Liquidity in the Covid-19 Era

Finlay G. Benton

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Abstract

This paper documents significant empirical evidence surrounding liquidity in the new and compelling data point of the Covid-19 pandemic. Evidence is produced through established methods, providing insights into investor behavioural change around groups of stocks from the S&P500 index, sorted by liquidity sensitivity. Furthermore, the market pricing of liquidity is observed throughout periods surrounding monetary policy announcements by the Federal Open Market Committee, in response to the outbreak. Observations of the existence of a liquidity premium are documented in periods of Quantitative Easing and Quantitative Tightening, as well as during the control period from before the outbreak of Covid-19. However, the liquidity premium is absent during the period of the outbreak and subsequent market crash, adding to evidence of the pertinence of liquidity during times of market downturn. Other evidence suggests the capacity of Quantitative Easing and Quantitative Tightening to influence liquidity through innovations in the degree of pricing. Overall, this paper helps to build the link between aggregate (market) liquidity and stock-level liquidity concerning the S&P500 stocks.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Finlay G. Benton

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1. Introduction

Over the last four decades, liquidity has become one of the finance profession's biggest centres of attention. While numerous prior studies have provided extensive theoretical and empirical documentation, a complete definition and measurement for liquidity alludes us. However, it is generally described as the ability to trade large quantities of an asset at low cost, with efficient pace and little impact on price. In times of market downturns, and especially in the case of outright market crashes, liquidity becomes an especially important matter. With much of the recent literature completed on the Global Financial Crisis (GFC) of 2007-09, there is incentive to discover other pertinent data points. The recent and ongoing Covid-19 pandemic appears to be a suitable candidate, given the scale of implications for the global economy and the unprecedented monetary policy response by central banks around the globe.

The outbreak of Covid-19 and the corresponding lockdowns and restrictions on gatherings, during March of 2020, lead to mass amounts of layoffs and shut-downs in manufacturing, retail, and hospitality. The implications of these drastic measures caused one of the worst stock market crashes in recent history. Largely due to excessive fear and uncertainty surrounding the outbreak, stock markets faced record volatility, with circuit breaker mechanisms being hit four times in ten days (Zhang et al, 2020). On March 31st, 2020, the Standard and Poors 500 index (S&P500 hereafter) fell ~20%, while the Dow Jones Industrial Average (DJIA) and FTSE100 declined ~23% and ~25%, respectively (Li et al, 2021). As such, central banks around the world took extraordinary measures to end the bloodshed in asset prices and begin stimulating the economy towards recovery. On March 15th, 2020, the United States Federal Open Market Committee (FOMC hereafter) announced its intension to provide stimulus to the US economy in the form of Quantitative Easing (QE), with total purchases of $500 billion in Treasury securities and $200 billion in Mortgage-backed securities. In doing so, the FOMC essentially flooded markets with a record amount of liquidity. However, as the pandemic wore on, criticism of the extent to which the US Federal Reserve balance sheet had been expanded began to arise, with questions about how this would affect inflation. In turn, the Federal Reserve went on to taper their asset purchases over a series of months throughout 2021 and early 2022. Then, the FOMC announced on May 4th, 2022, the intension to begin reducing the balance sheet, through the inverse of QE, Quantitative Tightening (QT). Quantitative Tightening (the selling of debt securities) was signalled to be completed at a maximum pace of $60 billion of Treasury securities and $35 billion of Mortgage-backed securities per month. Prior literature has shown that these types of monetary policy have pervasive effects on aggregate liquidity (referring to the ease of execution for transactions within an entire market, which largely depends on the size of a nation's money supply), thereby affecting market directionality and stock returns.

Though the literature on liquidity is already extensive, the unprecedented monetary response to the Covid-19 pandemic provides a unique opportunity to investigate ideas surrounding liquidity. As such, this study investigates investor behavioural changes, specific to the S&P500 stocks, as well as innovations in the pricing of liquidity during different stages surrounding the Covid-19 pandemic and the initial announcements of QE and QT. Finally, I investigate the presence of a liquidity premium, referring to the additional return that a security yields to compensate an investor for the potential loss of monetary utility incurred through price impact costs. That is, the additional compensation an investor requires for holding securities that are illiquid. The sample chosen for this study is the constituents of the S&P500, given its popularity as a suitable proxy for the US economy. While the DJIA is perhaps more well-known and quoted more often, it is only made up of 30 stocks, offering much fewer observations and likely substantially less variation in the parameters estimated in the analysis. This study reveals that, compared to a control period from before the pandemic, investors become unwilling to invest in the S&P500 stocks that are less liquid during the period of the market downturn coinciding with the virus outbreak, during Quarter 1 of 2020. However, during the period of QE, the willingness of investors to take on the risk of holding these illiquid stocks increases once more, before falling again during QT. Evidence of a liquidity premium is also observed during the control, QE, and QT periods, helping to confirm these results. Moreover, I provide additional data points evidencing the degree to which liquidity is priced throughout, finding that the market prices liquidity higher during the period of the outbreak and during QT. Lastly, evidence suggesting the capacity for QE and QT to affect liquidity is found, overall helping to build the link between aggregate liquidity and stock-level liquidity.

The remainder of the paper is organised as follows. Section 2 provides an overview of the prior literature pertaining to liquidity and asset pricing. The section begins with works completed under association with monetary policy, moving through into liquidity descriptions and testing methods, a deep dive into the methods of testing employed in this study, as well as a brief history of asset pricing and multifactor modelling before ending with the central ideas of the study. Section 3 provides a description of the data set, including descriptions of the company characteristics and the methods of sorting by way of liquidity sensitivity, as well as portfolio construction. Further, omitted companies and the description of the construction of the Fama and French factors, as well as the liquidity factors used in the analysis are included. In Section 4, the methodology of the analysis is described, with formulas for each method specified alongside explanations of what each method attempts to achieve. Assumptions of what I expect to document are also included here. Section 5 provides the results of the analysis and interpretations. Section 6 concludes.

2. Literature Review

Various forms of monetary policy have been studied in relation to liquidity, with evidence confirming its ability to drive the expectations of market participants and the overall sentiment of the market. Bernanke and Kuttner (2005) had success investigating FOMC policy, finding that stock prices were impacted positively (negatively) to targeted federal funds rate cuts (hikes), (see also Rigobon and Sack, (2004)). Further, Fernandez-Amador et al (2013) provide evidence in Italian, German, and French markets that the expansionary monetary policy of the European Central Bank (ECB) led to higher stock market liquidity. Mishra et al (2020) investigate the impacts of conventional and non-conventional monetary policy, with findings that have reference to this study. They found evidence that suggests that the FOMC's purchases of Treasury securities, in response to the GFC, positively affected stock-level liquidity. In contrast, however, the purchase of Mortgage-backed securities had minimal or even negative impacts. Moreover, Christensen and Gillan (2019) argue for the potential of QE to reduce priced frictions to trading through an observed liquidity channel. Having analysed the link between Treasury Inflation Protected Securities (also known as TIPS) and the market for inflation swaps (a market heavily tied to investor sentiment around inflation), they found that QE can significantly improve the functionality of financial markets. This was evidenced through the reduction of the liquidity premium in the observed liquidity channel, i.e., the liquidity premium decreases when aggregate liquidity increases and vice versa. Furthermore, Kappor and Peia (2021) studied the effects of QE on liquidity creation, through commercial bank lending. Specifically, they found that banks with a large portion of pre-existing mortgage-backed securities produced significantly more real estate and commercial loans, thereby increasing overall market liquidity. However, other findings in the study point to some asymmetry in the effects of QE across commercial banks, that is, the new liquidity creation wasn't entirely consistent throughout the whole period of the QE program. Thus, there is evidence of some ambiguity.

Liquidity is said to be multidimensional, considering trading cost, tradable quantity (or depth), price impact (how easy it is to trade a given quantity with minimal impact on price) and time, as exhibited through resiliency in liquidity in the wake of order-flow shocks (Black et al, 2016; Le and Gregoriou, 2020). As such, many methods of testing liquidity sensitivity have arisen over the years, like the turnover measurement of trading quantity produced by Datar et al (1998). Other methods include the bid-ask spread of Amihud and Mendelson (1986), a way of measuring liquidity through the trading costs dimension, and the multidimensional measurement of Liu (2006), known as the standardised turnover-adjusted number of zero daily trading volumes. This study, however, focusses on two price impact methods. Price impact, as described by Stange and Kaserer (2009), is a consequence of the imperfect elasticity of demand and supply curves for a security at a particular moment (Reflected in the size and quantity of orders). Given this logic, the price impact increases along with the size of transactions. It is said that if an asset is perfectly liquid, in terms of price impact, then the asset can be traded in any quantity without influencing its future price. The first method I employ is that of Amihud (2002). The 'Return to Volume Ratio' measures the average daily ratio of absolute stock return to dollar volume, following the intuition that a security is illiquid if its price moves significantly in response to low trading volume. Simply put, the method measures the price impact for a security on a given day, in response to a dollar of trading volume. Lou and Shu (2017) posit that a large part of the value derived from the return to volume ratio is the correlation with trading volume, enabling an accurate representation of price impact, given the logic of Stange and Kaserer (2009). Furthermore, the Amihud (2002) method displays benefits over other methods, requiring only data on daily return and volume, which are readily available in most, if not all markets. Some methods involving trading costs require detailed data on transactions that are harder to obtain, especially in emerging markets. The return to volume ratio may act as a proxy to help deal with this issue, using the data that is available from these smaller markets, due to the ability to capture price impact and convert it into transaction costs (Acharya and Pederson, 2005).

Although the return to volume ratio is a more convenient and accurate measure than some, there are a few drawbacks. According to Cochrane (2005), there is a significant bias associated with the size of a company. It is found that stocks with larger market capitalizations will tend to be more liquid, automatically. This poses a problem because stocks with different market values are unable to be accurately compared. Further, while Amihud (2002) assumes that trading frequency is similar across stocks and should not have a significant effect on liquidity premia, Florackis et al (2011) argue otherwise. They point to evidence, produced by Datar et al (1998), that the assumption is unrealistic given that there is substantial cross-sectional and time-series variation in trading frequency across stocks. Considering these drawbacks, another method of measuring liquidity sensitivity has been employed to provide robustness. The 'Return to Turnover Ratio' produced by Florackis et al (2011) was proposed, having considered the drawbacks of the Amihud (2002) method. As shown in Section 3, the denominator in the return to volume ratio formula (volume) is replaced by the turnover ratio in the return to turnover ratio method. As such, the return to turnover ratio provides a similar inherent explanation of liquidity sensitivity, reflecting the impact of 1% of turnover ratio on price. The method also benefits from requiring similarly easy to obtain data as the return to volume ratio, meaning it is equally as convenient for use in analysis. Furthermore, according to Florackis et al (2011), the return to turnover ratio can overcome the size bias of the Amihud (2002) method, in that there is no observed relationship between firm size and turnover ratio. So, firms of differing size may be more accurately compared. They also contend that because the return to turnover ratio integrates trading costs with frequency effects, the method is superior. This point is made by referencing the first proposition of Amihud et al (2005), that the expected return on a security for a risk-neutral investor is given by:

$$E(r_i) = R_f + \mu \frac{C_i}{P_i}$$

Where, $E(r_i)$ is the expected return of asset i, R_f is the risk-free rate, C_i represents transaction costs, P_i represents the price of asset i and μ is the trading intensity of the investor. The proposition suggests that the expected return is positively correlated with both transaction costs and trading frequency, thus, price is impacted by a combination of both aspects.

In asset pricing theory, the seminal work of Sharpe (1964) and Lintner (1965) suggested that an asset's expected return could be explained as a positive linear function of the asset's individual beta and the market beta. In simple terms, the expected returns of assets are proportional to beta, i.e., a stock with a beta lower than 1 will produce lower returns proportional to the return on the market, and vice versa. Further, the traditional static Capital Asset Pricing Model (CAPM) assumes that the market return is adequate to explain the cross-section of returns. However, it is likely that this hypothesis will never truly be tested, as Roll (1977) famously criticised, because the true market portfolio is unobservable. This is largely because the exact composition cannot be known, thanks to intangibles such as human labour making the endeavour next to impossible.

Building off the static model, Merton (1973) introduced the dynamic Intertemporal version of the CAPM, ridding the primitive model of many objections of the Markowitz mean-variance criterion. In more recent years, Fama and French (1992) introduced the famous Fama French three-factor model, with the factor loadings; excess market return (Mkt), size or “Small minus big” (SMB) and book-to-market equity or “High minus low” (HML). Each of the factors have been found to have significant power in explaining returns, with the likes of Liew and Vassalou (2000) revealing that both SMB and HML contain important information about future GDP growth. Moreover, they find that the predictive power of SMB and HML is not absorbed when including the market factor or other business cycle related factors. Over the years, researchers have constructed other factor loadings in attempt to fully capture the explanation of the cross-section of returns, see Basu (1977), Hansen and Jaganathan (1997), Jegadeesh (1990), Bhandari (1988) and Fama and French (2015) for more.

Perhaps the most central ideas to this study are the following: firstly, Pastor and Stambaugh (2001) found that aggregate liquidity is an important state variable in pricing securities. They posit that the more sensitive a security is to changes in aggregate liquidity, the higher the return on that security can be expected. Secondly, Acharya and Pederson (2005) predicate that liquidity is unobservable as a variable and as such, there is great motivation to find suitable proxies for liquidity to be used in analysis. They further contend that some proxies used in the past, such as techniques involving the bid-ask spread, are improper. While bid-ask-spread related proxies may give accurate measurements of share sale costs in small trading lots, much of their accuracy is lost when the trading lot size in increased. However, according to O’Hara (2003), both risks of price discovery and transaction costs need to be integrated into asset pricing models. As such we follow the method of Liu (2006) in constructing a liquidity proxy for use in this study. Liu (2006) utilises a mimicking portfolio that buys $1 of a portfolio of the lesser-liquid stocks and sells $1 of the portfolio of the more-liquid stocks, after sorting. The usage of mimicking portfolios is well-documented, as Breeden et al (1979) provided; state variables may be replaced by appropriate mimicking portfolios in the intertemporal asset pricing model of Merton (1973). Further, Chen et al (1986) constructed several macroeconomic factors using mimicking portfolio techniques, which went on to be used by Breeden et al (1989) as proxies for aggregate consumption growth. Even Fama and French (1996) constructed their SMB and HML factors using the technique, in efforts to capture distress risk. Finally, Liu (2006) found that the liquidity mimicking portfolio is significantly negatively correlated with the market, which is logical as investors require a higher liquidity premium as compensation for bearing higher liquidity risk during times of poor economic performance, or market downturns.

3. Data Description

3.1 Sample Data

The sample used in this study is the constituents of the S&P500, for the period of January 1st, 2019, to June 30th, 2022. The following companies, however, have been omitted due to data constraints: Dow, Amcor, Fox (A and B shares), Carrier Global, Otis Worldwide, Corteva, Organon, Constellation Energy, and Bath and Body Works. The data set for each stock includes observations of the daily adjusted close price, daily trading volume and daily number of shares outstanding. The datasets were obtained through DataStream. A description of the firm characteristics is given in Table 1:

Table 1

Firm Characteristics

	Market Value ($000's)	Market To Book
Minimum	3,415.625	-418.79
Maximum	1,778,432.51	215.66
Median	25,872.26	3.205
Average	61,648.93	2.72

There is quite a wide range of firm size between the constituents that make up the sample. Given that the smallest market capitalization is $3.4 billion, it can be said that the constituents range between medium and large companies, as small-cap firms are generally described as those falling under the market value of $2 billion. Similarly, the range of the market-to-book ratios is quite large, although it is likely there are outliers on both ends of the spectrum, given the comparatively small mean and median values.

Further, observations for the daily Fama and French Factors, size (SMB) and book-to-market (HML), as well as the market factor (Mkt) were obtained from Ken French's data library.

According to the website, the specification of the construction methods for each factor is as follows:

- Market Factor: the market factor is constructed as the value-weighted excess returns on all CRSP firms listed on the NYSE, AMEX, and NASDAQ, incorporated in the United States.
- 'Fama/French Factors': are formed using six value-weighted portfolios formed on size and book-to-market ratio. The six value-weighted portfolios are constructed, using all NYSE/AMEX/NASDAQ stocks, at the end of each June as the "intersections of two portfolios formed on size and three portfolios formed on the ratio of book equity to market equity." ("Details for 6 Portfolios Formed on Size and Market-to-Book," n.d.).

- SMB: from here, SMB is constructed as the average return on the three small company portfolios minus the average return on the three large company portfolios, i.e.,

SMB = 1/3 (Small Value + Small Neutral + Small Growth)
- 1/3 (Big Value + Big Neutral + Big Growth).

- HML: similarly, HML is constructed as the average return on the two value portfolios minus the average return on the two growth portfolios, i.e.,

HML =1/2 (Small Value + Big Value)
- 1/2 (Small Growth + Big Growth).

3.2 Liquidity Sensitivity, Sorting & Portfolio Construction

In testing the liquidity sensitivity of the S&P500 stocks, I first employ the use of the Amihud (2002) return to volume ratio. The liquidity measure (or more specifically illiquidity measure) simply relies on the daily return data and trading volume. The Amihud (2002) definition of illiquidity is the average ratio of the absolute return to the dollar volume on a given day. In other words, the return to volume method computes the average of absolute daily returns per dollar traded for a period of D consecutive trading days, i.e., solving for the following:

$$RtoV_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Di} \frac{|R_{idt}|}{DVOL_{idt}}$$

Where, $RtoV_{it}$ is the return to volume ratio for stock i in period t, D_{it} is the number of trading days in the period t for stock i, R_{idt} is the return of stock i on day d in the period t, and $DVOL_{idt}$ is the dollar volume of stock i on day d in the period t. Essentially, the ratio provides that a stock is illiquid if the return to volume ratio is high, insinuating that stock price moves substantially in response to little change in volume.

To ensure the analysis is robust, I employ the second method of testing liquidity sensitivity, the return to turnover ratio of Florackis et al (2011). Firstly, however, I compute the individual turnover ratio of each constituent, that is, the ratio of trading volume to the number of shares outstanding each day. Then, the return to turnover ratio is calculated, defined as the daily absolute return scaled by the turnover ratio. Formally, it is defined as:

$$RtoTR_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{TR_{idt}}$$

Where, $RtoTR_{it}$ is the return to turnover ratio of stock i in period t, D_{it} is the number of valid trading days of stock i over time t, R_{idt} is the daily return of stock i in day d, and TR_{idt} is the turnover ratio of stock i in day d, for period t.

Then, for each method of testing, the stocks are sorted into deciles from least liquid to most liquid. Portfolios are constructed for each decile, using the equal-weighted returns, resulting in a total of 20 portfolios.

4. Methodology & Assumptions

4.1 Construction of Liquidity Factors & Observing Investor Behavioural Change

To construct a liquidity factor, I follow Liu (2006). After sorting the stocks into deciles and forming portfolios for each, a liquidity mimicking portfolio is constructed as the profit from buying one dollar of the equally weighted least-liquid portfolio (LL) and selling one dollar of the equally weighted most-liquid portfolio (ML). This process is completed for both versions, RtoV and RtoTR, to form two separate liquidity factors. Table 2 provides the descriptive statistics of each liquidity factor below:

Table 2

Liquidity Factor Descriptive Statistics

	RtoV	**RtoTR**
Minimum	0.000459	-0.00033
Maximum	0.001855	0.000841
Median	0.001123	0.000327
Mean	0.001249	0.000213

To investigate formally whether investor behaviour, concerning the S&P500 stocks, changes significantly surrounding the monetary policy announcements in response to the Covid-19 pandemic, I make observations on the return difference between LL and ML during four respective time periods. Firstly, January 2nd, 2019, to December 31st, 2019 – a period from before the pandemic, for use as a benchmark/control. Secondly, a period during Quarter 1 of 2020 during the outbreak and consequent market crash, i.e., January 1st, 2020, to March 13th, 2020. Next, from the day after the announcement of QE and throughout QE, up until the day before the announcement of QT – March 16th, 2020, to May 3rd, 2022. Lastly, from the day of the announcement of QT and the period of QT up until as recent as available data would allow at the time of this analysis, May 4th, 2022, until June 30th, 2022. The return differences in each period are contrasted against each other, using T-tests to inform on the significance of results.

4.2 Observing the Liquidity Premium: Decile Portfolio Regressions

To observe the liquidity premium, I estimate time-series regressions for five decile portfolios per method of liquidity testing, following Liu (2006). The returns of each portfolio are used as the dependent variable, regressed on the Fama/French factors. The decile portfolio regressions are also accompanied by two other regressions using the liquidity factors as the dependent variables. Specifically, these regressions help to inform on the degree that the returns of each portfolio may be explained by the

Fama/French factors. However, in the case of the liquidity factor regressions, this provides the observation of the liquidity premium.

Formally, the following equation is estimated for each of the twelve portfolios:

$$R_i = \alpha_i + \beta_1 Mkt_t + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_{i,t}$$

Where, R_i is the return of each individual portfolio, Mkt, SMB and HML are the respective Fama/French factors in period t, β are the corresponding coefficients of each factor and $\epsilon_{i,t}$ is the residual error of the regression. The model implies that the expected returns of the portfolios are explained by the covariance of the return with Mkt, SMB and HML. Further, if the alpha (α_i) in the regression is significant, then some portion of the return is left unexplained by the model, meaning that liquidity is priced. The alpha of the liquidity factor regressions informs on the existence of the liquidity premium.

4.3 The Degree of Pricing: Pooled Regressions

In assessing the degree of pricing of liquidity, following Novy-Marx (2013), I run pooled regressions (Ordinary Least Squares method), using the pooled daily returns of the constituents as the dependent variable and again, the excess market return (Mkt), size (SMB), and book-to-market (HML) factors of Fama and French, as well as the liquidity factors (LIQ), as independent variables. Two of these regressions are completed, so that each of the liquidity factors, constructed from the products of each method of sorting, may be used to provide robustness to the results.

Thus, the following regression is performed in each instance:

$$R_{i,t} = \alpha + \beta_1 Mkt_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 LIQ_t + \epsilon_{i,t}$$

4.4 The Degree of Pricing: Fama MacBeth Regressions

Fama and MacBeth (1973) regressions (FM) are performed using the individual daily returns of each of the constituents, as the dependent variable. Again, the Fama/French factors, Mkt, SMB and HML are employed as regressors, alongside the liquidity factors. Two such regressions are completed once more.

The FM three-step regression provides a straight-forward approach for measuring how well factors explain asset or portfolio returns. The model's objective is to ascertain the risk premium linked with the exposure to the risk factors integrated into the model.

The first step of the FM method is to regress all individual returns of the constituents against the four factors outlined above, using the time-series approach. The model considers the following:

- The return of N assets denoted R_i for stock i observed over period [0, T].
- The risk factors denoted by (Market: Mkt, Small-minus-big: SMB, High-minus-low: HML, Liquidity: LIQ)

For each stock *i* from 1 to *N,* the following parameters are estimated:

$$R_{1,t} = \alpha_1 + \beta_{1,Mkt}Mkt_t + \beta_{1,SMB}SMB_t + \beta_{1,HML}HML_t + \beta_{1,LIQ}LIQ_t + \epsilon_t$$

$$R_{2,t} = \alpha_2 + \beta_{2,Mkt}Mkt_t + \beta_{2,SMB}SMB_t + \beta_{2,HML}HML_t + \beta_{2,LIQ}LIQ_t + \epsilon_t$$

$$\vdots$$

$$R_{N,t} = \alpha_N + \beta_{N,Mkt}Mkt_t + \beta_{N,SMB}SMB_t + \beta_{N,HML}HML_t + \beta_{N,LIQ}LIQ_t + \epsilon_t$$

From this first step, the risk exposure to each factor (the coefficient or beta, β) is obtained.

The second step is to regress the returns of each individual stock against the coefficients obtained from step one, using a cross-sectional approach. The risk premium for each factor is obtained from this regression.

Formally, for each period *t* from 1 to *T,* the following linear regression model is estimated:

$$R_{i,1} = \gamma_{1,0} + \gamma_{1,1}\hat{\beta}_{i,Mkt} + \gamma_{1,1}\hat{\beta}_{i,SMB} + \gamma_{1,1}\hat{\beta}_{i,HML} + \gamma_{1,1}\hat{\beta}_{i,LIQ} + \epsilon_{i,1}$$

$$R_{i,2} = \gamma_{2,0} + \gamma_{2,1}\hat{\beta}_{i,Mkt} + \gamma_{2,1}\hat{\beta}_{i,SMB} + \gamma_{2,1}\hat{\beta}_{i,HML} + \gamma_{2,1}\hat{\beta}_{i,LIQ} + \epsilon_{i,1}$$

$$\vdots$$

$$R_{i,T} = \gamma_{T,0} + \gamma_{T,1}\hat{\beta}_{i,Mkt} + \gamma_{T,1}\hat{\beta}_{i,SMB} + \gamma_{T,1}\hat{\beta}_{i,HML} + \gamma_{T,1}\hat{\beta}_{i,LIQ} + \epsilon_{i,T}$$

Lastly, the third step is to perform a T-test for the set of gammas (γ), obtaining the means and p-values to test the significance of results, i.e.,

$$t = \frac{m - \mu}{s/\sqrt{n}}$$

4.5 Assumptions

Concerning the market factor relation to the liquidity factor, the findings of Liu (2006) suggest that a negative correlation should be observed. This makes logical sense due to market participants requiring larger compensations for holding lesser liquid stocks during periods of uncertainty and when economic performance is poor, i.e., when the market falls, the liquidity premium rises and vice versa. Moreover, the expectation of the size factor beta is negative, reflecting the characteristics of the sample. That is, due to the constituents of the S&P500 being medium to large market capitalization stocks, a negative beta would suggest that the returns are moving in an opposite manner to the returns of small firms. Or, put another way, the constituents are sensitive to the way that other large stocks are moving. I do not have any prior assumptions of the results of the book-to-market factor as the S&P500 is made up of a mixture of both value and growth companies. It is also expected that the Fama/French factors will not be able to fully explain the cross-section of returns, as it has been proven many times before. Furthermore, given the prior documentation of QE, I expect that during this period, there will be some evidence to suggest its ability to improve aggregate liquidity. That is, I expect to observe improvement in investor openness to investing in the lesser liquid stocks, as well as a reduction in the market pricing of liquidity. Logically, the opposite is expected of QT, that evidence should be found to suggest reduction of aggregate liquidity, through the inverse of reactions by market participants and increasing pricing of liquidity during this period.

5. Empirical Results & Interpretation

5.1 Investor Behavioural Changes

Table 3 displays the results of the return differences between the least and most liquid portfolios (LL-ML), as well as the T-statistics and P-values. The table shows the means and standard deviations of the return differences, revealing insights into how investor behaviour was influenced during the respective periods surrounding the monetary policy announcements in response to the Covid-19 pandemic, especially regarding the S&P500 stocks with different levels of liquidity.

Table 3

Return Differences

Panel 1: RtoV						
Stage	**I**	**II**	**III**	**IV**		
Period	Pre-pandemic	Pre QE	QE	QT		
Mean	0.000056	-0.0026	0.00044	-0.0007		
Std. Dev.	0.0049	0.0072	0.01	0.008		
T-test Results						
	II vs. I	**III vs. II**	**IV vs. II**	**III vs. I**	**IV vs. I**	**IV vs. III**
T-statistics	-2.46	2.72	1.28	-0.74	0.65	0.96
1-tail P-value	0.0084	0.004	0.10	0.23	0.26	0.17
2-tail P-value	0.107	0.008	0.20	0.46	0.52	0.34
Panel 2: RtoTR						
Stage	**I**	**II**	**III**	**IV**		
Period	Pre-pandemic	Pre QE	QE	QT		
Mean	-0.00019	-0.001	-0.0002	0.00023		
Std. Dev.	0.006	0.0082	0.01	0.013		
T-test Results						
	II vs. I	**III vs. II**	**IV vs. II**	**III vs. I**	**IV vs. I**	**IV vs. III**
T-statistic	-0.64	0.62	0.58	0.009	-0.24	-0.24
1-tail P-value	0.26	0.27	0.28	0.5	0.41	0.41
2-tail P-value	0.52	0.53	0.56	0.99	0.81	0.82

Statistically significant results are found, specifically relating to the pre-QE period (during Quarter 1 2020), from the results of the RtoV return differences. During Stage I, the pre-pandemic period of January 2nd, 2019, to December 31st, 2019, the liquidity factor was 0.000056, a number which I assume to be 'normal' and suitable for use as a benchmark to compare the other stages with. Because the figure is positive but insignificant, it reveals that investors had no preference to hold the lesser liquid stocks over the more liquid stocks among the group of S&P500 stocks during normal market conditions. In contrast, during Stage II (pre-QE), the return difference reduced significantly to - 0.0026, indicating that during the period between January 1st, and March 13th, 2020, liquidity became a much more important issue than before the pandemic. During this time, market participants were becoming fearful and uncertain of the implications of the Covid-19 outbreak and beginning to panic sell their assets. The reduction in the return difference between LL and ML reflects the likelihood of investors' reluctance to hold lesser liquid stocks during this time, even among large firms. Perhaps in relation to the idea of price impact costs, there will likely have been a rush to exit such securities. That is, investors who were aware of the existence of price impact costs will have rushed to exit their illiquid holdings before others could do so, knowing that as the selling went on, the impacts on price would be worsening. Further, it is possible that some investors were more comfortable buying or holding highly liquid stocks during this period, due to the ease of transacting such stocks, i.e., there was likely more time to assess the situation before converting these assets back to cash.

Results from Stages III and IV, as well as the RtoTR return differences are insignificant, meaning that QE/QT did in fact affect aggregate liquidity, i.e., there is no added concern over liquidity in relation to the Covid-19 pandemic, during this time. These results are logical considering the characteristics of the S&P500 firms, being large market capitalization and very popular among investors. Thus, the findings are consistent with previous studies, that QE and QT affect aggregate liquidity.

5.2 Observing the Liquidity Premium

The outputs of the decile portfolio regressions are documented in Tables 4 and 5, providing observations of the existence of and innovations in the liquidity premium. Following Liu (2006), the intercept (or alpha) of the LL-ML regression can be used as a proxy for the liquidity premium. After having controlled for the Fama/French factors, there are statistically significant positive alphas in the LL-ML regressions seen in Stages I, III and IV. Therefore, these results provide evidence of the existence of the liquidity premium. During Stage I, the liquidity premium of 0.001 (RtoV) adds to the documentation that investors were willing to take on the risk of holding the illiquid S&P500 stocks to obtain the liquidity premium. Further, a gap between Stage I and III is observed, i.e., the results in Stage II are not significant. In other words, during Stage II, the liquidity premium disappears. Thus, it can be said that during the period of the outbreak and market crash, investors were reluctant or not willing to take on the necessary risk to receive the liquidity premium. However, during Stages III and IV, the liquidity premium appears once more, meaning that during the subsequent periods, after the initial market downturn, investors once more become willing to buy and hold the lesser liquid stocks from the S&P500 to obtain the liquidity premium. This is likely explained by the massive QE program initiated by the FOMC in response to the market crash, further suggesting the ability of QE to improve market liquidity. Moreover, although QT is intended to reduce aggregate liquidity, the affect was likely not as influential during the sample period, due to the historically elevated level of liquidity in the monetary system. That is, although QT was ongoing, the persistence of liquidity already in the system meant that investors were still willing to take on the risk to receive the liquidity premium during the period of QT (Stage IV).

Regarding all tables involving regression results, figures captured in brackets are the T-statistics, and the stars refer to the following:

*** = P-value < 0.01

** = 0.01 < P-value < 0.05

* = 0.05 < P-value < 0.10

Table 4

RtoV Decile Portfolio Regressions

Pre-Pandemic (RtoV)	Portfolio	Intercept		Mkt		SMB		HML	
	ML	- 0.000027		0.010169	***	- 0.001401	***	- 0.000647	***
		(-0.3)		(91.07)		(-7.135)		(-4.29)	
	3	0.000002		0.008094	***	- 0.000900	**	0.000074	
		(0.011)		(39.6)		(-2.5)		(0.27)	
	5	0.000175		0.010278	***	0.000249		0.000465	*
		(1.07)		(49.73)		(0.685)		(1.665)	
	7	0.000363	***	0.009853	**	0.001368	***	0.002534	***
		(2.18)		(46.84)		(3.70)		(8.92)	
	LL	0.000211		0.010200	***	0.003719	***	0.002178	***
		(0.96)		(36.89)		(7.65)		(5.83)	
	LL - ML	0.001053	***	0.000002		- 0.000003		- 0.000001	
		(369.03)		(0.68)		(-0.445)		(-0.115)	

Pre QE (RtoV)	Portfolio	Intercept		Mkt		SMB		HML	
	ML	0.000001		0.010405	***	- 0.000210		- 0.000833	***
		(0.01)		(101.38)		(-0.61)		(-3.14)	
	3	- 0.000167		0.009914	***	0.002390	**	0.000096	
		(-0.26)		(35.195)		(2.545)		(0.13)	
	5	- 0.000454		0.011392	***	0.006236	***	0.001277	
		(-0.55)		(31.60)		(5.19)		(1.37)	
	7	0.000211		0.010632	***	0.004252	***	0.004363	***
		(0.345)		(40.26)		(4.83)		(6.39)	
	LL	0.000450		0.011383	***	0.006425	***	0.002666	***
		(0.58)		(33.71)		(5.705)		(3.05)	
	LL - ML	0.000449		0.000978	***	0.006635	***	0.003499	***
		(0.59)		(2.99)		(6.08)		(4.13)	

QE (RtoV)	Portfolio	Intercept		Mkt		SMB		HML	
	ML	-0.000219	***	0.009685	***	-0.001614	***	0.000642	***
		(-2.345)		(147.81)		(-14.23)		(9.85)	
	3	-0.000299	*	0.008831	***	-0.000839	***	0.002964	***
		(-1.88)		(79.31)		(-4.36)		(26.76)	
	5	-0.000305		0.010676	***	0.000828	***	0.003005	***
		(-1.57)		(78.62)		(3.52)		(22.25)	
	7	-0.000266		0.010762	***	0.001451	***	0.004249	***
		(-1.43)		(82.23)		(6.41)		(32.64)	
	LL	-0.000251		0.011483	***	0.003876	***	0.004009	***
		(-1.01)		(66.18)		(12.91)		(23.23)	
	LL - ML	0.001351	***	-0.000003		-0.000028		0.000023	*
		(79.14)		(-0.27)		(-1.37)		(1.93)	

QT (RtoV)	Portfolio	Intercept		Mkt		SMB		HML	
	ML	0.000246		0.009309	***	-0.002505	***	-0.000109	
		(0.92)		(60.78)		(-5.00)		(-0.42)	
	3	-0.000333		0.008618	***	-0.001127		0.000941	
		(-0.57)		(25.61)		(-1.02)		(1.64)	
	5	-0.000718		0.009750	***	0.003425	***	0.001871	***
		(-1.40)		(33.00)		(3.55)		(3.71)	
	7	-0.000581		0.010032	***	0.003680	***	0.002514	***
		(-1.14)		(34.30)		(3.85)		(5.03)	
	LL	-0.000538		0.010761	***	0.009316	***	0.001567	**
		(-0.78)		(27.22)		(7.21)		(2.32)	
	LL - ML	0.001321	***	0.000016	**	0.000034		0.000033	***
		(106.06)		(2.20)		(1.44)		(2.72)	

Table 5

RtoTR Decile Portfolio Regressions

	Portfolio	Intercept		Mkt		SMB		HML	
Pre-Pandemic (RtoTR)	**ML**	0.000182		0.009482	***	0.001647	**	-0.003014	***
		(0.62)		(25.58)		(2.53)		(-6.02)	
	3	0.000269	*	0.008836	***	0.001793	***	0.001292	***
		(1.71)		(44.41)		(5.13)		(4.81)	
	5	0.000098		0.009720	***	0.001061	***	0.001356	***
		(0.76)		(59.44)		(3.69)		(6.14)	
	7	-0.000010		0.010271	***	-0.000489	*	0.000252	
		(-0.076)		(63.16)		(-1.71)		(1.145)	
	LL	0.000060		0.009651	***	-0.000248		0.000869	**
		(0.30)		(37.62)		(-0.55)		(2.51)	
	LL - ML	-0.000234	***	0.000004		0.000004		0.000003	
		(-58.21)		(0.84)		(0.435)		(0.40)	

	Portfolio	Intercept		Mkt		SMB		HML	
Pre QE (RtoTR)	**ML**	0.001186		0.012206	***	0.007256	***	-0.003134	**
		(1.07)		(25.39)		(4.53)		(-2.52)	
	3	0.000104		0.010324	***	0.005395	***	0.000478	
		(0.17)		(39.10)		(6.13)		(0.70)	
	5	-0.000254		0.010700	***	0.005895	***	0.002298	***
		(-0.37)		(35.70)		(5.90)		(2.96)	
	7	-0.000294		0.010439	***	0.003523	***	0.001569	***
		(-0.64)		(52.29)		(5.29)		(3.04)	
	LL	-0.000177		0.010651	***	0.001586	**	0.000473	
		(-0.345)		(48.03)		(2.145)		(0.825)	
	LL - ML	-0.001363		-0.001555	***	-0.005670	***	0.003607	***
		(-1.18)		(-3.105)		(-3.40)		(2.785)	

	Portfolio	Intercept		Mkt		SMB		HML	
QE (RtoTR)	**ML**	-0.000121	*	0.010770	***	0.002121	***	-0.000701	***
		(-0.43)		(54.95)		(6.25)		(-3.60)	
	3	-0.000282	*	0.009401	***	0.000921	***	0.003201	***
		(-1.76)		(83.745)		(4.74)		(28.66)	
	5	-0.000393	**	0.010427	***	0.001526	***	0.003987	***
		(-2.27)		(85.94)		(7.27)		(33.03)	
	7	-0.000300	*	0.010526	***	0.000134		0.003160	***
		(-1.855)		(92.98)		(0.68)		(28.06)	
	LL	-0.000362	*	0.010055	***	-0.001498	***	0.003242	***
		(-1.76)		(69.84)		(-6.01)		(22.64)	
	LL - ML	0.000445	***	0.000002		-0.000007		0.000000	*
		(64.41)		(0.38)		(-0.82)		(-0.08)	

	Portfolio	Intercept		Mkt		SMB		HML	
QT (RtoTR)	**ML**	-0.000888		0.012129	***	0.003866	**	-0.001132	
		(-0.82)		(19.38)		(1.89)		(-1.06)	
	3	-0.000352		0.008338	***	0.001678		0.001619	**
		(-0.56)		(23.10)		(1.42)		(2.63)	
	5	-0.000876	*	0.010179	***	0.004219	***	0.002615	***
		(1.895)		(38.33)		(4.86)		(5.77)	
	7	-0.000172		0.009827	***	0.001185		0.001587	***
		(-0.44)		(44.14)		(1.63)		(4.18)	
	LL	0.000006		0.008289	***	-0.000017		0.001001	
		(0.007)		(18.41)		(-0.01)		(1.30)	
	LL - ML	0.000102	***	0.000010		-0.000007		0.000004	
		(9.32)		(1.64)		(-0.345)		(0.36)	

5.3 The Degree of Pricing

In Table 6, the pooled regressions provide evidence of the pricing of liquidity, after controlling for the Fama/French factors. It is documented that across stages, the market price of liquidity is generally increasing in magnitude. Specifically, during Stage II, the market prices liquidity at more than double than that of the pre-pandemic period, from a coefficient of 0.19 to 0.44. Again, during Stage II, with such great levels of uncertainty about the near future, this adds to the evidence of liquidity becoming a much greater concern during the virus outbreak and market crash. Further, during Stage III, the liquidity beta falls back to 0.25. While this level is still elevated above that of the pre-pandemic period, this result corroborates the capacity of QE to improve aggregate liquidity. That is, as QE expands the money supply, thereby increasing the level of available liquidity, the market pricing of liquidity falls. As this was the intention of the FOMC, clearly the QE program performed its objective adequately. Lastly, during Stage IV, the liquidity beta is observed rising once more to 0.35. As QT performs the opposite function of QE, this provides evidence of its capacity to reduce aggregate liquidity, thereby increasing the market price of liquidity. This links back to the Section 5.1 conclusion that during both Stages II and IV, market participants become more concerned about risks associated with liquidity and therefore are more reluctant to invest in the lesser liquid S&P500 stocks.

Concerning the size factor, the negative correlation to the returns of the constituents is significantly documented throughout Stages I, III and IV of the RtoV results. However, throughout the RtoTR results, statistically significant positive relations are also captured. Therefore, there is evidence of some ambiguity in this regard. The relation of liquidity and the market factor is consistent with the assumption of Liu (2006), showing that between Stage I and Stage II, the market factor increases, while the liquidity factor decreases at statistically significant levels.

Table 6

Pooled Regressions

	Periods	Pre Pandemic		Pre QE		QE		QT	
RtoV	**Intercept**	0.0000719	*	-0.00105	***	-0.00017591	***	0.00000936	
		(1.94)		(-8.39)		(-5.13)		(0.07)	
	Mkt	0.00927	***	0.00836	***	0.00856	***	0.00822	***
		(180.13)		(101.74)		(208.66)		(85.18)	
	SMB	-0.00050838	***	0.00142	***	-0.00089076	***	-0.00234	***
		(-5.82)		(5.48)		(-13.66)		(-5.33)	
	HML	0.0002923	***	-0.00161	***	0.00189	***	0.00061254	***
		(3.59)		(-6.28)		(51.38)		(3.90)	
	Liquidity	0.19129	***	0.44479	***	0.24999	***	0.34975	***
		(18.63)		(12.3)		(30.26)		(10.07)	
	# of obs.	122,933		22,415		40,263		16,977	
	R-squared	27.02%		50.13%		26.29%		47.50%	

	Periods	Pre Pandemic		Pre QE		QE		QT	
RtoTR	**Intercept**	0.00012179	***	-0.0007865	***	-0.00021457	***	-0.00056972	***
		(3.26)		(-5.72)		(-6.11)		(-4.05)	
	Mkt	0.00926	***	0.00828	***	0.00854	***	0.009	***
		(178.25)		(99.64)		(176.42)		(91.1)	
	SMB	0.00051275	***	0.00029296		0.00082225	***	0.00163	***
		(6.04)		(1.25)		(15.8)		(6.38)	
	HML	0.00068356	***	-0.0007525	***	0.00189	***	0.00083862	***
		(8.45)		(-4.58)		(48.3)		(5.62)	
	Liquidity	0.0303	***	0.07205	***	0.0978	***	0.07087	***
		(4.20)		(3.74)		(15.74)		(3.07)	
	# of obs.	121,958		22,491		220,116		14,585	
	R-squared	26.63%		53.49%		28.88%		45.56%	

Table 7 provides the results of the Fama and MacBeth (1973) regressions. Notably, after controlling for the Fama/French factors, during Stage II, the RtoTR version of this regression provides that the SMB beta is significantly negative, consistent with the assumptions. That is, due to the sample being made up of only large and medium capitalization companies, the returns are related to the directionality of other large stocks. Further, while there was no prior assumption of HML, I document, in both RtoV and RtoTR that the coefficient is marginally significantly negative, i.e., generally the stock returns are behaving more like growth stocks. Liquidity, during Stage II of the RtoV regression, was again found to be significantly priced at the 1% threshold. This further refutes the evidence that during the pre-QE period, investors are unlikely to invest in the S&P500 stocks that are illiquid, instead choosing to buy/hold the highly liquid stocks. While the results of these regressions are not exactly consistent with those of the pooled regressions, this can be explained in some part by the difference in frequency. Normally, the FM regressions would be used for larger time-frame analyses, usually utilising monthly data. However, in this case, due to the shorter periods used in the analysis, I rely on daily data. Thus, the frequency of observations is much higher. Furthermore, in the case of the size and book-to-market factors, the variation on a day-to-day basis is low, as market values and book-to-market ratios generally do not change significantly daily. Liquidity, on the other hand, is related to price (and price impact) and transaction costs, which change frequently throughout the trading day. No further significant results are found in Stages I, III, or IV in either of the RtoV or RtoTR versions of the FM regressions.

Tabel 7

Fama MacBeth Regressions

	Periods	Pre Pandemic		Pre QE		QE		QT
RtoV	**Intercept**	0.0003		-0.0005		0.0003		0.001
		(0.94)		(-0.20)		(0.44)		(0.47)
	Mkt	0.0725		-0.1824		0.0717		-0.3691
		(1.24)		(-0.55)		(1.16)		(-1.26)
	SMB	-0.0141		-0.158		0.0135		-0.0598
		(-0.36)		(-1.55)		(0.27)		(-0.63)
	HML	-0.0601		-0.2071	*	-0.0155		0.0862
		(-1.38)		(-1.86)		(-0.26)		(0.42)
	Liquidity	0.0000		-0.0024	***	0.0000		-0.001
		(-0.04)		(-2.97)		(-0.05)		(-0.95)

	Periods	Pre Pandemic		Pre QE		QE		QT
RtoTR	**Intercept**	0.0006		-0.0005		0.0002		0.0003
		(1.52)		(-0.42)		(0.55)		(0.19)
	Mkt	0.0558		-0.3335		0.0715		-0.2907
		(0.99)		(-1.20)		(1.11)		(-1.14)
	SMB	-0.0144		-0.1601	*	0.0229		-0.06
		(-0.37)		-1.78		(0.52)		(-0.74)
	HML	-0.0578		-0.3169	**	-0.0177		0.0803
		(-1.33)		(-2.40)		(-0.27)		(0.39)
	Liquidity	-0.0007		0.0008		0.0003		0.0017
		(-1.51)		^(-0.86)		(0.59)		(1.07)

6. Conclusions

Considering the historically unprecedented response of the FOMC to the outbreak of Covid-19 and the ensuing pandemic, this study finds robust evidence adding to the pertinence of liquidity. Having studied the difference in returns between sets of illiquid and highly liquid stocks from the S&P500, I show how investor behaviour changed substantially in response to the outbreak and market crash during Quarter 1 of 2020. Results from this period show that, compared to the control period of 2019, market participants become largely unwilling to invest in the lesser liquid stocks. This conclusion is further evidenced by the findings of the decile portfolio regressions, showing that the liquidity premium is unobservable at any statistically significant level. Therefore, in Quarter 1 2020, investors were not willing to take on the necessary risk to obtain the liquidity premium associated with the S&P500 stocks, as it is not observable in this period. Comparatively, during the QE period, the return difference is observed to be higher than the pre-pandemic level, suggesting the notion that QE has the capacity to improve aggregate liquidity. During QT the opposite is observed, with the return difference once more turning negative.

The pooled regressions suggest similar findings as the above, with the market pricing of liquidity observed to be increasing substantially during Quarter 1 2020, before lowering again during QE and climbing once more during QT. Concerning the findings of the period of the outbreak and crash, the results add to the evidence that during market downturns, liquidity becomes more expensive, as it dries up. Further, the findings during QE and QT indicate the capacity of both to impact on aggregate liquidity, thereby reducing (increasing) the pricing of liquidity. The Fama MacBeth regressions further provide that liquidity is significantly priced during Quarter 1 2020.

Concerning the Fama and French factors, size is found to be logically negatively related to the returns of the constituents of the S&P500, reflecting the majority large-cap makeup of the index. The book-to-market factor had evidence of ambiguity, showing statistically positive and negative relations during analysis. The correlation between liquidity and the market factor was found to be negative, consistent with the assumption of Liu (2006), that during market downturns, liquidity becomes more sought after and therefore more highly priced.

In closing, this study has found significant results around liquidity, utilising established methods to investigate a new and compelling data point in that of the Covid-19 pandemic. Future studies surrounding liquidity and Covid-19 should look to employ other methods of construction for the liquidity factors, thereby offering more robust results than those offered in this study. Further, looking into how other monetary policy impacted liquidity during the pandemic is important, particularly that of the Federal Funds Rate. Doing so may be useful in discovering the extent to which QE and QT specifically impacted liquidity, as QE/QT and rate cuts/hikes are often used hand in hand. Finally, larger datasets comprising of a more diverse and complete array of stocks would likely be more suitable for use in analysis, allowing for more substantial variation in terms of firm size and thereby liquidity.

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