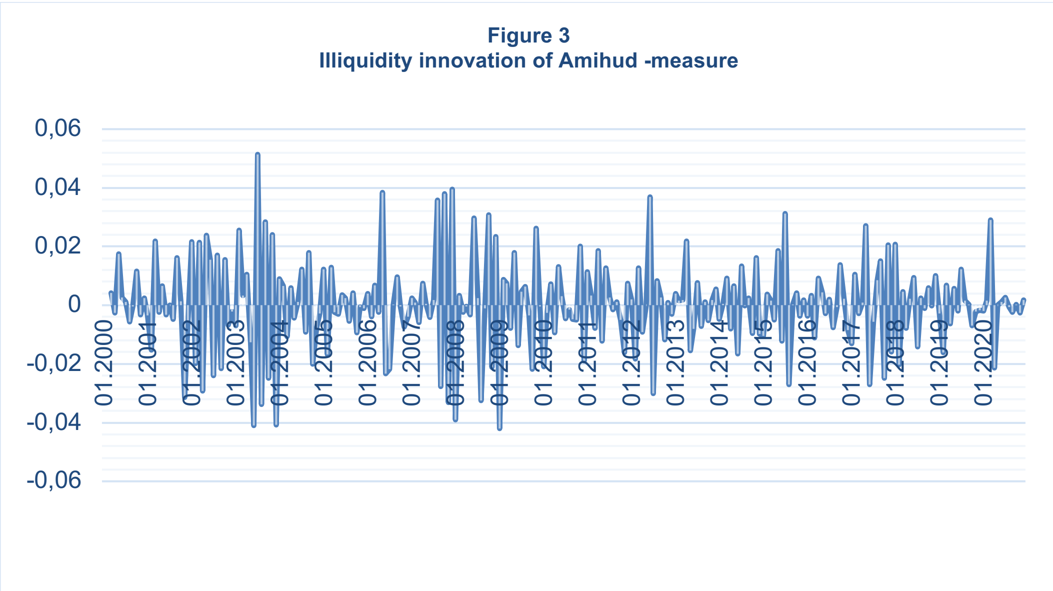
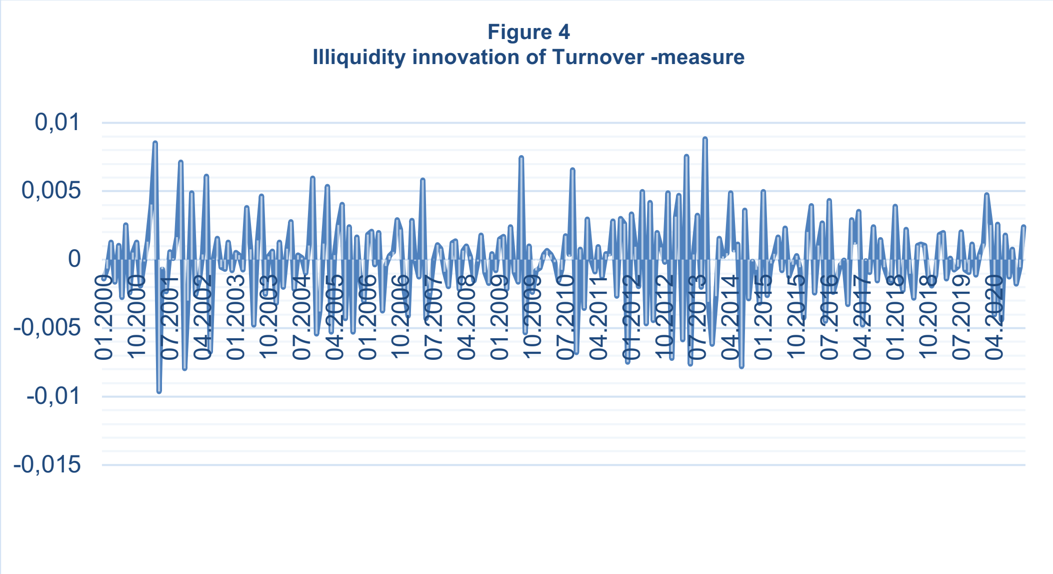


Figure 4. presents the innovation of market illiquidity using Turnover (il)liquidity measure throughout March 2000 December 2020.



4.6 Liquidity Betas

In line with Acharya and Pedersen (2005), Lee (2011) and Vu et al. (2014) the liquidity betas are possible to calculate only after we have obtained illiquidity innovation variables (that are calculated in previous section). In this section we will calculate the market risk beta (β^{1p}) and liquidity risk betas (β^{2p}, β^{3p} and β^{2p}).

Liquidity betas are retrieved by calculating the equations (12-15) that represents each individual beta equation. In this thesis the study is conducted based on portfolios and therefore each individual beta is calculated on a monthly level based on innovation illiquidity portfolios.

The standard procedure for a beta calculation utilizing Fama & Macbeth (1973) procedure requires pre-estimation period of 60 months (5 years) to attain pre-ranking betas, which are prerequisite for a post-ranking beta that are used accordingly in final regressions. The time sample used in this thesis is rather short spanning 20 years, to maximize the study period sacrificing 5 years of this sample would miniscule the results. Therefore, following Cochrane's (2005) we omit from calculating pre-ranking betas and instead use the full period (2000-2020) for a beta calculation.

Table 2 presents betas according to liquidity portfolio, which subsequently is ranked by its illiquidity. β^1 is rising which explains that more illiquid stocks are more related to market returns than the most liquid stocks, which is in line with Acharya and Pedersen's (2005) initial results. There is through a drop with Turnover's medium 40 portfolio.

β^2 also known as commonality in liquidity risk beta found by Chordia et al. (2000), have upward trend with Amihud which makes sense as more illiquid stocks naturally have more co-movement with market wide illiquidity. Turnover in contrast have downward movement, which could be because of turnover's natural negative relation to expected returns. This can be also observed over turnover's illiquidity logic on portfolio ranking where the smaller number equals more illiquid portfolio, when with Amihud it's vice versa. Both measure's β^2 are positive as they are expected to be.

β^3 which relates to flight to liquidity phenomena shows to be mostly negative as it should be. Amihud's Top 30 portfolio flips the beta as positive, but it is extremely low in value and can be attributed as a parameter error. Also, Turnover measure even though shows expected negative sign, the movement is upward. β^4 also known as wealth shock beta shows negative sign and downward trend for Amihud measure, which is in line with expectations, but turnover shows upward trend with Medium 40 portfolio having a smaller number compared to Low 30 portfolio, the sign is negative as expected. Overall, there seems to be some incoherency with the betas which can be addressed with different explanations, likes parameter errors, liquidity proxy's peculiarities and sample noisiness to name a few.

The correlation between betas reveals low correlation with market beta (and even negative sign for turnover) but as predicted by Acharya & Pedersen (2005) the collinearity issue is present with liquidity betas ($\beta^1 - \beta^4$) which shows mainly high correlation rates. Correlation between β^3 and β^4 shows especially extremely high correlation and subsequently collinearity.

Table 2. shows the Beta movements according to liquidity measure and portfolio and correlation coefficients (Pearson correlation test) of liquidity Betas according to a liquidity measure. This table reports of β^{1p}-β^{4p} for the 3 equal-weighted illiquidity portfolios formed for each year during 2000-2020.

Variable	β^{1p}	β^{2p}	β^{3p}	β^{4p}
Panel A. Beta values (Amihud)				
Top 30	0,5073	0,0005	0,0004	-0,0050
Medium 40	0,6639	0,0105	-0,0830	-0,0149
Low 30	0,7127	0,2131	-0,1225	-0,2569
Panel B. Beta values (Turnover)				
Top 30	0,6617	0,0965	-0,1440	-0,0729
Medium 40	0,4140	0,01241	-0,0439	-0,0084
Low 30	0,6639	0,003551	-0,0055	-0,0137
Panel C. Correlation Amihud				
β^{1p}	1			
β^{2p}	0,3297	1		
β^{3p}	-0,8528	-0,7741	1	
β^{4p}	-0,3376	-0.9999	0,7793	1
Panel D. Correlation Turnover				
β^{1p}	1			
β^{2p}	-0,3894	1		
β^{3p}	-0,2131	0,9828	1	
β^{4p}	-0,5318	0,9870	0,9072	1

5. Empirical Results

In this thesis we employ Fama and Macbeth procedure (1973) when running a cross-section regression for liquidity, liquidity risk and expected returns. This model is rather simplistic and widely used by the academia.

We run cross-sectional regression at each period time t which from technical perspective will equal to time-series equivalent cross-section utilized with OLS (Ordinary Least Squares) and standard errors corrected for cross-sectional correlation (Cochrane, 2005). Alongside with Chai et al. (2013) we run the gathered data (dependent and independent variables) through regressions at each time t to attain average coefficient and standard deviations of residuals. Moreover, the simplistic regression, which we expand to include multiple variables, can be written as:

$$R_t^p \ = \ \beta_p \lambda_t + u_t^p$$

Where λ_t and u_t^p are the averaged values of the cross-sectional regression's estimates obtained using OLS method:

$$\lambda_t = \frac{1}{T}\sum_{t=1}^{T} \lambda_t \qquad u^p = \frac{1}{T}\sum_{t=1}^{T} u_t^p \qquad (33)$$

Furthermore, the standard deviations are used to generate residual errors of these estimates:

$$\delta^2(\lambda_t) = \frac{1}{T^2}\sum_{t=1}^{T} (\lambda_t - \lambda) \qquad \delta^2(\ u^p) = \frac{1}{T^2}\sum_{t=1}^{T} (u^p - u) \ \ (34)$$

Even though this model is widely used, it is important to acknowledge that it doesn't take into account the autocorrelation of time-series but automatically considers them to be not autocorrelated. Nevertheless, due to its simpleness we will run our regressions with this model. In addition, according to Asparouhova et al. (2010) security prices are correlated on a security with microstructure-based noise when utilizing Ordinary Least Square (OLS, hereafter) -method arguing that the noise causes upward biased in observed returns and therefore use of Weighted Least Square

(WLS) method was preferred. Hasbrouck (2009), Vu et al. (2014), Nguyen et al (2013) provided contradictive evidence as they calculated their estimates with both method showing that that there was no considerable difference to their final conclusions when utilizing side by side OLS and WLS methods of portfolio construction.

5.1 Final regression analysis

In this chapter we estimate the final seven regressions (regressions 22 – 27) with alternative LCAPM specifications. Moreover, in line with Acharya and Pedersen (2005), Vu et al. (2014) we have created aggregate risk The final Fama-Macbeth regression results for each portfolio ranked by illiquidity measure is presented in Table 3. To lighten the representation, outlook the first row represents a regression combination of each individual liquidity beta regressions combined into a one section (22-25). Row 4 represents joint effect of liquidity betas, regression (28). In this thesis k is set to only as non-constant variable, and can deviate freely, yet bearing in mind a short selling constraint. The full results with R-squared and individual beta regressions' values are provided in Table 8 Appendix 3.

Panel A shows us that from first row neither market risk beta nor any individual liquidity beta is priced. Also, the illiquidity level is insignificant in all individual regression cases. Aggregate market risk liquidity and aggregate liquidity risk from rows 2 and 3 respectively are insignificant. Row 4 presenting the joint effect of liquidity betas shows statistical significance with illiquidity level, but the sign is wrong sided. In addition, β^{4} also known as wealth shock beta is significant and correctly negative. One must bear in mind that fourth row is a joint regression which is subordinate to multicollinearity issue.

Panel B presents interesting news as aggregate liquidity risk beta is significant, but it is with negative sign, which means that it is against the short selling restriction and therefore we cannot take this into account as we use non-constant k attribute. Row three with β^{net} which is relating to aggregate systematic risk is insignificant. Row 4 shows that market liquidity beta is significant and positive.

Both liquidity measures showed varied results, as for Amihud it seems that only the β^{4} also known as wealth shock liquidity risk, which relates to the shares sensitivity of its illiquidity to market return seems to be significant. The problem with β^4 is that it shows in joint liquidity beta regression which is bound to multicollinearity problems.

The illiquidity level in fourth row for Amihud is also significant but with negative sign, therefore we cannot accept this result due to short sale restrain. Turnover showed that market risk beta is priced in two occasions, first as an individual regression representing classical CAPM model and second within joint liquidity beta regression (28). Our focus is within liquidity betas, therefore neither illiquidity level nor market risk beta is central to our interests, but it is good to acknowledge especially the negative sign of illiquidity level referring possibly to a negative return premium. It is interesting to see how these two measures provide different results as well as to observe that it seems that there is no widely spread liquidity discount, nor the liquidity risk is priced factor. The coefficient of determination values (Appendix 3, Table 8) are also on rather low side, deviating between 43%-59%, which refers to low explanatory power of our model and variables and possibly to a poor model fit.

Table 3. Cross-sectional Fama-Macbeth regressions for Illiquidity portfolios. * and ** denote significance level at the 5% and 1% level, respectively.

	Intercept	***E(c)***	β^1	β^2	β^3	β^4	β^5	β^{net}
Panel A. Amihud								
1.	(-)	(-)	0.0201	0.018	-0.04	-0.032		
2.	0.031*	-0.019	0.062				0.039	
3.	0.025	-0.023						0.032
4.	0.036	-0.076*	0.064	0.021	-0.09	-0.056*		
Panel B. Turnover								
1.	(-)	(-)	0.082*	0.025	0.017	0.0046		
2.	-0.05	0.027	0.019				-0.066*	
3.	-0.019	0.023						0.067
4.	-0.027	0.030	0.087*	0.049	0.019	0.050		

5.2 Robustness checks

To ensure validity of our empirical results we perform two robustness tests to confirm whether the initial results of liquidity risks will hold under a different setting. Firstly, we will consider differently ranked portfolios as one of the most used robustness tests is to rearrange the stocks into portfolios that are ranked in accordance with company's market capitalization, also known as Size. Our sample is skewed towards smaller sized companies (Table 7, Appendix 2). Therefore, it is natural to conduct a robustness test where we have reconstructed our portfolios in ascending order from market capitalization point.

Secondly to study an existence of a possible time variable that has effect on liquidity pricing and risk we divide initial period into separate sub-periods each representing different time period. Within this thesis our time-period of 20 years will be divided into two 10 years periods: 2000-2010 and 2010-2020. Each sub-period includes the financial market shock of 2008, but the first period also contains dot-com crash and latter one, 2010-2020, a COVID-19 induced global financial markets shock of 2020. In addition, the latter sub-period represents a sample period that has yet been studied.

5.2.1 Robustness check for Size portfolios

Table 4 presents the results of Fama & Macbeth regressions of robustness check with portfolio sorting criteria of Size (market capitalization) variable. From Table 4 Panel A we can observe that the results seem to be in line with the initial results of illiquidity portfolios. Row 1 shows that none of the separate liquidity risk betas are priced, but we do find that illiquidity level is priced within β^4 regression yet the liquidity beta is not priced. Second row shows that the aggregate liquidity risk is not significant which is in line with initial illiquidity portfolio results. Third row presents the insignificant net beta regression. Fourth row shows that the β^4 is interestingly once again priced but now within joint effect regression (28).

Panel B shows that when running individual beta regression market beta seems to be priced. Second row shows that the aggregate liquidity risk (26) is priced, but with wrong sign, as we use non-constant parameter, we cannot confirm the validity of this result. Row three shows that aggregate market liquidity risk (27) beta is non-significant. From fourth joint effect regression (28) we can observe that the market risk beta is priced like with illiquidity portfolio ranking regression. We can also observe that the intercept (α) is priced, which is interesting as in Acharya and Pedersen (2005) paper authors don't consider intercept to play any role within their framework.

Overall, it seems that there is some evidence from β^4 liquidity risk beta which significance is hindered by the multicollinearity problem. Turnover shows us that that there is evidence from market risk beta when we run each beta regression individually. Bryant and Eleswerapu (1997) concluded that the CAPM wasn't fit for NZ market, yet this result should be considered with a scepticism as they studied only the shares included in the NZSE-40 index representing the largest stocks of NZ market. Also, their sample from 1971-1993 represents different time period which is therefore not comparable to the sample of this thesis. In addition, the aggregate liquidity risk beta (β^5) is priced but with wrong sign and there's also market beta priced when running joint effect beta regression (28). Interesting observation is that all illiquidity level coefficients are positive with Turnover proxy when other hand with Amihud measure they are negative, latter indicating possibly to the ''illiquidity discount'' found by Nguyen and Lo (2013).

After conducting robustness check for Size factor, we concluded that the results are mainly like the initial illiquidity ranked portfolio regressions, which possibly indicates that there is no firm size related illiquidity within New Zealand. This would be in line with the findings of Bryant and Eleswerapu (1997) relating to miniscule impact of Size factor within New Zealand. Also, the β^4 showed up once again with Amihud measure. Robustness check didn't provide any help for our initial low R-squared values are also still rather, now deviating between 40%-63%, which again refers to low explanatory power of our model and variables.

Table 4. Cross-sectional Fama-Macbeth regressions for Size portfolios. * and ** denote significance level at the 5% and 1% level, respectively.

	Intercept	***E(c)***	β^1	β^2	β^3	β^4	β^5	β^{net}
Panel A. Amihud								
1.	(-)	(-)*	0.023	0.030	-0.078	-0.051		
2.	0.043	-0.034	0.070				0.045	
3.	-0.058	-0.056*						0.043
4.	0.023	-0.0101	0.124	0.052	-0.13	-0.069*		
Panel B. Turnover								
1.	(-)	(-)	0.090*	0.056	-0.020	0.0071		
2.	-0.35**	0,027	0,023				-0.073*	
3.	-0.045*	0.030						0.076
4.	-0.045*	0.046	0.103*	0.063	-0.032	0.064		

5.2.2 Robustness check for sub-periods

To make sure that our results are not derived by a time factor, we divide the initial illiquidity portfolio regression period into two separate sub-periods, each representing a 10-year period. Intuition behind this is that the possible prior results are characterized by a certain time-period. As we can observe from the illiquidity measure Figures 1 and 5, that turnover and volume increase during the second period beginning 2010, yet there seem to be more pronounced noisiness and large movements during pre-2010 period

Panel A shows Amihud measure's coefficients for the first period between 2000-2010. From first row we can observe that the β^4 is significant when regressing individual betas, this is a new finding which is not observed in other regressions. All the illiquidity level coefficients within row 1 show a negative sign but are not significant. Row 4 which represents the joint effect liquidity beta regression shows that illiquidity level is priced, and negative, market beta is priced and is positive, commonality in liquidity was priced and wealth shock beta is priced as well yet one have to bear in mind that this regression is bound to multicollinearity and it is hard to separate whether these betas actually are effecting individually or whether they are just effecting jointly to each other which leads to statistical significance. The multicollinearity might be the initial cause of this result as during 2000-2010 is observable how noisy both measures have been.

Panel B presents the results for Turnover measure. First row shows that the market beta is significant, which is in line with the initial results. From row two it shows that aggregate liquidity risk beta is priced but with wrong sign therefore as we use only non-constant k variable which requires only a positive results this result is invalid. In addition, illiquidity level is priced and equipped with positive sign. Similar things occur in row three where the B^{net} is significant but negative and illiquidity level is significant and positive. Joint effect beta regression reveals that market risk beta is priced and positive and β^2 and β^4 are significant and positive. β^2 is in line with theory but $\beta^4$is positive as it should be negative. This result is inconclusive, and one might say even a topsy-turvy. Possible reasons for this could be many, firstly the sample size is considerably smaller for 2000-2010 which also contained several extreme price deviations which we didn't remove to maintain a sample size somewhat sizeable. Also, Turnover measure logic is perverted compared to Amihud, and this result might be a manifestation of that logic.

Panel C presents Amihud results for 2010-2020, which provides rather interesting result. There is no significance in any regressions including liquidity betas, illiquidity levels and even interceptor. This result is in line with Nguyen and Lo (2013) that the liquidity risk is not priced within New Zealand, but neither we can confirm their negative illiquidity level finding. Intuitively this makes sense as the illiquidity levels have become more moderate when observing Figures 2 and 3 which shows Amihud measure's illiquidity level and innovation of illiquidity's.

Panel D shows result for Turnover for a latter sub-period spanning between 2010-2020. The result is rather like Amihud's in Panel C, there seems to be no effect of il(liquidity) throughout all the betas. Only illiquidity level is significant at row 4 when regressing the joint effect of liquidity betas (28).

All in all, this shows that the time factor indeed plays possibly a significant role when considering the (il)liquidity level and liquidity risk effect on expected returns from NZ perspective. The results are hindered by rather incoherent first period, which ask a question whether our data, framework or calculation process altogether contain severe misspecifications. R-squared values are once again rather low, even though a small improvement happened compared to the first period.

Table 5. Cross-sectional Fama-Macbeth regressions for Illiquidity portfolios using sub-periods. * and ** denote significance level at the 5% and 1% level, respectively.

	Intercept	***E(c)***	β^1	β^2	β^3	β^4	β^5	β^{net}
Sub-period 2000-2010								
Panel A. Amihud								
1.	(-)	(-)	0.040	0.033	-0.160	-0.210*		
2.	-0.032	-0.047	0.027				0.065	
3.	-0.075	-0.031						0.0410
4.	-0.052	-0.16*	0.203*	0.120*	-0.110	-0.19*		
Panel B. Turnover								
1.	(-)	(-)	0.33*	-0.055	0.032	0.040		
2.	-0.052	0.18*	0.022				-0.13*	
3.	-0.024	0.28*						-0.25*
4.	-0.034	0.044	0.46*	0.21*	0.059	0.074*		
Sub-period 2010-2020								
Panel C. Amihud								
1.	(-)	(-)	0.003	0.012	-0.006	-0.001		
2.	0.002	0.012	0.002				0.011	
3.	0.010	0.02						0.021
4.	0.016	0.002	0.023	0.016	-0.002	-0.016		
Panel D. Turnover								
1.	(-)	(-)	0.027	0.0026	0.016	0.0017		
2.	0.0034	0.0061	0.023				0.024	
3.	0.0027	0.0058						0.043
4.	0.0041	0.045*	0.042	0.034	0:023	0.009		

We didn't include any additional controlling variable like Size, B/M or Momentum to run a regressions with controlling factors. Reasoning behind this was as following: Book-to-Market was not readily available, studying Momentum factor was not within scope of this thesis and Size, represented as company's market capitalization, variable was already partly included as robustness tests. Moreover, Bryant and & Eleswerapu (1997) noticed that within context of New Zealand Size variable didn't have any substantial effect on the share returns of New Zealand and even book-to-market had only a partial effect when conducting sub-period robustness tests. Therefore, we are now ready to discuss more about our findings and possible shortcomings of this thesis and conclude our findings with propositions for a future avenues of liquidity risk research within New Zealand. Also, the results for Size portfolios were rather similar to the ones with illiquidity portfolio, therefore their robustness checks so far were enough.

In this thesis we didn't use 10% significance level, which is used in part of the studies, yet we maintain our goal to find evidence from more rigor levels of significance. Therefore, we acknowledge that some of the results' significance that might be considered significant as in some studies up to 10% are considered insignificant in this study.

6. Conclusions

In this thesis we have conducted research on whether liquidity level and liquidity risk are priced within New Zealand stock market using Liquidity-Adjusted Capital Asset Market liquidity risk framework developed by Acharya and Pedersen (2005) for the first time. We utilized the Turnover and the Amihud-ratio, two well-known and widely used liquidity measures, as our liquidity proxies. Our sample period covered 20 years beginning from January 2000 and ending in December 2020 extending previous research by almost a decade with fresh data sample. The study was conducted based on portfolios ranked by their illiquidity and later with robustness test by market capitalization (firm size). In addition, sub-period robustness test regressions were conducted for the illiquidity portfolios.

Firstly, our results showed that the liquidity level and risk vary according to liquidity proxy and that the time-period plays a role within context of New Zealand. The illiquidity level was significant for Amihud with illiquidity portfolio's joint effect regression and sub-period of 2000-2010 and furthermore with aggregate market liquidity risk size portfolios. This could be interpreted as possible liquidity discount premia that was found previously by Nguyen and Lo (2013), but the validity of this result is not that high as two times the significance was found from regression that is bound to multicollinearity issue.

Aggregate liquidity risk (β^5) manifested itself three times for Turnover measure, on illiquidity and size portfolios and on sub-period robustness test for 2000-2010 period. Each time the sign of this beta was negative which is against the theoretical prediction. Also, as we employed only non-constant holding period, k -value, the short selling restriction invalidates these findings. Market risk beta (β^1) was found to be significant on 4 occasions and within three same occasions as was the aggregate liquidity risk. Market risk beta contained a correct positive sign, but it showed joint effect liquidity risk beta regression within three times out of four, therefore this result should be taken with a good pinch of salt.

The most interesting finding was the β^4 that followed the Amihud measure throughout almost all the tests. This beta is due to a covariation between security's illiquidity and the market return. According to Acharya and Pedersen (2005) β^4 effect stems from situations where the market dries up, investors are poor and therefore accepts the discount (low expected rate of return) for liquid stocks in exchange for illiquid stocks. When considering the fragments of these findings one can construct a rationale for this.

Firstly, the rate of return for New Zealand stocks have been rather low, we found it to be on average 1% and Amihud et al. (2015) a 0.38% (0.19%) for return- and value-weighted -portfolios respectively. Secondly, according to Cameron (2007) the growth and stagnation problems with New Zealand stock markets were derived from investor's poor savings rate, adverse tax policies against financial investments and the financial market co-integration with Australia, which draws the IPOs outside the NZ and indicate to a local segmentation. Thirdly, the evidence of Nguyen and Lo (2013) that in contrary to theory of liquidity and asset pricing, showed that there was no positive return premium for illiquid companies, but a negative return. Therefore, in case of highly illiquid market which constitutes of rather low number of shares that are locally segmented, the investors are local with low savings rate (translates possibly into a low number of investors) therefore during a downturn they have two options: either to keep or sell the illiquid shares and suffer the losses or to sell the stocks and shift to a liquid stock. If adverse tax policy exists, therefore the threshold to shift to another stock is higher. In this scenario, the investors will simply sell the stocks, suffer the losses, and move out of the market and the few ones that decide to stay within the market will decide to shift to more liquid stocks. This might result that the more liquid stocks do not offer a higher rate of return, and in exchange a security of a low (even negative) return but with high liquidity. Possibly the small size of the market exacerbates this effect. The author cannot provide cohesive statistical proof behind this rationale but emphasizes that this could be an interesting venue for future research.

We can therefore conclude our hypotheses that firstly whether there is evidence of a positive relation between stock market illiquidity and market illiquidity the answer is no, we were not able to observe a commonality in liquidity.

According to our second hypothesis whether there is evidence of negative relation between stock returns and market illiquidity (β^3) also known as flight to liquidity beta, we were unable to find any evidence on this liquidity risk.

Our third hypothesis related on the existence of negative co-movement between stock illiquidity and market returns represented by β^4. We can confirm that the wealth effect beta was observed by the Amihud measure throughout our tests, the finding occurred most of the times within joint effect liquidity beta regression which contains high multicollinearity between different betas. Results should be interpreted with skepticism as our test model contained several restrictions and on the other hand data processing had considerable exemptions. Yet a priori rationale can be drawn from this beta and its effect within New Zealand context. This might provide indeed an important part for the puzzle of New Zealand's stock market liquidity and also an explanation to the conflicting results in the prior research.

Our fourth hypothesis concerned the existence of aggregate liquidity risk and aggregate market liquidity risk. Aggregate liquidity risk emerged for the Turnover measure, but without consistency and most of the times the coefficient had a wrong expected sign. Therefore, we cannot verify this hypothesis either.

The author would also like to address the number of shortcomings of this study. It seems that our results from economical and statistical levels were on a low side, coefficient signs were not always what they should be according to a LCAPM's theoretical framework and R-squared explanatory power has provided low values throughout the different regressions. One of the reasons behind our results could derive from the model itself and its inability to capture the liquidity level and risk within New Zealand market. Limkriangrai et al. (2008) discusses this problematic issue from the Australian perspective where number of studies were conducted with contradicting results. The problem according to the authors was whether the liquidity factors merely captured characteristics of firms within portfolio or whether the portfolio itself captured the liquidity dimension. Marshall (2006) noticed that the traditional liquidity proxies such as bid-ask spreads and turnover rate produced inconsistent results deriving possibly from the order-driven market structure, the same that is used in New Zealand as well. On the other hand, Chan and Faff (2003) found strong evidence that turnover has significant negative effect on the return of Australian stocks. This underlines the problem at hand: studies from the same market with the same liquidity proxy can have contradicting results.

In addition, our sample size was extremely low throughout the study. On average the sample size was 108 companies and the number of shares per portfolio varied from 26-49, which is indeed rather low and can result noisy results as was pointed out by Chan and Faff (2005) when studying Australian market, which is substantially larger compared to the market in New Zealand.

By using individual shares instead of portfolios, we could have minimized the loss of information and provided stronger test results. On the other hand, using individual shares may cause noisy estimates and simultaneously worsen the results. Therefore, it is a double-edged sword, as both methods contain cons and pros, which requires that one should test both methods to make sure there is no substantial differences between the results. When pre-processing our data, there was no limitation regarding the price boundaries producing a base data with large price and return deviations that have possibly affected statistical results. Neither did we impose any caps on the values of illiquidity innovation values. We only used equally weighted method when calculating portfolios, trusting the outcomes of the previous research papers that there are no substantial differences between the results when equipping either of these weighting methods, we acknowledge that this might also have had an impact on our test results. For example, instead of using panel regression framework (Vu et al. 2014) or GMM method (Acharya and Pedersen 2005) we utilized Fama and Macbeth (1973) procedure known for its shortcoming relating to autocorrelation which can result in spurious results. It is crucial that that the model itself is selected as the most suitable, the question on how to select the most suitable model remains an open question as the most suitable model might be country and market specific.

In addition to save the sample length we used full sample betas, based on Cochrane (2005), instead of traditional pre-ranking beta calculation (which requires 5 years of pre-calculation) to obtain post-ranking betas as was done by Lee (2011), Vu et al. (2014), Kim and Lee (2014). Our controlling was limited only for initial regression with illiquidity portfolios and the robustness regressions with only the size portfolio ranking and the sub-period analysis respectively leaving controlling variable testing out of the study. This limitation might have had adverse impact on the final conclusions as part of the puzzle is possibly missing. Differentiative results could also be caused by much clearer reasons such as studies that are covering different samples of population, moreover different time periods (Chai et al. 2013).

The chosen liquidity measures might also be unfit for the New Zealand market as Amihud is a measure known for its usefulness for price impact and is also considered as a more useful proxy to capture a larger trade impact, moreover, trades of institutional investor’s trades. New Zealand stock market is small from market capitalization point of view and rather thin from volume perspective; therefore, a more delicate liquidity should consider to be used, preferably a one that could capture small trades and address the illiquidity within small exchange market with low number of traded companies. The Turnover measure is considered as a rather arcane measure of risk proxy which seems to work for more liquid markets like US, therefore perhaps instead of using the Turnover as a proxy, a preferable idea would be to use liquidity measures that incorporates the Turnover proxy as an additional characteristic within their measure.

Therefore, the author suggests for a future venue of research on New Zealand and markets alike to address the liquidity and liquidity risk dilemma with a longer sample period, run the data both with individual share and portfolio perspective, running LCAPM framework with more sophisticated and modern models (like GMM and panel regression) and utilize more delicate liquidity proxies that are more suitable to detect illiquidity of small and medium sized companies and that is most suitable for a small, developed yet partly illiquid market.

I. References

Articles

Acharya, V.V., and Pedersen L.H., 2005. Asset pricing with liquidity risk. Journal of Financial Economics, **77**(2), pp. 375-410.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets, **5**(1), pp. 31-56.

Amihud, Y. and Mendelson, H., 1986a. Asset pricing and the bid-ask spread. *Journal of Financial Economics,* **17**(2), pp. 223-249.

Amihud, Y. and Mendelson, H., 1986b. Liquidity and Stock Returns. *Financial Analysts Journal,* **42**(3), pp. 43-48.

Amihud, Y. and Mendelson, H., 1988. Liquidity and Asset Prices: Financial Management Implications. Financial Management, **17**(1), pp. 5-15.

Amihud, Y. and Mendelson, H., 1997. Market microstructure and securities values: evidence from the Tel Aviv Stock Exchange. Journal of Financial Economics, **45**, pp. 365-390.

Amihud, Y. and Mendelson, H., 2006. Stock and bond liquidity and its effect on prices and financial policies. Financial Markets Portfolio Management, **20b**, pp. 19-32.

Amihud, Y. and Mendelson, H., 2015. The Pricing of Illiquidity as a Characteristic and as Risk. Multinational Finance Journal, **19**(3), pp.149-168.

Amihud, Y. and Mendelson, H., and Pedersen L.H., 2005. Liquidity and Asset Prices. Foundations and Trends in Finance, **1**(4), pp. 269-364.

Amihud, Y., Hameed A., Kang W., and Zhang H., 2015. The illiquidity premium: International evidence. Journal of Financial Economics, **117**(2), pp. 350-368.

Amihud, Y., Mendelson, H. and Lauterbach, B., 1997. Market microstructure and securities values: Evidence from the Tel Aviv Stock Exchange. *Journal of Financial Economics,* **45**(3), pp. 365-390.

Asparouhova E., Bessembinder H., and Kalcheva I., 2010. Liquidity Biases in Asset Pricing Tests. Journal of Financial Economics, **96**(2), pp 215.237.

Atkins, A.B., and Dyl, E.A., 1997. Transactions Costs and Holding Periods for Common Stocks.Journal of Finance, **52**(1), pp.309-325.

Bailey, W. and Jagtiani J., 1994. Foreign ownership restrictions and stock prices in the Thai capital market. Journal of Financial Economics, **36**, pp. 57-88.

Baradarannia M.R., and Peat M., 2013. Liquidity and expected returns – Evidence from 1926 – 2008. International Review of Financial Analysis, **29**, pp. 10-23.

Bekaert, G., Campbell, H.R., Lundblad, C., 2007. Liquidity and Expected Returns: Lessons from Emerging Markets. The Review of Financial Studies, **20**(6), pp. 1783-1831.

Berkman. H., and Eleswarapu R., 1998. Short-term traders and liquidity: a test using Bombay Stock Exchange data. Journal of Financial Economics, **47**, pp. 353-364.

Bernstein P., L., 1987. Liquidity, Stock Markets, and Market Makers. Financial Management, **16**(2), pp. 54-62.

Black F., 1971. Toward a fully automated stock exchange. Financial Analysts Journal, **27**(4), pp. 28-35 + 44.

Brennan, M.J. and Subrahmanyam, A., 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics,* **41**(3), pp. 441-464.

Brennan, M.J., Chordia, T. and Subrahmanyam, A., 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. Journal of Financial Economics, **49**, pp 345-373.

Brunnermeier M., K., and Pedersen L., H., 2008. Market Liquidity and Funding Liquidity. The review of Financial Studies, **22**(6), pp. 2201-2239.

Bryant P., S., and Eleswerapu R., 1997. Cross-Sectional Determinants of New Zealand Share Market Returns. Accounting and Finance, **37**(2), pp. 181-205.

Butt H., A., and Virk N.,S., 2015. Liquidity and Asset prices: An Empirical Investigation of the Nordic Stock Markets. European Financial Management, **21**(4), pp. 672-705.

Cameron L, 2007. Investor Protection and the New Zealand Stock Market. New Zealand Treasury, 07/02.

Chai D., Faff R., and Gharghori P., 2013. Liquidity in asset pricing: New Australian evidence using low-frequency data. Australian Journal of Management, **38**(2), pp. 375-400.

Chan K., Hameed A. and Kang W., 2013. Stock price synchronicity and liquidity. Journal of Financial Markets **16**(1), pp. 414-438.

Chang, Y.Y., Faff, R. and Hwang, C., 2010. Liquidity and stock returns in Japan: New evidence. *Pacific-Basin Finance Journal,* **18**(1), pp. 90-115.

Chordia, T., Roll, R. and Subrahmanyam, A., 2008. Liquidity and market efficiency. *Journal of Financial Economics,* **87**(2), pp. 249-268.

Chordia, T., Roll, R. and Subrahmanyam, A., 2011. Recent trends in trading activity and market quality. *Journal of Financial Economics,* **101**, pp. 243-263.

Chordia, T., Roll, R. and Subrahmanyam, A., 2000. Commonality in liquidity. *Journal of Financial Economics,* **56**(1), pp. 3-28.

Chordia, T., Roll, R. and Subrahmanyam, A., 2001. Market Liquidity and Trading Activity. The Journal of Finance, **56**(2), pp. 501-530.

Czauderna K., Riedel C., and Wagner N., 2015. Liquidity and conditional market returns : Evidence from German exchange traded funds. Economic Modelling, **51**, pp. 454-459.

Datar, V.T., Y. Naik, N. and Radcliffe, R., 1998. Liquidity and stock returns: An alternative test. *Journal of Financial Markets,* **1**(2), pp. 203-219.

Demsetz H., 1968. The cost of transacting. The Quarterly Journal of Economics, **82**(1) pp. 33-53.

Fang, V.W., Noe, T.H. and Tice, S., 2009. Stock market liquidity and firm value. *Journal of Financial Economics,* **94**(1), pp. 150-169.

Fong, K.Y.L., Holden, C.W. and Trzcinka, C.A., 2017. What Are the Best Liquidity Proxies for Global Research?. Review of Finance, **21**(4), pp. 1355–1401.

Gibson R., and Mougeot N., 2004. The pricing of systematic liquidity risk: Empirical Evidence from the US stock market. Journal of Banking & Finance, **28**(1), pp. 157-178.

Glosten, L.R. and Harris, L.E., 1988. Estimating the components of the bid/ask spread. *Journal of Financial Economics,* **21**(1), pp. 123-142.

Goyenko, R.Y., Holden, C.W. and Trzcinka, C.A., 2009. Do liquidity measures measure liquidity? *Journal of Financial Economics,* **92**(2), pp. 153-181.

Grossman, S. J., and Miller M.H., 1988. Liquidity and market structure. Journal of Finance, **43**, pp. 617-633.

Hasbrouck, J., 1991. Measuring the information content of stock trades. Journal of Finance, **46**, pp. 179-207.

Hasbrouck, J., Seppi, D.J., 2001. Common factors in prices, order flows, and liquidity. Journal of Financial Economics, **59**, pp. 383-411.

Huberman, G. and Halka D., 2001. Systematic Liquidity. The Journal of Financial Research, **24**(2), pp. 161-178.

Isaenko S., and Zhong R., 2015. Liquidity premium in the presence of stock market crises and background risk, **15**(1), pp. 79-90.

Jacoby, G., Fowler, D.J. and Gottesman, A.A., 2000. The capital asset pricing model and the liquidity effect: A theoretical approach. *Journal of Financial Markets,* **3**(1), pp. 69-81.

Johnson T., C., 2008. Volume, liquidity and liquidity risk. Journal of Financial Economics, **87**, pp. 388-417.

Jun, S., Marathe, A. and Shawky, H.A., 2003. Liquidity and stock returns in emerging equity markets. *Emerging Markets Review,* **4**(1), pp. 1-24.

Kang, W. and Zhang, H., 2014. Measuring liquidity in emerging markets. *Pacific-Basin Finance Journal,* **27**(0), pp. 49-71.

Kim SH., and Lee KH., 2014. Pricing of liquidity risks: Evidence from multiple liquidity measures. Journal of Empirical Finance **25**, pp.112-133

Korajczyk R., A., and Sadka R., 2008. Pricing the commonality across alternative measures of liquidity. Journal of Financial Economics **87**(1), pp. 45-72.

Kyle, A., S., 1985. Continuous Auctions and Insider Trading. Econometrica, **53**(6), pp. 1315-1335.

Lam K., S.,K., Tam L.W.,K., 2011. Liquidity and asset pricing: Evidence from the Hong Kong stock market. Journal of Banking & Finance, **35**, pp.2217-2230.

Lee, KH., 2011. The world price of liquidity risk. Journal of Financial Economics, **99**, pp. 136-161.

Lesmond, D.A., 2005. Liquidity of emerging markets. *Journal of Financial Economics,* **77**(2), pp. 411-452.

Li, B., Sun, Q., and Wang, C., 2014. Liquidity, Liquidity Risk and Stock Returns: Evidence from Japan. European Financial Management, **20**(1), pp. 126-151.

Liang, S., X., & Wei, J.K.C., 2012. Liquidity risk and stock returns around the world. Journal of Banking & Finance, **36**(12), pp. 3274-3288.

Liu, W., 2006. A liquidity-augmented capital asset pricing model. *Journal of Financial Economics,* **82**(3), pp. 631-671.

Marcelo, J.L.M. and Quirós, M.D.M.M., 2006. The role of an illiquidity risk factor in asset pricing: Empirical evidence from the Spanish stock market. *The Quarterly Review of Economics and Finance,* **46**(2), pp. 254-267.

Marshall, B.R, Nguyen N.H., and Visaltanachoti N., 2015. Transaction costs in illiquid order-driven market. Accounting and Finance, **56**(4), pp. 917-933.

Marshall, B.R., 2006. Liquidity and stock returns: Evidence from a pure order-driven market using a new liquidity proxy. International Review of Financial Analysis, **15**, pp. 21-38.

Marshall, B.R., & Young, M.R., 2003. Liquidity and stock returns in pure order-driven markets: Evidence from the Australian Stock Market. International Review of Financial Analysis, **12**, pp. 173-188.

Naik, P., and Reddy, Y., V., 2021. Stock market liquidity: A Literature Review. Sage Open,**11**(1), pp. 1-15.

Ng, J., 2011. The effect of information quality on liquidity risk. Journal of Accounting and Economics, **52**, pp. 126-143.

Nguyen N., H., and Lo K., H., 2013. Asset returns and liquidity effects: Evidence from a developed but small market. Pacific-Basin Finance Journal, **21**(1), pp.1175-1190.

Pastor, L., and Stambaugh R., F., 2003. Liquidity Risk and Expected Stock Returns. Journal of Political Economy, **111**(3), pp.642-685.

Rouwenhorst G., K., 1999. Local Return Factors and Turnover in Emerging Stock Markets. The Journal of Finance, **54**(4), pp. 1439-1464.

Rösch, C., G., and Kaserer C., 2013. Market liquidity in the financial crisis: The role of liquidity commonality and flight-to-quality. Journal of Banking and Finance, **37**, pp 2284-2302.

Sadka R., 2006. Momentum and post-earning-announcement drift anomalies: The role of liquidity risk. Journal of Financial Economics, **80**, pp. 309-349.

Sarr, A., and Lybek T., 2002. Measuring Liquidity in Financial Markets. IMF Working Paper, **02**(232).

Vu V., Chai D., and Do V., 2014. Empirical tests on the liquidity-adjusted capital asset pricing model. Pacific-Basin Finance Journal, **35**(A), pp. 73-89.

Books

Brooks C., Introductory Econometrics for Finance, 2nd edition. Princeton University Press.

Cochrane J., C., 2005. Asset Pricing, Revised Edition. Princeton University Press.

Definitions and abbreviations

LCAPM – Liquidity Adjusted Capital Asset Pricing Model

CAPM – Capital Asset Pricing Model

ASX – Australian Stock Exchange

NZX – New Zealand Stock Exchange

NYSE = New York Stock Exchange

AMEX = American Stock Exchange

NASDAQ = National Association of Securities Dealers Automated Quotations

OLS = Ordinary Least Square

WLS = Weighted Least Square

Statistical Software

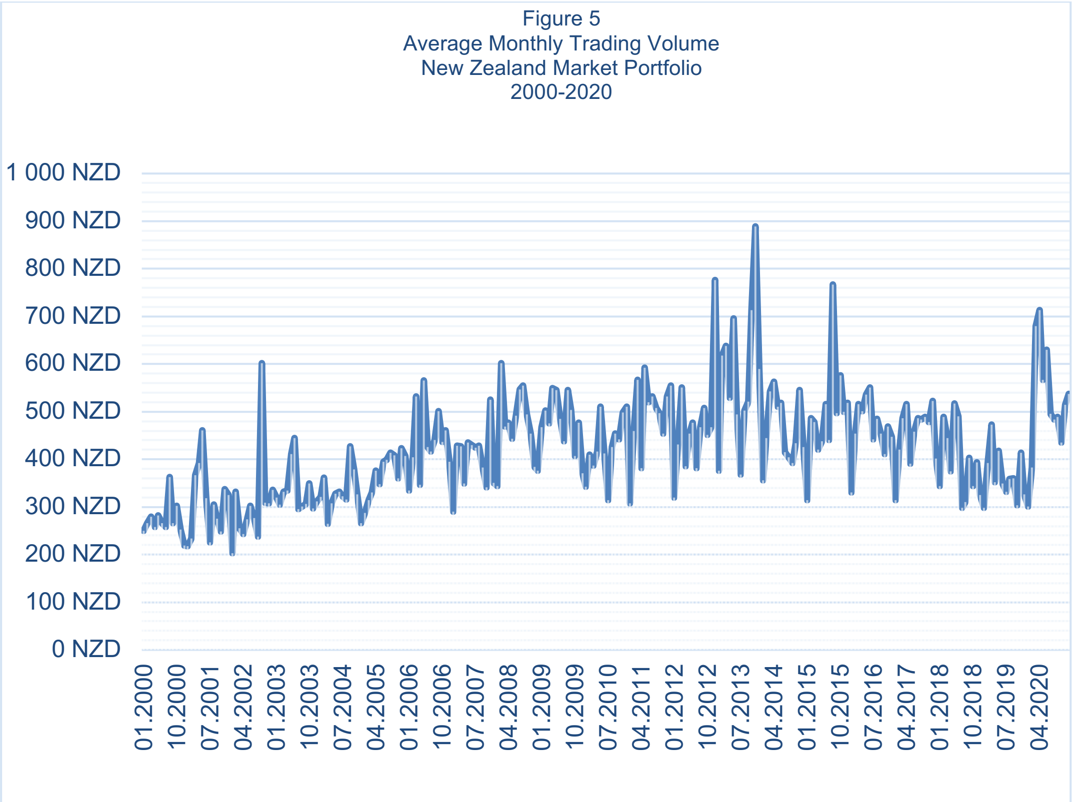
Rstudio Build 351

Packages: forecast, dplyr, lmtest, stats and tseries.

II. Appendices

Appendix 1. Figure of market portfolio trading volume

Figure 5 presents average market portfolio trading volume of New Zealand stock market over 2000-2020. Figure is based on the data sample specifically used in this thesis



Appendix 2. Summary statistics

Table 7. Summary statistics of individual shares (2000-2020) Monthly data summary statistics of liquidity measures (mean, median, standard error, standard error of mean, number of observations.

	Amihud	Turnover	MCAP (mNZD)	Returns
Nr of observations	44,961	48,538	40,100	44,549
Missing values	29,728	24,735	12,020	26,728
Mean	0.34187	0.0101	560.97	0,00925
Median	0.19722	0.0054	117,49	0,00110
Standard deviation	0.4919	0.0211	1321.49	0.0586
Max	9.12775	0.7740	20,743.29	2.4000
Min	0	0.0000055	0.12	-0.2440
Kurtosis	69.909	279.86	36.50	1.4458
Skewness	6.3270	12.91	5.13	-0.3372

Appendix 3. Fama and Macbeth cross-section regressions for illiquidity portfolios

Table 8. Cross-sectional Fama-Macbeth regressions for Illiquidity portfolios. The values that are in parentheses are the t-stat values of coefficients. R-squared (R^2) values are retrieved from cross-sectional regressions. *, ** and denote significance level at the 5% and 1% level, respectively.

	Intercept	***E(c)***	β^{1}	β^{2}	β^{3}	β^{4}	β^{5}	β^{net}	R^2
Panel A. Amihud									
1.	0.0087	-0.003	0.0201						41%
	(-0.55)	(-0.78)	(0.918)						
2.	0.002	-0.0041		0.018					43%
	(-0.32)	(-1.56)		(0.23)					
3.	0.019	-0.007			-0.04				48%
	(-0.91)	(-0.26)			(-0.29)				
4.	0.0056	-0.0082				-0.032			53%
	(-0.17)	(-0.24)				(-1.240)			
5.	0.031*	-0.019	0.062				0.039		42%
	(-2.56)	(-0.35)	(0.079)				(-0.86)		
6.	0.025	-0.023						0.032	48%
	(-1.25)	(-0.93)						(-0.73)	
7.	0.036	-0.076*	0.064	0.021	-0.09	-0.056*			59%
	(-0.87)	(-2.83)	(0.95)	(0.37)	(-0.47)	(-3.19)			
Panel B. Turnover									
1.	0.018	-0.007	0.082*						40%
	(-0.43)	(-0.32)	(-2.89)						
2.	0.029	0.017		0.025					45%
	(-0.14)	(-0.32)		(-0.18)					
3.	0.058	0.064			0.017				46%
	(-0.29)	(-0.15)			(-0.91)				
4.	-0.05	0.027				0.0046			41%
	(0.32)	(-0.88)				(-0.49)			
5.	-0.019	0.023	0.019				-0.066*		44%
	(1.92)	(-0.29)	(-0.27)				(-3.12)		
6.	-0.019	0.023						0.067	45%
	(-1.74)	(-1.18)						(1.79)	
7.	-0.027	0.030	0.087*	0.049	0.019	0.050			49%
	(-1.43)	(-0.87)	(3.27)	(-1.19)	(-0.86)	(-0.94)			

Appendix 4. Fama and Macbeth cross-sections regression for Size portfolios

Table 9. Cross-sectional Fama-Macbeth regressions for Size portfolios. R-squared (R^2) values are retrieved from cross-sectional regressions. The values that are in parentheses are the t-stat values of coefficients. *, ** and denote significance level at the 5% and 1% level, respectively.

	Intercept	***E(c)***	β^1	β^2	β^3	β^4	β^5	β^{net}	R^2
Panel A. Amihud									
1.	0.026	-0.007	0.023						63%
	(-1.19)	(-0.92)	(0.47)						
2.	0.0045	-0.015		0.030					52%
	(-0.80)	(-1.24)		(1.75)					
3.	0.0061	-0.014*			-0.078				58%
	(1.18)	(-2.85)			(0.92)				
4.	0.019	-0.027				-0.051			44%
	(-0.96)	(-0.95)				(1.89)			
5.	0.043	-0.034	0.070				0.045		51%
	(1.86)	(-1.11)	(0.65)				(1.72)		
6.	-0.058	-0.056*						0.043	59%
	(1.24)	(-2.72)						(-1.60)	
7.	0.023	-0.0101	0.124	0.052	-0.13	-0.069*			57%
	(1.032)	(-0.86)	(0.98)	(1.11)	(-0.93)	(3.13)			
Panel B. Turnover									
1.	0.087	0.034	0.090*						47%
	(1.86)	(-0.137)	(2.93)						
2.	0.063	0.017		0.056					40%
	(-1.28)	(-0.082)		(1.15)					
3.	0.043	0.032			-0.020				41%
	(-0.25)	(-0.096)			(-0.96)				
4.	0.065	0.082				0.0071			44%
	(0.75)	(0.42)				(0.40)			
5.	-0.35**	0.027	0.023				-0.073*		51%
	(-5.13)	(-0.34)	(0.87)				(-3.24)		
6.	-0.045*	0.030						0.076	50%
	(-2.98)	(0.91)						(1.73)	
7.	-0.045*	0.046	0.103*	0.063	-0.032	0.064			56%
	(-2.78)	(0.65)	(2.63)	(1.52)	(-1.63)	(1.49)			

Appendix 5. Fama and Macbeth cross-sections regression for Sub-periods with illiquidity portfolios

Table 10. Cross-sectional Fama-Macbeth regressions for Illiquidity portfolios using sub-periods with Size (Market Capitalization) effect. The values that are in parentheses are the t-stat values of coefficients. R-squared (R^2) values are retrieved from cross-sectional regressions. * and ** denote significance level at the 5% and 1% level, respectively.

	Intercept	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^{net}	R^2
Sub-period 2000-2010									
Panel A. Amihud									
1.	0.026	-0.007	0.040						42%
	(-0.024)	(-1.22)	(-0.82)						
2.	0.0045	-0.015		0.033					47%
	(-1.45)	(-0.24)		(-1.92)					
3.	0.0061	-0.04			-0.160				52%
	(-1.14)	(-0.85)			(-1.63)				
4.	0.019	-0.027				-0.210*			59%
	(-1.11)	(-0.95)				(-2.44)			
5.	0.043	-0.047	0.027				0.065		53%
	(-1.32)	(-0.71)	(0.25)				(-1.17)		
6.	0.075	-0.031						0.0410	51%
	(-1.24)	(-1.42)						(-0.92)	
7.	-0.052	-0.16*	0.020*	0.120*	-0.110	-0.190*			57%
	(-4.31)	(-2.72)	(-2.52)	(-2.70)	(-1.17)	(-2.64)			
Panel B. Turnover									
1.	0.026	-0.0042	0.033*						53%
	(-1.19)	(-0.92)	(2.67)						
2.	0.0045	-0.021		-0.055					53%
	(-0.80)	(-1.24)		(1.75)					
3.	0.0061	-0.071			0.032				52%
	(-1.18)	(-1.12)			(0.92)				
4.	0.019	-0.027				0.040			58%
	(-0.96)	(-0.95)				(1.89)			
5.	0.043	0.18*	0.070				-0.13*		44%
	(-1.86)	(-2.71)	(0.25)				(2.67)		
6.	-0.024	0.28*						-0.25*	51%
	(-1.61)	(-2.72)						(-3.60)	
7.	-0.034	0.044	0.46*	0.21*	0.059	0.074*			59%
	(-1.82)	(-0.86)	(2.98)	(2.71)	(2.87)	(2.53)			
Sub-period 2010-2020									
Panel A. Amihud									
1.	0.025	0.0016	0.003						42%

	(2.19)	(0.132)	(0.37)						
2.	0.0024	-0.015		0.012					45%
	(-0.89)	(-0.54)		(0.86)					
3.	0.0031	-0.04			-0.0006				41%
	(-1.18)	(-0.85)			(-0.016)				
4.	0.0015	-0.027				-0.001			47%
	(-0.66)	(-0.95)				(-0.034)			
5.	0.002	0.012	0.002				0.011		40%
	(-1.16)	(0.11)	(0.25)				(1.29)		
6.	0.010	0.02						0.021	51%
	(-1.24)	(0.59)						(1.10)	
7.	0.0016	0.002	0.023	0.016	-0.002	-0.016			56%
	(-1.4)	(0.19)	(0.76)	(1.73)	(1.24)	(0.73)			

Panel B. Turnover

1.	0.026	0.007	0.027						49%
	(-1.19)	(-0.09)	(0.37)						
2.	0.0045	0.0005		0.0026					55%
	(-0.80)	(-1.24)		(0.91)					
3.	0.0061	0.0031			0.016				52%
	(-1.18)	(-0.85)			(1.22)				
4.	0.0013	0.0026				0.0017			46%
	(-0.96)	(-0.95)				(0.89)			
5.	0.0034	0.0061	0.023				0.024		49%
	(-1.86)	(-0.11)	(0.25)				(0.72)		
6.	0.027	0.0058						0.043	51%
	(-1.24)	(-0.42)						(1.63)	
7.	0.041	0.045*	0.042	0.034	0.023	0.009			59%
	(-1.08)	(2.56)	(0.91)	(1.42)	(1.65)	(2.03)			