A Study of Stock Market Liquidity from 1973 to 2015

by

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Submitted to the Department of Electrical Engineering and Computer Science
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Abstract

In this thesis we analyze US stock market liquidity in the period of 1973 to 2015 from three perspectives: price impact, turnover ratio, and trading frequency. We use the Center for Research in Security Prices (CRSP) and Trade and Quotes (TAQ) databases to acquire stock data across different time spans to perform analysis across different time horizons, including stock listing and de-listing analysis using monthly trades data, price impact and turnover ratio analysis using daily trades data, and intraday trading frequency case studies using intraday trades data. We first analyze price impact of all common stocks in the US stock market from 1973 to 2015 using linear regression between the a stock’s holding period return and the natural log of its dollar trading volume to estimate the price impact. We then perform frequency decomposition of price impact time series and reconstruct price impact time series using Inverse Discrete Fourier Transform. We find market liquidity cycles of 8.6 years and 4.3 years and analyze the implications of these liquidity cycles in the context of economic cycles. Next we analyze turnover ratio of all common stocks in the US stock market from 1973 to 2015. We find evidence for the turnover ratio increasing more for illiquid stocks than liquid stocks in response to market events. Through an analysis of the trailing 2 year correlation between turnover ratio and price impact, we show that this correlation in liquid stocks steadily increases starting from the early 1990s, possibly due to the proliferation of day traders. Finally we perform intraday cases studies for the 2007 Quant Meltdown, first day of the 2008 Financial Crisis’ worst week, and the 2010 Flash Crash respectively. We use the number of trades within one minute as a proxy for trading frequency. We find evidence for most trades happening around 10am and towards the end of the trading day around 3:30pm; hence the market liquidity are most abundant during these peak time. We also provide a method to investigate irregular market behavior and intraday liquidity shocks from unusual increases and decreases in trading frequency during the day.

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Chapter 1

Introduction

The stock market has a long history since the trading of the stocks of the first joint-stock company, the Dutch East Indian Company, on the Amsterdam Exchange in the 17th century. In the US, the first stock exchange, Philadelphia Stock Exchange, was founded in 1790. It was quickly taken over by New York Stock Exchange (NYSE) in terms of trading volume and number of companies listed. In the next few centuries, stock trading mostly happened at the trading floor of the exchanges where buyers and sellers screamed their intentions of buying or selling the stocks; trying to find a match. However, in the 20th century, especially in the past few decades, many technological and strategic innovations and inventions initiated by investors, security dealers, and stock exchanges themselves propelled dynamic changes in the stock market and helped it evolve into its modern state today.

The financial industry and academia have always been closely tracking and studying the changes in the stock market. To measure the impacts of technological changes and regulations brought to the stock market in the past few decades and to quantify these impacts, many metrics of the stock market have been developed, including market size, trading volume, market liquidity, market volatility, and etc.

The paper aims to study market liquidity mainly from the three perspectives of price impact, turnover ratio, and trading frequency by applying time domain and frequency domain
techniques. The scope of analysis mainly ranges from 1973 to 2015. It is complemented by the broader overview of stock delisting and new stock listing from 1926 to 2015. From studying market liquidity in different time horizons ranging from decades to intraday liquidity cases studies, we hope to achieve an understanding of the reasons behind the market liquidity movements, the relationships among different liquidity measures, and their implications of the change in market microstructure.

The paper is organized as follows. In Chapter 1, we provide an introduction, literature review, and a brief history of the evolution of market microstructure. In Chapter 2, we describe the data we use for this paper and analyze stock delisting and new stock enlisting on US stock market from 1926 to 2015 using monthly data. In Chapter 3, we analyze price impact as a liquidity measure for all US common stocks from 1973 to 2015 and perform frequency decomposition to price impact time series using daily trade data. We also discuss the implications of the price impact cycles. In Chapter 4, we use daily trade data to analyze turnover ratio as a liquidity measure for all US common stocks from 1973 to 2015 and the relationship between turnover ratio and price impact as two liquidity measures. In Chapter 5, we use intraday trade data to perform intraday trading frequency case studies for the 2007 Quant Meltdown, the worst week of the 2008 Financial Crisis, and the 2010 Flash Crash. In Chapter 6, we conclude the paper.

1.1 Literature Review

In recent years, it has come to the public and regulators’ attention that the landscape of the US stock market has changed, notably the surging volume of trading activities triggered by various types of automated trading strategies on electronic exchanges. As the rules for order routing and execution at stock exchanges grow more complex and murky under the cloak of modern day computer technologies, many argue that US stock market is rigged to enable certain types of market participants to bypass the regulations and profit from the loopholes. Examples of such exploitation could be retraced back to 1993 when day traders, known as "SOES bandits", started to trade on the NASDAQ’s Small Order Execution System (SOES).
As Harris and Schultz (1998) pointed out, it is caused by the removal of the Professional Trader Rule, which prevented them from such practices. The day traders capitalize on the fact that some market makers update quotes slower than others. Day traders often buy stocks from slower market makers before the market makers update the quotes, only to sell the exact same stocks back to these slower market makers after they increase their quotes (Patterson 2012). The technological advancements in fiber optics and digital processors has led to the recent proliferation of high frequency trading (HFT) firms. Even though representing only 2% of all trading firms, HFT firms account for almost 75% of all trades and reduce the average holding time for a stock to 22 seconds (Solman 2012). These recent changes motivated the study of market liquidity to understand the modern stock market landscape.

Many methods have been applied to measure liquidity in the financial markets. This paper mainly studies three different measures of liquidity: price impact, turnover ratio, and trading frequency. This approach to studying multiple different measures of liquidity is inspired by Chordia, Roll, and Subrahmanyam’s (2000) paper in which they pointed out that studying one measure of liquidity is not sufficient because liquidity has a number of aspects that cannot be captured in a single measure. Chordia, Roll, and Subrahmanyam (2000) used the three liquidity measures of quoted bid-ask spreads, quoted depth, and effective spreads to study the co-movement of individual stock liquidity with market and industry liquidity, which is called commonality in liquidity.

We analyze price impact as a measure of illiquidity in Chapter 3 of this paper. This approach is motivated by Amihud (2002). He proposed an approach that studies the average ratio of absolute stock returns to dollar volume and called it ILLIQ since price impact is technically an illiquidity measure. The higher the price impact, the more illiquid an instrument is. He presented new tests for the proposition that stock excess return, or "risk premium", is not only a compensation for risk, but also a compensation for expected market illiquidity. In this paper, we measure price impact of a stock using linear regression between holding period returns of the stock and the natural log of dollar volume of the stock instead of average ratio between the two quantities used in Amihud (2002).
linear regression approach is first proposed by Kyle (1985) to investigate a model of insider trading with sequential auctions. This approach is also studied and applied in Khandani and Lo’s (2010) study of market liquidity to explain the Quant Meltdown in August 2007. Whereas in Khandani and Lo’s (2010) study, they applied this analysis on different index baskets of stocks from 1995 to 2007, we apply this analysis across all stocks in the broader US stock market from 1973 to 2015 to measure the price impact of the entire stock market. Furthermore, we also perform frequency decomposition of the price impact coefficients to identify and analyze liquidity cycles and their implications.

We analyze turnover ratio in Chapter 4 of this paper. Turnover ratio refers to the ratio of trading volume to the number of shares outstanding. In Amihud and Mendelson’s (1986) study of effects of bid-ask spread on stock return, they suggested that turnover is negatively related the illiquidity costs, meaning a highly illiquid stock will understandably have low turnover ratio because investors often need to cross wide bid ask spread to trade the stock. In this paper, we analyze turnover ratio of all common stocks in the US stock market from 1973 to 2015 and investigate the relationship between the two liquidity measures, price impact and turnover ratio, applying a similar approach to Chordia, Roll, and Subrahmanyam’s (2000) paper. Another study of turnover ratio is presented by Atkins and Dyl (1997). They found a strong positive relationship between transaction costs and holding periods which is measured by the reciprocal of the turnover ratio.

We perform intraday trading frequency case studies in Chapter 5 of this paper. Analyzing intraday trading frequency as another liquidity metric complements the analysis of price impact and turnover ratio, both of which use daily trading data. Whereas Chapter 3 and 4 provides insight into liquidity movements over the period of decades, studying intraday trading data of prominent market turmoil periods such as the Quant Meltdown in 2007, the worst week of Financial Crisis in 2008, and Flash Crash in 2010 in Chapter 5 will provide insight into how market liquidity responds to market shocks within the same day.
1.2 A Brief History of the Evolution of Market Microstructure

This evolution of modern day US equity markets could potentially be attributed to the technological advancements in computer networks, the development of electronic trading venues and dark pools, and the invention of various types of quantitative trading strategies. Up to the 1980s, the vast majority of stock trading volumes are from matching stock buy and sell orders performed by the market makers known as specialists on the NYSE trading floor and dealers for NASDAQ. The old tradition of quoting stock prices in bid-ask spreads, the difference between the bid (buy price) and ask (sell price), of one-eighth of a dollar (or, more often, one quarter of a dollar) enables the market makers to make large profits from the spreads. Every time sell orders match the bid prices provided by the market makers and buy orders match the higher ask prices provided by the market makers, they lock in the spread which is often one-quarter a dollar per share. The high bid-ask spreads quoted by market makers increase the trading costs for investors. As computer technology has advanced, Joshua Levine spearheaded the effort to bypass the market makers and save investors money by creating the new electronic exchange Island in 1997, which bypass market makers and automatically match crossing buy and sell orders (Patterson, 2012). After the immediate success of Island as more and more investors and trading firms routed their orders to Island, others soon followed, eventually there are many automated electronic exchanges including NYSE Arca and Globex, etc, which are known as electronic communication networks (ECNs).

The creation of these speed friendly automated exchange platforms encourages the development of electronic trading. Electronic trading enables trading decisions to be deployed remotely and more efficiently without the involvement of human communication, which is prone to error and delay. These electronic trading platforms enable the process of order execution to be completed by computers in an automated fashion and often within a split second, providing the infrastructure for high frequency trading (HFT) and algorithmic trading strategies. In high frequency algorithmic trading, traders often implement their trading strategies in computer code, which instructs the computer to analyze market condi-
tions and trade appropriate instruments automatically. These strategies are often known as systematic because the trading decisions are made by the algorithms based on preset rules and real time updating market data as opposed to by human traders, which is perceived to be more error prone due to human psychology and emotional instability.

Following these computerized electronic exchanges, NYSE and NASDAQ reduced the minimal tick size for stocks from 1/8th to 1/16th of a dollar in 1997 and eventually to one cent in on January 29, 2001 and April 9, 2001 respectively, reducing the bid-ask spread to often a few cents from a quarter of dollar before. While it reduces the profit of traditional market makers, it also greatly reduces trading costs for investors and encourages trading activities. Other than NYSE, NASDAQ, and ECNs, private exchanges known as dark pools proliferated. They are established by "internalizer" hedge funds and large security dealer firms including Citadel, Goldman Sachs, and others, to internally match buy and sell orders instead of routing the orders to public exchanges, generating trading volume and data which is not available to the general public, hence "dark" liquidity. These different types of trading venues combined with the advancements in computer networks and electronic data storage in the recent decades provide abundant data for analysis and back testing strategies, and propel the inventions of big data based quantitative trading strategies. The availability of tick data also helps the development of quantitative strategies with turnover horizons as short as milliseconds.

Regulations also play a key role in shaping the current eco-system of the stock markets. One of the most important regulation policy that resulted in massive market-structure change is instituted by the Security and Exchange Commission in 2007. Known as Reg NMS, short for Regulation National Market System, it was an attempt to protect investors by mandating that any order to buy and sell a stock has to go to the trading venue that has the best price. The implementation of this mandate requires all trading venues to monitor the prices of all stocks on all other trading venues and route the orders to the venues with the best prices. This implementation not only brought technical challenges to the trading venues, but also brought complexity to trading firms as their buy and sell orders often cannot be executed immediately. To reduce the technical challenges and ease
the complexity for their client trading firms, different stock exchanges and trading venues designed new mechanisms such as new order types to bypass the hassles without violating the Reg NMS. Many of these practices have been controversial. Many industry professionals suspect that these practices provide opportunities for specific trading strategies to exploit the rest of the market. As various quantitative strategies are designed to suit the ins and outs of trading venues and regulations, the competition between quantitative strategies has grown ever more intense, generating daily trading volume comparable to months worth of trading volume a few decades ago.

The large trading volume generated and fast trading speed enabled by advanced computerized trading platforms and sophisticated trading strategies seem to indicate a growth and improvement of market liquidity. Indeed investors usually never have to pay big spreads anymore to trade stocks. However, the seemingly abundant liquidity provided in the modern day stock market eco-system is not without risks. On May 6, 2010, Flash Crash occurred at 2:32pm EDT and lasted for about 36 minutes. Within 36 minutes, S&P 500 index, Dow Jones Industrial Average, NASDAQ Composite, and other major stock indexes plunged before bouncing back to their previous levels. During the event, the liquidity in the stock market seemingly vanished, causing hundreds of thousands of sell orders to be executed at extremely low prices or extremely high prices. The stocks of eight major companies in the S&P 500 fell to one cent per share for a short time, including Accenture, CenterPoint Energy and Exelon; while stocks of other major companies, including Sotheby’s, Apple Inc. and Hewlett-Packard, increased in value to over $100,000 in price (Grocer 2010; Lauricella & McKay 2010). Many studies and analysis had been done to explain the reasons behind the Flash Crash but there have not been a complete explanation that is unanimously accepted. Many studies point out that the ultra-low and ultra-high prices where the stocks traded during the flash crisis were caused by the very low "stub-quotes" posted by security dealers at the exchanges for various reasons. When the liquidity vanished, these stub quotes surfaced to the top of the queues and were executed, leading to a domino effect that plunged the market (Flood 2010; Nanex 2010). This incident demonstrates the devastating effects a 36 minute long liquidity crisis has on the broader US stock market—temporarily, $1 trillion
in market value disappeared (Wall Street Journal 2010).
Chapter 2

Data

2.1 Data Source

In this research project, we use the Center for Research in Security Prices (CRSP) database and the NYSE Trade and Quote (TAQ) database from Wharton Research Data Services (WRDS). We use the CRSP database to extract daily and monthly common stocks data for all common stocks. We use the TAQ database to extract intraday trading data for all common stocks.

2.2 Stock De-listing Analysis

Before we use CRSP daily stocks data and TAQ intraday data to analyze stock market liquidity, we want to have an overview of the number and composition of stocks in the US stock market throughout the past few decades. Thus, we will analyze stocks de-listing and new stock listing using monthly stocks data for all common stocks in the entire CRSP database from January 1926 to December 2015. This analysis will not only help us understand the data we are working with, but also ties closely to the study of stock market liquidity. A sudden increase of stock de-listing often indicates harsh economic environment and decreasing market liquidity because during economic downturns, investors often pull out from stock
market and rush into safer assets such as gold. On the contrary, an increasing number of new stock listing suggests investors are more confident in the economic environment and are willing to put money into stock market, often leading to a more liquid market. By studying the monthly stock de-listing and new stock listing trends, we will have an understanding of the movement of market liquidity on monthly horizon.

We first use Kenneth French’s 10 industry mapping to put all common stocks into the following 10 industry categories using their SIC code in our analysis: NonDurable, Durable, Manufacturing, Energy, High Technology, TeleCom, Shops, Healthcare, Utility, and others, which includes Mines, Construction, Building Management, Transportation, Hotels, Bus Services, Entertainment, Finance, etc.

Figure 2-1: Number of listed common stocks by industries 1926-2015

Figure 2-1 shows the number of listed common stocks in each industry from 1926 to 2015. The numbers of listed common stocks in each industry are aggregated from CRSP monthly data. We can see from Figure 2-1 that the industry category "The rest" composes the biggest proportion of the 10 industries every year which shows that many stocks cannot be categorized into the other 9 specific industries. The number of listed common stocks in "Utility", "Energy", "Durable", "NonDurable", and "TeleCom" industries stayed 30-100 throughout this period, suggesting these industries have high entry barriers and are generally dominated by several companies. On the contrary, the number of listed common stocks in "High Tech", "Shops", "Manufacturing", "Healthcare" industries increased from 1985 to
1999 then gradually decreased after 2000. This trend is likely led by technology companies rushing to IPO riding the dot com bubble in the 1990s and went bust in the Tech-Bubble burst in the early 2000s. Overall, the number of listed stocks peaked in 1997 at 8229 and almost continuously decreased to 4026 by the end of 2015. This observation is also confirmed in Doidge, Karolyi, and Stulz’s (2015) analysis of the reasons that the US has many fewer listed firms given its level of economic development and the quality of its institutions relative to other institutions. We have the following two hypotheses for the declining of listed stocks after 2008. First hypothesis is that it is caused by the increasing number of de-listing across all industries after 1997 due to the Tech Bubble Burst and the later 2008 Financial Crisis. Second hypothesis is that it is caused by the decreasing number of new stocks listed every year after 1997. We will show in the following analysis that the low new stock listing after 1997 is a more important reason than the high de-lists after 1997 for the decreasing number of listed firms after 1997, consistent with Doidge, Karolyi, and Stulz’s (2015).

We find that the CRSP database only includes daily stock files and Nasdaq data starting in 1962 and 1972 respectively, which caused the sudden increase of the number of listed stocks in 1962 and 1972.\(^1\)

![Delisting stocks by Industry](Image)

Figure 2-2: Number of de-listed common stocks by industries 1926-2015

Figure 2-2 shows the number of de-listed common stocks in each industry from 1926 to 2015. Similar to the number of listed common stocks, "The rest" category which includes

\(^1\)The number of listed stocks in CRSP database jumps to 1965 on July 31st 1962 from 1133 on June 29th 1962. The number jumps to 5538 on December 29th 1972 from 2667 on November 30th 1972.
industries such as Mines, Construction, Building Management, Transportation, Hotels, Bus Services, Entertainment, Finance, etc has the biggest number of de-listing stocks. The de-listing pattern for the other industries is similar to the pattern of the number of listed stocks in Figure 2-1. It shows that during years when certain industries are booming, for example high technology industry from 1995 to 2002, there are also more business competitions in those industries which leads to more corporate mergers and bankruptcy, causing an increase in the number of stock de-listings.

Figure 2-3: Common stocks de-listing categories 1926-2015

Figure 2-3a shows a breakdown of the different categories of de-listing and the number of de-listed common stocks in each category from 1926 to 2015. We summarize the
various types of de-listing into five big categories to help our analysis:

- Bankruptcy: Companies went bankrupt.

- Issue exchange for another stock: Companies convert one class of stocks to another class of stocks, de-listing the former class in the process.

- Liquidations: Special purpose companies redemption of common stocks and dissolution (i.e. Special Purpose Acquisition Companies).

- Mergers: Companies acquired by or merged with other companies, de-listing their common stocks in the process.

- Voluntary de-listing, or removal from one exchange to be listed on another (i.e. de-listed from NASDAQ GM to be listed on NASDAQ CM), or de-listing because of missing the requirements of the exchanges or SEC.

Because the number of both listed and de-listed stocks are relatively small before 1972 due to the limited stocks data in CRSP database before the end of 1972, we also generate the ratio representation of common stocks de-listed from 1926 to 2015 in each of the five categories, which help smooth out the data deficiency before 1972. The results are shown in Figure 2-3b. From Figure 2-3a and Figure 2-3b, we can see that mergers is the biggest category of de-listing, followed by de-listing due to missing requirements or forced by SEC. De-listing caused by bankruptcy is a relatively small portion of overall de-listings. Both the number and the ratio of de-listing common stocks in all the above three categories peaked around 1931, 1987, 1999, and 2008\(^2\). These time periods correspond to the Great Depression, the 1987 Black Monday, the Tech Bubble burst, and the 2008 Financial Crisis. This suggests that firms suffering market stress would be more likely to miss exchanges requirements, acquired by other firms to seek exits for investors, or go bankrupt. The sudden jump of the number of de-listed stocks in 1973 is caused by the inclusion of NASDAQ stocks in the CRSP database at the end of 1972.

\(^2\)These four local peaks have a de-listing ratio of around 3.9%, 9.6%, 12.8%, and 8.3% respectively.
Furthermore, we see that both the number and the ratio of de-listed stocks generally decreased after 1997. Thus, the decreasing of the number of listed stocks after 1997 is not caused by the increasing de-listing ratio after 1997. Thus, it is probably caused by the decreasing number of new stocks listed after 1997. We can confirm that by computing the number of new stocks listed. We compute the number of new stocks listed every year by subtracting the number of listed stocks carried over from the previous year from the number of listed stocks in the current year. Figure 2-4 shows the result.

![Figure 2-4: Number of newly listed common stocks by industries 1927-2015](image)

In Figure 2-4, we remove the data on 1962 and 1973 as they are inconsistent with the rest of the years due to CRSP’s inclusion of daily stock data and NASDAQ stocks data at the end of 1962 and 1972 respectively. We notice some trends such as companies in the high-tech industry boomed and rushed to IPO in the years from 1992 to 1999 then stopped after 2000 as the Tech Bubble burst. More importantly, we indeed see a decreasing number of new stock lists after 1997, which provides evidences for our second hypothesis that the decreasing number of listed stocks after 1997 is caused by the decreasing number of new stocks listed after 1997. This finding also is also supported by Doidge, Karolyi, and Stulz’s (2015) analysis which shows that the low new lists after 1997 is a more important reason than the high de-lists after 1997 that explains the decreasing number of listed firms after 1997.
Because CRSP database only includes NASDAQ stocks data after December 1972, we use CRSP data from January 1973 to December 2015 for the analysis in Chapter 3 and Chapter 4.
Chapter 3

Market Liquidity and Price Impacts Analysis

3.1 Price Impacts and Kyle’s Lambda

There are many methods that have been applied to measure market liquidity in financial markets. Brennan, Chordia, and Subrahmanyam (1998) used trading volume in their analysis of the relationship between non-risk security characteristics and expected stock returns. Chordia, Roll, and Subrahmanyam (2000) used quoted bid-ask spreads, depths, and effective bid-ask spreads to study the relationships between individual stock liquidity and the industry and market liquidity. Amihud (2002) used the ratio of absolute stock returns to dollar volume as the liquidity measure which ties into our analysis in this chapter. In this chapter, we analyze price impact as a market liquidity metric.

Price impact means the impact of trading volume on the stock’s price. Here we use linear regression estimates between the daily holding period return of a stock and the natural log of its daily dollar trading volume to estimate price impact. It is an approach motivated by Kyle’s (1985) model to investigate insider trading and sequential auctions. Thus it is commonly referred to as "Kyle’s lambda". This metric is actually an illiquidity measure,
as pointed out by Amihud (2000) in his metric ILLIQ. A higher value of lambda implies larger price impacts hence lower liquidity and lower market depth. Because of the existence of "iceberg" order types in which outsiders do not see the whole order size, this measure of market liquidity is better than quoted depth. This linear regression estimate of price impact is also applied by Khandani and Lo (2010) in their study of the Quant Meltdown in August 2007. Whereas Khandani and Lo (2010) applied this analysis on stocks within S&P 1500, S$P 500, and other index baskets to analyze the price impacts on stocks with different market capitalization, we apply this linear regression estimate on all common stocks in the entire US stock market.

We use daily trading data from CRSP database to analyze all listed common stocks\(^1\) in the US stock market from 1973 to 2015 for the analysis of price impact. We do not analyze data earlier than January 1973 because CRSP database only includes NASDAQ stocks data starting from December 1972. For every month from January 1973 to December 2015, for every stock \(i\) listed at the end of that month, we have the time series of daily holding period returns, \(R_{i,1}, R_{i,2}, \ldots, R_{i,T}\), daily closing prices, \(p_{i,1}, p_{i,2}, \ldots, p_{i,T}\), and daily volumes, \(v_{i,1}, v_{i,2}, \ldots, v_{i,T}\), for \(T\) trading days within that month, we estimate the following regression:

\[
R_{i,t} = \hat{c}_i + \hat{\lambda}_i \cdot Sgn(t) \log(v_{i,t}p_{i,t}) + \epsilon_{i,t}
\]

(3.1)

In this equation, \(Sgn(t) = \{+1 \text{ or } -1\}\) depending on the direction of the trade. We define \(Sgn(t)\) using the following rule: if \(R_{i,t}\) is positive, we assign value +1 to \(Sgn(t)\) for that entire day, indicating net buying, hence the security has a positive return. If \(R_{i,t}\) is negative, we assign value −1 to \(Sgn(t)\) for that entire day, indicating net selling, hence the security has a negative return. If \(R_{i,t} = 0\), we assign \(Sgn(t)\) to be the same value as the previous day. Hasbrouck (1991), Dufour and Engle (2000), Bouchaud, Farmer, and Lillo (2008) have shown evidences that the impact of trade size on price adjustment is concave, thus we use the natural logarithm of dollar volume in our analysis. In the regression, we drop days when the stocks have zero trading volume. \(\hat{\lambda}_i\) is the price impact measure of stock \(i\). Its unit is

\(^1\)with sharecode 10 or 11
%, log($), meaning the increase of daily return for that stock in response to an increase of trading dollar volume by 1 percent. We calculate $\hat{\lambda}_i$ for every stock in the US stock market at the end of every month from January 1973 to December 2015 using Equation 3.1.

3.2 Price Impacts of all stocks from 1973 to 2015

We computed Kyle’s $\lambda$ values at the end of each month from January 1973 to December 2015 for all listed common stocks with at least 15 trading days in the previous month using linear regression Equation 3.1. At the end of each month, we only include the stocks trading between $5 and $2000 in that month in our analysis. This is because the stocks trading above $2000 or below $5 are likely to be illiquid and infrequently traded small cap stocks. We found that by including these small amount of relatively illiquid stocks with much lower liquidity than the rest of the stocks, the price impact metric computed will be skewed upwards. This approach to include only stocks trading between $5 and $2000 is motivated by Khandani and Lo (2010) in their analysis of average price impact of different stock baskets. Instead of just studying the average, we study the distribution of the monthly cross-sectional price impact of all common stocks trading between $5 and $2000 by showing their price impact coefficients, $\hat{\lambda}_i$s, in the following 7 percentiles 99th, 90th, 75th, 50th, 25th, 10th, 1st. The results are in Figure 3-1.

In Figure 3-1, the Kyle’s $\lambda$ values are in basis points. It means the amount of basis points the stock holding period return will increase for a 1% increase in the stock’s daily trading dollar volume. Excess stock returns can be viewed as compensation for not only the risk, but also the expected illiquidity of the stock, as suggested by Amihud (2002). A higher $\lambda$ value means the price impact on the stock is larger, hence the stock has less liquidity. Each curve shows the movement of $\lambda$ value of a particular percentile, computed every month using all common stocks trading between $5 and $2000 for at least 15 days in that month. We observe that the stocks composing the 99th percentile price impact curve, which are the most illiquid stocks with the highest price impact, reached over 90 basis points in 2001 and 2009, meaning a 1% increase in the daily dollar trading volume in those stocks will increase.
Figure 3-1: Kyle’s λ in percentiles for common stocks trading between $5 and $2000

their daily return by 0.9%. The sharp increases in price impact of those stocks are likely caused by the Tech Bubble burst and 2008 Financial Crisis respectively.

In order to study the timing and reasons that might cause the movement of the price impact curves, especially the peaks where the liquidity dries out, in Figure 3-1, we pick out and incorporate in the plot the following prominent events which impacted the stock market and potentially cause the market liquidity conditions to change. The events are marked with corresponding numbers with vertical time stamp bars in Figure 3-1.

1. October 1, 1974: 1973-1974 stock market crash during which the Dow lost over 45% in 2 years.

2. October 1, 1978: 1978 October market decline because of economy deterioration.

3. May 1, 1980: US economy decline in first half of 1980; unemployment rate rose to 7.7% (Burger 1980).

5. July 3, 1990: Iraq invaded Kuwait, causing oil price to increase; Dow dropped 18% in the following 3 months.

6. June 2, 1997: NASDAQ changed its minimum tick size from 1/8th to 1/16th. NYSE followed suit 22 days later.


8. April 3, 2000: NASDAQ-100 dropped over 7.3% in one day, and dropped over 13.4% in past 5 trading days.

9. January 29, 2001: NYSE changed its minimum tick size from 1/16th to 1/100th of a dollar.

10. April 9, 2001: NASDAQ changed its minimum tick size from 1/16th to 1/100th of a dollar.


14. March 14, 2008: Bear Stearns suffered one-day loss of -47.4%.

15. October 6, 2008: Start of the worst week for the stock market in 75 years.


We can see in Figure 3-1 that during market stress scenarios caused by global events, market microstructure changes, and US economy downturns, the price impact coefficient curves of all percentiles increase. We can associate almost every spike in the price impact with a marked event. The most prominent price impact spikes from 1973 to 2015 happened
on Black Monday on October 19, 1987, April 3, 2000 as NASDAQ-100 dropped over 7.3% in one day, and October 6, 2008 which marked the start of the worst week for the US stock market in 75 years. During these periods, the 99th percentile price impact curve shots up to 85 basis points from around 50 basis points in quiet market conditions, meaning a 1% increase in the daily trading dollar volume of these most illiquid stocks will increase their daily returns by 0.85%. The next tier of price impact spikes happened on October 1, 1974 in response to the 1973-1974 stock market crash, on August 17, 1998 when Russia defaulted on its sovereign debt and devalued the ruble, and when NYSE changed its minimum tick size from 1/16th to 1/100th of a dollar on January 29, 2001. This shows that stock market liquidity dries up not only during domestic stock market crashes but also in response to foreign market events that are likely to trigger systematic market crashes globally. The liquidity dries up because investors pull their money from the stock market fearing that the unexpected foreign market shocks will be contagious to the US stock market. Market microstructure changes, such as NYSE changing its minimum tick size from 1/16th to 1/100th of a dollar, can also decrease market liquidity, though only temporarily. This might be because liquidity providers, usually the market makers, are unsure about the short term impacts of the microstructure changes to individual stocks, and therefore quote stocks with wide bid-ask spreads.

We observe the general decreasing trend in all price impact percentiles from 2002 to 2007 before the Quant Meltdown, marked as the 13th vertical line in Figure 3-1. This is likely caused by the proliferation of high frequency traders and the increasing competition among market makers due to the decimalization of stock prices in 2001, which reduces the bid-ask spread. Chaudhuri (2014) confirmed this by analyzing the cross-sectional bid-ask spread in both percentile and dollar forms of NMS stocks with large, middle, and small capitalization. The bid-ask spread in all three groups decreased from 2002 to 2007. The decreasing of the bid-ask spread during this period is another evidence of the increasing market liquidity as Chordia, Roll, and Subrahmanyam (2000) showed that quoted bid-ask spreads can be used as a market liquidity measure.

We also note the differences in the movements of the price impact coefficient curve in different percentiles. We found higher percentile price impact coefficients, representing
stocks with less liquidity, have higher variance than their lower percentile counterparts. For example, the 99th percentile price impact coefficients have mean of 45.32 basis points and standard deviation of 10.16 basis points, whereas the 50th percentile, or the median, price impact coefficients have mean of 13.87 basis points and standard deviation of 3.69 basis points. This is also shown in Figure 3-1. During big market stress scenarios such as on April 3, 2000, when NASDAQ-100 dropped over 7.3% in one day, the median price impact coefficient increased to 25.10, an 81.0% increase from its average of 13.87 basis points, whereas the 99th percentile price impact coefficient spiked up to 94.50, a 108.5% increase from its average of 45.32 basis points.

We hypothesize the reason for these behaviors is that the illiquid stocks with high price impact are more sensitive to market liquidity changes comparing to more liquid stocks. In order to find out, we turn to Khandani and Lo’s (2010) analysis of the price impact of basket of stocks with different market capitalization. They showed in their analysis that stocks with small market capitalization have higher price impact than stocks with large market capitalization. Thus it is likely that the stocks with price impact coefficients in the 99th percentile curve have a greater portion of small market-cap stocks than the stocks in the 50th percentile curve. In addition, Chaudhuri (2014) has shown that stocks with small market capitalization have higher percentage bid-ask spread, and hence are less liquid, than stocks with large market capitalization. Thus, during market stress scenarios when investors sell stocks, they need to cross a wider percentage bid-ask spread for small market-cap stocks than for large market-cap stocks. This further increases the bid-ask spread, decreases liquidity, and increases the price impact of small cap stocks, pushing up the 99th percentile price impact curve more than the median price impact curve.

In the next section, we perform spectrum analysis to analyze market liquidity cycles.

### 3.3 Spectrum Analysis and Liquidity Cycles

In this section, we apply Discrete Fourier Transformation (DFT) to perform frequency decomposition of the monthly price impact coefficients time series from January 1973 to De-
cember 2015 of all listed common stocks that are trading between $5 and $2000 per share. Our goal is to distinguish periodic movements of market liquidity from market noises.

Many studies have been done to analyze stock market liquidity cycles. Næs, Skjeltorp, and Ødegaard (2011) have shown that Amihud (2002) illiquidity ratio (ILLIQ) for the US over the period 1947 to 2008 surges during the NBER recession periods released by the National Bureau of Economic Research, indicating a high correlation of liquidity cycle and business cycle. Switzer and Picard (2016) have analyzed the relationship between three different liquidity measures, Amihud’s (2002) ILLIQ, Lesmond, Ogden, and Trzcinka’s (1999) LOT, and Roll’s (1984) effective spread liquidity measure, incorporating NBER recession periods. They proposed time-vary parameter models to study the relationship between market liquidity and economic cycles. This is because financial and economic indicators tend to behave differently during high and low economic cycles.

We try to provide further insights to the relationship between liquidity cycles and economic cycles in this paper by using price impact as a liquidity measure. We also try to analyze other liquidity cycles outside of the economic cycles.

3.3.1 Discrete Fourier Transformation Introduction

Fourier Transformation is a method to transform data from time domain to frequency domain. We often apply this method to analyze the frequency properties of signal data. The Discrete Fourier Transformation (DFT) is the equivalent of the continuous Fourier Transformation for signals known only at $N$ instants separated by sample time $T$, or a finite sequence of data (Professor S. Roberts, signal processing & filter design, May 12, 2003).

Let $f(t)$ be the continuous signal which is the source of the data. Let $N$ samples be denoted $f[0], f[1], f[2], \ldots, f[k], \ldots, f[N-1]$. The Fourier Transformation of the original signal, $f(t)$, would be

$$F(jw) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t}dt$$

(3.2)
Let us regard each sample \( f[k] \) as it has area \( f[k] \). Because the integrand exists only at sample points:

\[
F(jw) = \int_{0}^{(N-1)T} f(t)e^{-jwt}dt \\
= f(0)e^{-j0} + f(1)e^{-jwT} + \cdots + f(k)e^{-jwkT} + \cdots + f(N-1)e^{-jw(N-1)T} \\
= \sum_{k=0}^{N-1} f(k)e^{-jwkT}
\]  

(3.3)

In both equation 3.2 and equation 3.3, \( w \) is the angular frequency. Because there are only a finite number of input data points, the DFT treats the data as if it were periodic and the sequence of \( N \) data points as one cycle (i.e. \( f(N) \) to \( f(2N-1) \) is the same as \( f(0) \) to \( f(N-1) \).) Because of that, we evaluate the DFT equation for the fundamental frequency (one cycle per sequence) and its harmonics. Hence we set \( w = 0, \frac{2\pi}{NT}, \frac{2\pi}{NT} \times 2, \ldots, \frac{2\pi}{NT} \times n, \ldots, \frac{2\pi}{NT} \times (N-1) \).

Thus, we have

\[
F(k) = \sum_{n=0}^{N-1} f(n)e^{-j\frac{2\pi}{N}nk}, (0 \leq n \leq N - 1)
\]  

(3.4)

In equation 3.4, the sequence \( F(k) \) is the Discrete Fourier Transform of the sequence \( f(n) \).

Similarly, we can transform a discrete data sequence from frequency domain back to time domain using Inverse Discrete Fourier Transformation (IDFT) as presented in equation 3.5:

\[
f(n) = \frac{1}{N} \sum_{k=0}^{N-1} F(k)e^{j\frac{2\pi}{N}nk}, (0 \leq k \leq N - 1)
\]  

(3.5)

A spectrum is a collection of sine waves that, when combined properly, produce the time-domain signal under examination. Through DFT, we are able to display the amplitude of the sine wave for each frequency, which together construct the price impact \( \lambda \) value time series. By constructing a power spectrum, we are then able to show the power each frequency has on constructing the price impact time series. Price impact \( \lambda \) values display the most significant periodicity at frequencies with the biggest power. Note in treating the frequency-domain magnitude and power series, we only consider the first half of the series because the first half and second half of the magnitude and power series are symmetric about \( N/2 \), where
$N$ is the length of the series. A theory introduction and proof of the symmetry in spectral analysis can be found in Appendix A.

### 3.3.2 Frequency Decomposition and Spectrum Analysis

Displaying the DFT results for all 7 price impact percentile curves will be a bit confusing and redundant since the periodicity of liquidity will be similar for all 7 percentile curves. Therefore, we pick the 50th percentile, which is the median, price impact coefficient time series from Figure 3-1 to perform frequency domain analysis. We follow the following process: remove the mean, or the DC component, of the curve; perform Discrete Fourier Transformation; construct the power spectrum for the 50th percentile using DFT coefficients; reconstruct the time domain 50th percentile price impact time series using the frequencies that have significant power on the spectrum via Inverse Discrete Fourier Transformation. In this way, we are able to remove the noises which often appear as small liquidity cycles and focus our analysis on real market liquidity cycles.

Figure 3-2 shows the process of reconstructing the 50th percentile price impact coefficient (Kyle’s $\lambda$) curve using DFT and Inverse DFT. Figure 3-2b shows the DFT coefficients, $F(k)$ series, after removing $k = 0$, or the DC component. We compute the series by using the 50th percentile price impact coefficients sampling series as $f(n)$ in the equation:

$$F(k) = \sum_{n=0}^{N-1} f(n) e^{-j2\pi nk}, (0 \leq k \leq N - 1).$$

Here $N = 516$, representing the 516 months in 43 years. The DFT coefficients are symmetric around $k = 258$. Because the sampling frequency in our time domain, $f_s$, is once per month, $f_s = \frac{1}{1\text{month}}$. The step size of the X axis in the DFT frequency domain, $\Delta k = \frac{f_s}{N} = \frac{1}{516\text{months}} = \frac{1}{43\text{yrs}} = 0.023$ cycles/yr.

Figure 3-2c shows the normalized power spectrum with power (Y axis) versus frequency (X axis). In this figure, we can see from the symmetric halves that frequency index $k = 2, 5, 10$, with powers around 7.35%, 21.33%, 7.85% respectively, are the most significant frequencies. They correspond to cycles $\frac{43\text{yrs}}{2} = 21.5$ years, $\frac{43\text{yrs}}{5} = 8.6$ years, and $\frac{43\text{yrs}}{10} = 4.3$ years respectively. We treat the power at the other frequencies as spurious noises and we modify series $F(k)$ by changing the values at all other frequency indexes to be 0. We then
(a) Remove mean

(b) DFT magnitude (x axis: cycles/year)

(c) DFT power spectrum (x axis: cycles/year)

(d) Reconstruct using IDFT

Figure 3-2: Reconstructing 50th percentile price impact coefficient time series using DFT and Inverse DFT

\[ f(n) = \frac{1}{N} \sum_{k=0}^{N-1} F(k)e^{\frac{2\pi i}{N}nk}, \quad (0 \leq n \leq N - 1), \]

where \( N = 516 \), to reconstruct the 50th percentile price impact coefficient sequence, which is shown in Figure 3-2d.

As we can see the cyclical behavior of the new reconstructed median price impact series is more apparent than that of the original price impact series in Figure 3-2a.

Through the spectrum analysis, we can see the significant liquidity cycles are 21.5 years, 8.6 years, and 4.3 years with 7.35%, 21.33%, and 7.85% spectrum power respectively. We now try to analyze the causation and economic meanings of such liquidity cycles. We map the reconstructed median price impact coefficient series to the original 50th percentile price impact coefficient series in Figure 3-3 with the same set of global and market events mapped in vertical lines. In addition, we also map NBER recession periods in yellow. Now that the reconstructed 50th percentile price impact coefficient sequence (blue) is smooth in Figure 3-3, we can visualize that the most prominent liquidity cycle shown in our spectrum analysis is 8.6 years with a corresponding 21.33% power. This corresponds to economic cycle.
We can see from Figure 3-3 that the biggest peaks in the blue curve, the period during which price impact are the highest and market liquidity lowest, happen around 1973-1974, 1981-1982, 1991, 2001, and 2008-2009 economic recession periods indicated by the NBER recession periods in yellow. These big economic recession periods have a gap of 8 to 9 years from each other. Our findings are consistent with Næs, Skjeltorp, and Ødegaard’s (2011) analysis of comparing Amihud (2002) illiquidity ratio ($ILLIQ$) for the US over the period 1947 to 2008 and the NBER recession periods. Switzer and Picard (2016) also showed a similar analysis by comparing Lesmond, Ogden, and Trzcinka’s (1999) $LOT$, and Roll’s (1984) effective spread liquidity measure and NBER recession periods.

It is a common observation that stock market liquidity tends to be lower during economic downturns. There are a few different explanations for this phenomenon. Næs, Skjeltorp, and Ødegaard (2011) argue that these effects are the results of investors adjusting their portfolio activities based on their expectations of the real economy. Hence when economy is perceived to worsen, investors shift investments in the stock market to less risky assets such as gold, further drying up the stock market liquidity. Brunnermeier and Pedersen (2009) explain these effects with an alternative reason. They argue that liquidity providers’ ability to provide liquidity depends on their capital and margin requirements. During economic downturns, liquidity providers tighten their liquidity provision due to reduced funding liquidity and increased risk control, creating a a downward liquidity spiral. Another expla-
nation is that the lowered market liquidity has a causal effect on the real economy through investment channels. When the market liquidity dries up, institutional investors become more conservative and put less money into stock market which hinders companies’ ability to absorb public investments. This might hamper companies’ financing operations and trigger financial problems which lead to liquidation and bankruptcy of companies as shown in Chapter 2 in this paper. This causes slowdown in real economy.

The second most prominent liquidity cycle shown in our spectrum analysis is 4.3 years with 7.85% spectrum power. This liquidity cycles can be visualized in Figure 3-3, appearing as the smaller peaks on the blue curve between the big peaks caused by the economic cycles. These smaller peaks are on average 4 to 5 years apart from one of the big peaks. Price impact also rises during these smaller peaks, though not as much as during the economic downturns. If we look closely, we can see that these smaller price impact peaks reflect different types of market events. For example, the small peak in 1978 happen during the small economic contraction in 1978. The small peak in 1987 corresponds to the 1987 Black Monday which caused a huge price impact spike in reality. Though there weren’t prominent market turmoil events during the small peak in 1996, we do observe a small increase in the original price impact coefficient (the green curve) in 1996.

This phenomenon can be caused by many different reasons. One possible explanation is that as the stock market recovers in 4 to 5 years from large economic recessions with the help of special economic policies designed to stimulate the economy, these policies and measure are gradually reduced or repealed, creating temporary liquidity shocks to the market. A recent example is Federal Reserve’s tapering of quantitative easing and hiking of interest rates. Quantitative Easing was a monetary policy implemented by the Federal Reserve after the 2008 Financial Crisis to expedite the recovery of economy by injecting money into the market through purchasing US treasury bonds and mortgage-backed securities. As the US economy recovered, the Federal Reserve gradually decreased the amount of purchase until it finally stopped in October 2014, six years after Financial crisis. Even though the market anticipated these changes, after the Federal Reserve stopped Quantitative Easing and increased interest rate a year later in 2015, we see a slight increase in the
original median price impact curve (green curve) in 2014 and 2015. Similarly, the Federal Reserve increased its benchmark rate from 3% to 6% from February 1994 to February 1995, as cited by Moore and Harper (2013). This resulted in the collapse in bond prices and stock market in 1995. Monetary contraction policies such as increasing interest rate and reducing quantitative easing often results in collapse of both stock markets and bond markets because investors now have more incentive to increase the portion of risk-less assets such as treasury bonds in their portfolios due to the increased interest rates, in the process decreasing their positions in the stock market and non-treasury bonds. This will reduce the liquidity in the stock market as we can see from the price impact increase during 1996.

The third liquidity cycle shown in our spectrum analysis is 21.5 years with 7.35% spectrum power, the least of the three. As our analysis only covers 43 years from 1973 to 2015, we don’t have enough cycles of 21.5 years to analyze the reasons behind the existence of this cycle period. In fact, we can’t validate the existence of this liquidity cycle period as this pattern might be caused by the idiosyncratic features of the limited price impact sample data we use for this analysis. An analysis of longer periods of market liquidity will help confirm the existence of this market liquidity cycle.
Chapter 4

Turnover Ratio

In this chapter, we analyze the second metric of market liquidity, Turnover Ratio. Turnover of a stock generally means the volume of shares traded in a time span for that stock. Turnover ratio of a stock is the volume of shares traded over the total number of outstanding shares for that stock. In this way, we also take into consideration the total number of shares outstanding for that stock. In Amihud and Mendelson’s (1986) study of effects of bid-ask spread on stock return, they suggested that turnover is negatively related to illiquidity costs, meaning a highly illiquid stock will understandably have low turnover ratio because investors often need to cross a wide bid-ask spread to trade the stock. Thus, having a high turnover ratio often indicates narrow bid-ask spread and high liquidity in the stock. This is the opposite of price impact analyzed in Chapter 3 because a stock with high price impact indicates low liquidity whereas a stock with high turnover ratio indicates high liquidity. Another study of turnover ratio is presented by Atkins and Dyl (1997). They found a strong positive relationship between transaction costs and holding periods which is measured by the reciprocal of the turnover ratio. Campbell, Grossman, and Wang (1993) also used this turnover measure to analyze the relationship between aggregate stock market trading volume and the serial correlation of daily stock returns. In this paper, we analyze turnover ratio of all US stocks from 1973 to 2015 and study its correlation with price impact and investigate the similarities and differences between the movements of these two liquidity measures.
4.1 Turnover Ratio of all stocks from 1973 to 2015

We first acquire daily data for all common stocks from CRSP database from January 1973 to December 2015. We calculate turnover ratio for every common stock at the end of every month. Given the daily trading volumes $v_{i,1}, v_{i,2}, \ldots, v_{i,T}$ and shares outstanding $S_{i,1}, S_{i,2}, \ldots, S_{i,T}$ for stock $i$ during a specific month with $T$ trading days, we define the turnover ratio $Turnover_i$ for that month as following:

$$Turnover_i = \frac{1}{T} \sum_{t=1}^{T} \frac{v_{i,t}}{S_{i,t}}$$ (4.1)

Similar to our analysis in Chapter 3 section 2, we screen all common stocks to sift out the stocks trading below $5$ and trading above $2000$ a share. At the end of every month from 1973 to 2015, we only include all listed common stocks which have closing prices between $5$ and $2000$ for more than 15 trading days in the past month in our analysis. Figure 4-1 shows the distribution of turnover ratio throughout this period by showing the turnover ratio in 7 percentiles (99th, 90th, 75th, 50th, 25th, 10th, 1st), the same with price impact analysis in Chapter 3. We create the percentile curves by connecting the turnover ratio at the end of every month of the same percentile. In Figure 4-1, we also mark the NBER recession periods in yellow.

Figure 4-1: Turnover ratio from 1973 to 2015 with NBER recession periods marked in yellow
Similar to price impact, we mark the following market events in Figure 4-1 with vertical lines:

1. October 1, 1974: 1973-1974 stock market crash during which the Dow lost over 45% in 2 years.

2. October 1, 1978: 1978 October market decline because of economy deterioration.

3. May 1, 1980: US economy decline in first half of 1980; unemployment rate rose to 7.7% (Burger 1980).


5. July 3, 1990: Iraq invaded Kuwait, causing oil price to increase; Dow dropped 18% in the following 3 months.

6. June 2, 1997: NASDAQ changed its minimum tick size from 1/8th to 1/16th. NYSE followed suit 22 days later.


8. April 3, 2000: NASDAQ-100 dropped over 7.3% in one day, and dropped over 13.4% in past 5 trading days.

9. January 29, 2001: NYSE changed its minimum tick size from 1/16th to 1/100th of a dollar.

10. April 9, 2001: NASDAQ changed its minimum tick size from 1/16th to 1/100th of a dollar.


14. March 14, 2008: Bear Stearns suffered one-day loss of -47.4%.

15. October 6, 2008: Start of the worst week for the stock market in 75 years.


The first thing we notice from Figure 4-1 is that the turnover ratio of higher percentiles generally increase from 1973 to 2015, indicating increasing stock daily trading volume relative to shares outstanding. This upward trend in turnover ratio for stocks with higher relative trading volumes resonates with Campbell, Grossman, and Wang’s (1993) analysis as they found an upward trend in turnover ratio of the 32 stocks with large market capitalization that were traded throughout the 1962-1988 period. Campbell, Grossman, and Wang’s (1993) noted that the growth of turnover ratio in the 1980s may be due to technological innovations that have lowered transactions costs. The continuation of this trend after 1980s and into 2000s supports this reason as the decreased minimum tick size on stock exchanges and increased competition among high speed automated market making firms help drive down the transaction costs.

We can see that higher percentile turnover ratio increased for a larger amount throughout this period than their lower percentile counterparts. This can be interpreted as the more liquid and frequently traded stocks lowered their trading costs more than the relatively illiquid stocks. We use linear regression to analyze the relationship between the turnover ratio and the number of months from January 1973. The linear regression between the 99th percentile turnover ratio time series and the number of months starting from January 1973 has a coefficient of 0.0106 with R-squared value of 0.82, meaning every additional month from January 1973 leads to a 0.0106% increase in the 99th percentile turnover ratio, which represents the most liquid and highly traded stocks. This coefficient is 0.0013 for the 50th

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1 The 32 stocks are American Home Products, AT&T, Amoco, Caterpillar, Chevron, Coca Cola, Commonwealth Edison, Dow Chemical, Du Pont, Eastman Kodak, Exxon, Ford, GTE, General Electric, General Motors, ITT, Imperial Oil, IBM, Merck, 3M, Mobil, Pacific Gas and Electric, Pfizer, Procter and Gamble, RJR Nabisco, Royal Dutch Petroleum, SCE, Sears Roebuck, Southern, Texaco, USX, and Westinghouse.
percentile turnover ratio series with R-squared value of 0.82, meaning every additional month from January 1973 leads to a 0.0013% increase in the median turnover ratio. The coefficient value for the 1st percentile turnover ratio is only 0.00003 with a low R-squared value. This shows that the most illiquid stocks have almost the same relative trading volume throughout these 43 years. One possible explanation is that market makers favor the stocks that are trading more frequently as they are more comfortable providing competitive markets in those stocks knowing they can offload their positions in those stocks minutes or even seconds later. However, even with the decimalization of minimum tick size and enhancement in speed trading technologies, market makers still have to provide wide bid-ask spreads in the most illiquid stocks to protect themselves from the risks of carrying the positions for a longer time. Because of this, trading costs of these illiquid stocks in the 1st percentile turnover ratio never quite improved throughout this period.

4.2 Correlation between price impact and turnover ratio

We can also visualize in Figure 4-1 that large market events marked by the vertical lines generally impacted the turnover ratio in lower percentiles more than the turnover ratio in higher percentiles. This is understandable because the stocks composing the higher turnover percentiles are likely to be more liquid large market-cap stocks whereas the stocks composing the lower turnover percentiles are likely to be less liquid stocks as we already discussed. Though we need more evidences to discern whether investors are more likely to close out their positions in the less liquid small stocks than the more liquid large stocks in a market stress scenario, the action of rapidly selling the less liquid small stocks will accumulate a larger temporary turnover increase in these less liquid stocks because normally they are traded very infrequently.

In contrast to the sharp increase of price impact during the NBER recession periods as we analyzed in Chapter 3, we found that the turnover ratio of all percentiles generally decrease during NBER recession periods as shown by the 1973-1974 recession period, the 1982-1983 recession period, and the 1990 recession period. This is likely because investors
move their investments from stock market to safer assets during recession periods, causing a decrease in the trading activities in the stock markets in general.

We are now interested in studying the relationship between turnover ratio and price impact these two liquidity estimates. Because we expect the relationship between price impact and turnover ratio to be different for relatively liquid stocks and less liquid stocks, we want to analyze them separately. Thus, at the end of each month, we first calculate the 2 year trailing average price impact coefficient, $\lambda$, for each stock and group stocks based on their $\lambda$ values into 3 tercile groups: stocks with $\lambda$ values in the top tercile, 66 – 100%, are the stocks with highest price impact of all stocks hence the least liquid. The stocks with $\lambda$ values in the 3rd tercile 0 – 33% have the least $\lambda$ values hence are the most liquid. The stocks with $\lambda$ values in the 33 – 66% are between the 1st and 3rd tercile groups in terms of price impact. We then use a rolling window of 2 years to calculate the correlation between trailing 2 year monthly price impact coefficients and turnover ratio for each stock in these five groups. Then we calculate the median of the correlation coefficients for the stocks within each group. We perform the above steps at the end of each month from February 1975 to December 2015. We use median instead of mean here to reduce the impact of outliers. The results are shown in Figure 4-2 with vertical lines marking the same set of market events and NBER recession periods marked in yellow.

Figure 4-2: Trailing 2 year correlation between price impact coefficients and turnover ratio of individual stocks in price impact groups
We can see from Figure 4-2 that generally stocks in all three groups have relatively low correlations between their price impact coefficient and turnover ratio, around 0.2 to 0.3 for most of this period. This is expected as a liquid stock generally has lower price impact but higher turnover ratio. We can interpret price impact as a measure of illiquidity whereas turnover ratio is a measure of liquidity. However, we find that price impact and turnover ratio generally do not move in strictly opposite directions based on Figure 4-2, which would cause a negative correlation. This is particularly true for relatively liquid stocks with low price impact represented by the blue and green curve in Figure 4-2. This is likely because price impact for these relatively liquid stocks often increases during market stresses. Meanwhile, turnover ratio for these relatively liquid stocks also increases temporarily in response to market stresses as investors sell large amount of stocks. Thus during market stresses, both measures often move in the same direction, leading to a positive correlation.

However, we observe the stocks with very high price impact in the first tercile represented by the red curve have a decreasing correlation between their price impact and turnover ratio in the periods of 1984-1995 and 2008-2009. While it is hard to map the observed results to any specific events as Figure 4-2 plots the trailing 2 year correlation, we provide a hypothesis for this observation. As we can see from Figure 3-1 in Chapter 3 that the price impact for the most illiquid stocks (99th percentile) sharply increases in both periods of 1984-1995 and 2008-2009. The latter can be contributed to the starting of the 2008 Financial Crisis. On the contrary, the turnover ratio for these two periods for the most illiquid stocks (1st percentile) as we can see from Figure 4-1 did not increase much, creating a difference in the direction of movement of these two measures. Thus, the correlation of these two measures drops in these two periods. One possible explanation for this phenomenon in 2008-2009 is that liquidity providers fearing economic downturn make the already wide bid-ask spread for these illiquid stocks even wider, dramatically increasing the trading costs and price impact of these illiquid stocks. However, the trading volume of these stocks did not dramatically increase because they have low trading volume to begin with and investors still do not trade these stocks that much during the market shocks, leading to a relatively stable turnover ratio for these stocks during 2008-2009.
We now instead calculate the 2 year trailing average turnover ratio for each stock at each end of month and group the stocks into 3 groups based on the 2 year trailing average turnover ratio. Similar to the previous case, we then use a rolling window of 2 years to calculate the correlation between trailing 2 year monthly price impact coefficient and turnover ratio for each stock in these 3 groups and compute the median of the correlation coefficients within each group. We perform the above steps at the end of each month from February 1973 to December 2015. The results are shown in Figure 4-3 with same set of market events marked with vertical lines and NBER recession periods marked in yellow.

Figure 4-3: Trailing 2 year correlation between price impact coefficients and turnover ratio of individual stocks in turnover ratio groups

Comparing to Figure 4-2 in which we plotted correlation based on price impact groups, the trends in Figure 4-3 are more straightforward. We see in Figure 4-3 that the most traded stocks with turnover ratio in the $66-100\%$ tercile, represented by the red curve, have the highest correlation with between turnover ratio and price impact. By contrast, the least traded stocks with turnover ratio in the $0-33\%$ tercile represented by the blue curve, have the lowest correlation between turnover ratio and price impact. The correlation of stocks in the three groups generally move with the same pattern until around 1992. The observation that more frequently traded stocks with high turnover ratio have higher correlation between turnover ratio and price impact and vice versa can be attributed to the fact that price impact and turnover ratio of these liquid stocks will both sharply increase in response to market shocks as we discussed previously. This is because investors are rapidly trading these stocks.
in and out their portfolios. However, the less liquid stocks’ turnover ratio mostly stay at the same low level whereas their price impact nevertheless increase as trading costs increase and quoted depths get shallower during market shocks, resulting in a low correlation between the two measures.

Another observation is that the price impact turnover ratio correlation of stocks in the three groups generally move in similar patterns until 1992. Then the price impact turnover ratio correlation of the most traded stocks, represented by the red curve, increases from 1992 to 2015. The same pattern appears on the green curve, representing the next tercile of frequently traded stocks, though not as much. We provide a hypothesis for this observation. The advancement in trading technology and the proliferation of high speed market makers enable the investors to rapidly adjust their portfolios in response to market events, which causes the turnover ratio to move in the same direction as price impact more often and increases the correlation between the two measures.

This applies more to the popular and more frequently traded stocks than small market cap stocks that are not well known because of two possible reasons. The first is that large institutional investors prefer to trade large and liquid stocks as pointed out by Blume and Keim (2012) in their analysis of the relationships between institutional investors and stock market liquidity. Blume and Keim (2012) also showed in their analysis that the percentage of the stocks held by institutions have steadily grown in the period from 1982 to 2010. This creates a self-reinforcing trend which makes large market cap liquid stocks trade more frequently and respond to market events more promptly. This result is also supported by Bennet, Sias and Starks’ (2003) analysis which shows there is a positive relation between the percentage of a stock owned by institutions and turnover. The second reason can also potentially explain the start of this trend in the early 1990s. Starting from the early 1990s, day trading gradually became more popular because of the removal of the Professional Trader Rule which prevented them from such practices, as noted by Harris and Schultz (1998). Examples include the "SOES bandits" who trade on the NASDAQ’s Small Order Execution System (SOES) and take advantage of the delay when market markers adjust their quotes (Chaudhuri 2014). Day traders often prefer large market-cap liquid stocks because of the
lower transaction costs in these stocks. The turnover ratio of these liquid stocks increases more promptly in response to daily market events because of day traders’ preference to them and an increasing amount of day trading activities starting from the early 1990s. This explains the increasing correlation between price impact and turnover ratio starting from the early 1990s.
Chapter 5

Trading Frequency

In this chapter, we analyze the market liquidity using intraday trading frequency. There have been a number of studies analyzing intraday stock trading activities. Jain and Joh (1988) analyzed hourly common stock trading volume and returns on the New York Stock Exchange and found that the average trading volume is highest during the first hour, declines until the fourth hour, but increases again on the fifth and the sixth hours, which is consistent with our findings in this chapter. Whereas Jain and Joh (1988) studies hourly trading volume for common stocks on the New York Stock Exchange, we study the number of trades in intervals of one minute during the trading hours from 9:30 EDT to 4:00 EDT for all common stocks trading on US stock market. Although trades are often executed in a split second today with the help of modern trade execution technologies and platforms, the number of trades executed in a short interval such as one minute still approximates trading frequency. A higher number of trades within a minute indicates higher trading frequency within that minute and vice versa. At the same time we analyze the implications of the movement of this statistic. We acquire intraday trades data for all stocks from NYSE Trade and Quote (TAQ) database. We will perform the analysis in the following case studies.
5.1 Quant Meltdown: August 6, 2007

Quant Meltdown was a crisis that started on Monday, August 6, 2007 and lasted for about 3 days during which all the quantitative hedge funds and trading shops suffered major loses in their equity portfolios whereas the larger equity market indexes seemed not to be impacted. Many theories have tried to explain the reasons behind the Quant Meltdown. Khandani and Lo (2010) found that the loss in the equity portfolios can be explained by the triggered systematic unwinding of the equity positions in many hedge funds’ portfolios. Quant Meltdown is a classic example of equity market crisis in which only certain type of quantitative strategies suffer but the larger market is less impacted.

We first compute the number of trades that happened in every minute interval from 9:30am to 4:00pm EDT for every stock. Because different stocks have vastly different number of trades and it is pointless to compare the sheer number of trades between different stocks, for every stock we compute the ratio of minute level number of trades to the total number of trades on this day for every minute interval from 9:00am to 4:00pm on this day. Then for every minute interval, we compute the median weight of number of trades across all stocks analyzed within this minute interval. We present the results in Figure 5-1. From Figure 5-1, we can see that most minute intervals contain a median number of trades weight of 0.1% to 0.4% of all trades within that day. The peaks happen at around 10am and towards the end of the trading day. The high trading volume at the beginning of the day and towards the end of day are likely caused by trading activities to re-balance portfolio positions based on overnight news at the beginning of the day and to adjust the portfolios before market closes. The low volume during the middle of the day is likely caused by quiet market conditions and lunch breaks. Even though there seem to be cyclic patterns in the minute level number of trades, frequency decomposing analysis indicates that the biggest cycle is still the trading day from 9:30am to 4:00pm indicated by the peaks around 10am and 4pm and the bottom during the middle of the day around 1pm.
5.2 First day of the worst week in 2008 Crisis: October 6, 2008

The same analysis and computation is applied to all the stocks on Monday, October 6, 2008, which is the start day of the worst week during the 2008 financial crisis. During the week of October 6th, 2008, S&P 500 index dropped 200.01 points or -18.20%. The results are shown in Figure 5-2. From Figure 5-2 we can see that most intervals contain a median number of trades weight of 0.1% to 0.4% of all trades within that day, similar to August 6, 2007. The peaks again happen between 10am to 11am and after 3pm in the afternoon. Comparing to August 6, 2007 in Figure 5-1, a lot more trades happen after 3pm on October 6th, 2008. This can be interpreted as the following: whereas the Quant Meltdown on August 6, 2007 impacts more specifically the equity portfolios of quantitative hedge funds, the start of the worst week in 2008 Crisis impacts the whole general equity market. As time approaches 4:00pm, more and more market participants rushed to sell their positions or adjust their portfolios, causing the spike in the trading activities in the US stock market.
5.3 Flash Crash: May 6, 2010

Now we analyze the trading activities on Thursday, May 6, 2010 which is the day of the 2010 Flash Crash. In Kirilenko, Kyle, Samadi, and Tuzun’s (2014) analysis of the Flash Crash, the CFTC-SEC reports noted that the Flash Crash started at 2:32pm EDT and lasted for about 36 minutes. Within 36 minutes, S&P 500 index, Dow Jones Industrial Average, NASDAQ Composite, and other major stock indexes plunged before bouncing back to their previous levels. During the event, the liquidity in the stock market seemingly vanished, causing hundreds of thousands of sell orders to be executed at extremely low prices or extremely high prices. The stocks of eight major companies in the S&P 500 fell to one cent per share for a short time, including Accenture, CenterPoint Energy and Exelon; while other stocks, including Sotheby’s, Apple Inc. and Hewlett-Packard, increased in value to over $100,000 in price (Grocer 2010; Lauricella & McKay 2010). A study of intraday trading patterns on this day will provide us with more insights of how minute level trading activities respond to market shocks. We apply the same computation to all stocks on May 6, 2010 as we did in
the previous two sections and show our results in Figure 5-3.

![Figure 5-3: Minute interval number of trades weight on May 6, 2010]

We can clearly visualize the impacts of the Flash Crash in Figure 5-3. We actually see the number of trades started to increase dramatically at around 2:15pm EDT, about 15 minutes earlier than the start time noted in the CFTC-SEC report. The minute level trading frequency decreased to normal level around 3:00pm EDT. At the peak in this period, the minute level number of trades reached 0.76% of all the trades within that day at around 2:45pm. This observation generally matched with the timeline in Kirilenko, Kyle, Samadi, and Tuzun’s (2014) analysis of the Flash Crash. The CFTC-SEC report marked the start of the Flash Crash as 2:32pm because a large fundamental trader initiated a sell program to sell a total of 75,000 E-Mini contracts at 2:32pm, which contributed to the steep decline of the price of the S&P 500 index according to the CFTC-SEC report. Our analysis shows that the start time of maniac trading activities on that day can be as early as 2:15pm EDT, as shown by the sharp increase in the number of trades starting around 2:15pm EDT.

The movement of minute level median number of trades weight sheds light on the movement of intraday trading frequency and market liquidity. We find that the trading frequencies are higher around 10am and after 3pm possibly due to investors responding to
overnight news and adjusting portfolios before the market closes. Companies often release earnings data soon after the market closes, which also contributes to the increasing number of trades towards the market close as investors responds to information right before the earnings data. Temporary intraday market shocks such as the Flash Crash will dramatically increase the trading frequency right after the market shock happen. The sudden increasing of trading activities also indicate a sudden decrease in the market liquidity as trading costs often increase during these market shocks.
Chapter 6

Conclusion

In this thesis we study the liquidity aspect of the US stock market microstructure from 1973 to 2015. With knowledge of the US stock market microstructure changing throughout this period due to the technological changes in stock exchanges and proliferation of quantitative trading strategies, we delve deep into the analysis of US stock market liquidity from the three perspectives of price impact, turnover ratio, and trading frequency. We use the Center for Research in Security Prices (CRSP) and Trade and Quotes (TAQ) databases to acquire stock data across different time span to perform analysis across different time horizons, including stock listing and de-listing analysis using monthly trades data, price impact and turnover ratio analysis using daily trades data, and intraday trading frequency case studies using intraday trades data.

We start by using monthly stocks data for all stocks from The Center for Research in Security Prices (CRSP) database to perform stock listing and de-listing analysis and inspect the composition of the stocks applying Kenneth French’s 10 industry categorization. This analysis is important for the analysis of market liquidity not just because it provides us with an overview of the composition of the stock market, but more importantly, because sudden decreases in new stock enlisting and increases in stock de-listing often associate with tight funding liquidity during economic downturns, which likely leads to market selloffs and
decreasing market liquidity. In this analysis, we find that the biggest type of de-listing is mergers for all industries and we see a sharp increase in de-listing due to bankruptcy during the periods of market turmoils. We also visualize the impacts of the tech bubble burst by observing the steady increase in new stock enlisting from 1991 to 1996 and a rapid decrease in the new stock enlisting and increase in de-listing after 1997. Through the enlisting and de-listing analysis, we also arrive at the same conclusion as Doidge, Karolyi, and Stulz’s (2015) that the low new stock lists after 1997 is a more important reason than the high delists after 1997 that explains the decreasing number of listed firms after 1997.

With an understanding of the number of the stocks listed on the US stock market and its implications, we analyze price impact of all common stocks in US stock market from 1973 to 2015 using daily trading data from CRSP database. We use linear regression between the a stock’s holding period return and the natural log of its dollar trading volume to estimate the price impact. This approach is inspired by Kyle’s (1985) model and applied in Khandani and Lo’s (2010) analysis of price impact of stocks within S&P 1500, S&P 500, and other index baskets. We find that price impact sharply increases in response to market selloffs and global events which might negatively impact the US stock market. Price impact for illiquid stocks also increase more than for liquid stocks understandably because of the much deeper quoted depth and tighter bid-ask spread for the liquid stocks. We then perform frequency decomposition of price impact coefficients using Discrete Fourier Transform (DFT) and reconstruct price impact coefficient series using Inverse Discrete Fourier Transform (IDFT) from 1973 to 2015. We find important price impact cycles, hence market liquidity cycles, of 8.6 years and 4.3 years. The price impact cycle of 8.6 years can be interpreted as economic cycles as the occurrences of the peaks in price impact generally match with the NBER recession periods. Though this smaller price impact cycle of 4.3 years are triggered by different type of events such as small economic downturns or single usually large market selloffs (1987 Black Monday), we find evidences that show the reason behind this smaller price impact cycle is that the economic stimulating policies designed to help the economy recover from large recessions are reduced or repealed 4 to 5 years after large recessions, creating small market downturns and increasing price impact.
We then analyze turnover ratio for all common stocks from 1973 to 2015 using daily trading data from CRSP database. Turnover ratio is the ratio of trading share volume to shares outstanding. We find that the turnover ratio decreases during NBER economic recession periods likely because investors stay away from the US stock market fearing market decline during economic downturns. We also find that the turnover ratio increases more for illiquid stocks than liquid stocks in response to market events. We interpret this observation as a large amount of investors rush to trade these illiquid stocks to respond to the market events when they rarely trade these illiquid stocks normally. We then group stocks based on price impact and turnover ratio respectively and in each case analyze the trailing 2 year correlation between turnover ratios and price impacts within each group. We find that the liquid stocks with higher turnover ratio exhibit higher correlation between their turnover ratios and price impacts than illiquid stocks with lower turnover ratio. This is because the high liquidity in the liquid stocks allow investors to more rapidly adjust their positions in these stocks, leading to increasing turnover ratio, in response to market events during which the price impact increases. This causes turnover ratio for these liquid stocks to move in the same direction as the price impact more often, resulting in a higher correlation. By contrast, for illiquid stocks, the price impact quickly increases to respond to unfavorable market events but the turnover ratio responds slower because of the higher transaction costs in these stocks and low trading volume in these stocks. The observation that the correlation between turnover ratio and price impact for liquid stocks with high turnover ratios steadily increase starting from the early 1990s can be contributed to the proliferation of day trading starting from the early 1990s and the advancement of trading technologies, both of which help investors in these liquid stocks react to market events faster and faster. This increases turnover ratio more promptly following the increase in price impact.

Finally we perform intraday cases studies using intraday trades data from NYSE Trade and Quote (TAQ) database on August 6, 2007, October 6, 2008, and May 6, 2010 for the 2007 Quant Meltdown, first day of worst week in the 2008 Financial Crisis, and the 2010 Flash Crash respectively. We inspect the number of trades for every stock every minute from 9:00am EDT to 4:00pm EDT for these three cases. We use the number of trades within one
minute as a proxy for trading frequency. We find evidences that most trades happen around 10am and towards the end of the trading day around 3:30pm hence the market liquidity are most abundant during these peak time. Our findings are consistent with Jain and Joh’s (1988) analysis of hourly common stock trading volume and returns in which they found that the average trading volume is highest during the first hour, declines until the fourth hour, but increases again on the fifth and the sixth hours. This pattern is likely caused by investors adjusting their portfolio soon after market opens based on overnight news and before market closes in preparation for market close. We can also deduce irregular market behavior and liquidity shocks from unusual increase and decrease in trading frequency during the day, such as from 2:15pm to 3:00pm on May 6, 2010 for the Flash Crash.

The range of techniques that we use and different time horizons we inspect for different liquidity measures in this study provide us important insights to the movement of market liquidity under the context of the changing market microstructure due to advancements in both technology platforms and trading strategies. This also paves the road for future research to understand and preempt systematic breakdown and liquidity shocks in the stock market.
Appendix A

Symmetry in Spectral Analysis

Here we will show that $Re(F_1[k])$, for $k = 1, \ldots, N - 1$, is symmetric about $N/2$. Proof:

From Equation 3.4 we know that for $k = 0, \ldots, N - 1$,

$$F_1[N - k] = \sum_{n=0}^{N-1} f_1[n] e^{-j \frac{2\pi}{N} n(N-k)} \quad (A.1)$$

$$F_1^*[N - k] = \sum_{n=0}^{N-1} f_1[n] e^{j \frac{2\pi}{N} n(N-k)} = \sum_{n=0}^{N-1} f_1[n] e^{-j \frac{2\pi}{N} n(k)} = F_1[k], \quad (A.2)$$

where $F_1^*[k]$ is the complex conjugate value of $F[k]$. Here we distribute the complex conjugate in addition. From Equation A.2, we can see that $F_1[k] = F_1^*[N - k]$. Thus,

$$Re(F_1[k]) = Re(F_1^*[N - k]) = Re(F_1[N - k]). \quad (A.3)$$

From Equation A.3, it shows that $Re(F_1[k])$, for $k = 1, \ldots, N - 1$, is symmetric about $N/2$. Therefore it is sufficient to consider only frequencies where $0 \leq k \leq \left\lfloor \frac{N}{2} \right\rfloor$ when performing
spectral analysis.
References


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