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Asset Pricing

Testing the Liquidity Factor for the Cross-Section of Stock Returns

Abdullah Alsubaie
Jón Sveinbjörn Halldórsson
Kyrillos Philippou
Neel Sachania
Tinashe Allen Makamure

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Abstract

This project investigates the ability of both CAPM as presented by Sharpe (1964)[1] and Lintner (1965)[2] and the liquidity factor as in Pastor and Stambaugh (2003)[3] to explain the cross-section of portfolio returns. We use the same aggregate liquidity factor as Pastor and Stambaugh (2003) which is defined to be an average measure of individual portfolio measures estimated with monthly data. Over both our initial period (Jan-1968 to Aug-2008) and subsequent period (sep-2008 to Dec-2018), we also use innovations in liquidity and traded liquidity as additional factors. Over these periods we find that average return on our portfolios with high sensitivities to liquidity exceeds that for portfolios with lower sensitivities. We can then conclude, contrary to Pastor and Stambaugh did, that liquidity risk is not a priced factor.

Key words: Asset Pricing; CAPM; Liquidity; Beta; Portfolio

1 Introduction

In economic and asset pricing theory, it seems reasonable that investors require higher returns on investments that have a higher risk. [Measured by either volatility, Glosten Jagannathan and Runkle (1993)[4] or sensitivity to risk factors as presented by Chan, Karceski and Lakonishok (1988)[5]]. Hence, we set out to research the extent to which one factor, in particular, market-wide liquidity, accounts for systematic variations in portfolio returns and the extent to which it can explain the cross-section of portfolio returns.

We run Fama Macbeth regressions on excess returns and liquidity factors and measure how those returns change for in an out of sample data. Ever since Fama, Macbeth and Black, Jensen and Scholes began forming portfolios of betas with the market, the testing of asset pricing models has followed a simple procedure:

1. Find a characteristic or factor that you think is associated with average returns. Sort stocks into portfolios based on the characteristic, and check if there is a difference in average returns between portfolios.
2. Calculate betas for these portfolios and assess whether or not the average return is accounted for by the spread in betas.
3. If not, you have an anomaly. Consider multiple betas.

brief results: This study finds that the expected return on a portfolio in excess of the risk-free rate is partially explained by the sensitivity of its return to liquidity factors. This model containing aggregate liquidity captures the cross-sectional variation of average stock returns; however, as we do not accommodate for size and momentum, our results are inconclusive.

2 Literature Review

Aside from work done by Pastor and Stambaugh, the analysis process described above has been repeated for several different factors as well as for different ways to measure the same factor. In particular, in this section we will consider the illiquidity factor proposed by Amihud (2002)[6] as well as the third measure of liquidity proposed by Sadka (2006)[7] Liquidity in itself is a broad factor that represents a range of characteristics such as trading costs, ease of sale, necessary price discounts to affect a quick transaction and price predictability (Bodie et al. 2018)[8]. Because of this, it is difficult to measure with a single statistic, so it is not surprising that popular measures of liquidity focus on the "price impact dimension," i.e., the price a seller may have to accept to complete a large sale of an asset or equally, what premium a buyer needs to offer to make the purchase.

Amihud's measure for illiquidity is defined to be:

$$\text{ILLIQ} = \text{Monthly Average of Daily}\frac{\text{Absolute value (stock return)}}{\text{Dollar volume}}$$

It essentially measures the impact on prices that a dollar's worth of transactions accounts for.
Acharya and Pedersen (2005)[9] use Amihud's illiquidity measure to assess how both the average level of illiquidity and liquidity risk premium affect prices. Their work concluded that several liquidity/illiquidity betas were required to fully capture and explain the expected asset returns in addition to CAPM. The liquidity betas they ultimately decided were sufficient enough to explain returns were:

- The sensitivity of individual stock illiquidity to market illiquidity
- The sensitivity of stock returns to market illiquidity and
- The sensitivity of stock illiquidity to the market return

The third liquidity measure is Sadka's measure that uses "trade-by trade" data. This measure attempts to observe the part of the price impact that is due to asymmetric information. This measure changes depending on the volume of "informationally motivated" trades.

Both Amihud and Sadka's measure can be averaged across stocks or portfolios and used to devise a measure of market-wide (il)liquidity that can be used to measure a liquidity beta for individual portfolios.

In more recent literature, however, the idea that liquidity is priced has been brought into question. Hou, Xue, and Zhang (2017)[10] argue that 95 of 102 documented liquidity – related measures are completely insignificant if portfolio construction is done by giving slightly smaller weights to microcaps. Furthermore, Li, Novy-Marx, and Velikov (2017)[11] argue that Pastor and Stambaugh's liquidity factor is overly sensitive to the construction of portfolios used and a value-weighted structure statistically generates insignificant returns.

The existence of a priced liquidity factor is an issue that is still, to this day, being argued and assessed and revised in real-time. In our data we consider aggregate liquidity which indicates how easily financial transactions can be made in the market or in our case since we consider stocks, we have a measure of how easily a stock/asset can be traded.

Undoubtedly liquidity is a measure of representation of the state of the market. For instance, during a market crisis, we can see that there is a drop in liquidity in the market since transactions cannot be executed as quickly as other times. We can observe this by looking at the following graph from Pastor and Stambaugh's data, which we include in our project. We can identify some notable spikes in the graph of aggregate liquidity during world-renowned market crashes such as:

- Black Monday in 1987 when there was a sudden market crash in October that lasted a day and the market recovered after two years.
- The Dot-com Bubble burst, which happened in March of 2000 and would take another 15 years for the market to regain its dot-com peak. It is necessary here to comment on the rise of liquidity in the late '90s since investors were affected by the rapid technological development and were investing irresponsibly in companies that were doomed to fail, which eventually lead to the bubble burst in 2000.
- The Great Recession which lasted from 2007 to 2009 after the housing market crash and the bankruptcy of Lehman Brothers

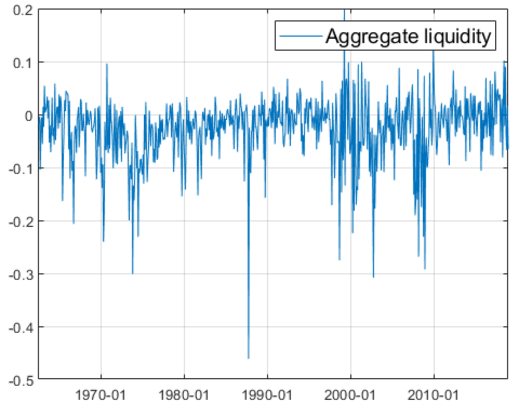


Figure 2.1: Aggregate liquidity as a function of time from 1968-2018.

2.1 Expected Conclusions:

Consequently, if we consider the above, we can argue that the returns of our stock portfolios would have also been affected by such market crashes. Intuition supports the fact that after a market crash, we will see a violent change in our returns and liquidity factors. However, we need to contemplate also the role that the Federal Reserve System or central banks, in general, have in such circumstances. Central banks aim to stabilize economic growth when a market crisis happens. One of the monetary policies that a central bank will conduct is, they will generally lower interest rates and thus lowering financing costs, which will promote borrowing and investing. For example, after the Housing market crash, the Fed lowered a key interest rate to virtually zero while also providing the banks with an amount of $7.7 trillion of emergency loans, a monetary policy also known as quantitative easing (`theweek.com`, 2011)[12].

These tools helped stabilize the liquidity in the market after the crisis. In conclusion, our expected returns should be lower when we re-fit the model out-of-sample (including the period from September 2008 to 2019). Although we expect to see a massive drop in our expected returns the following years and to continue decreasing, the Fed's immediate actions and measures contained the catastrophe. The (aggregate)liquidity factors and hence our expected returns should be stabilized through the following years, but they will not reach the same height they had before the market crash since, after 2008, banks adapted to a more restrictive policy for lending money.

Also, assuming the investors are rational, i.e., our portfolios should be diversifiable (since you do not get compensated for taking on a risk that could be diversified away) we can interpret our results as follows: If we include the dates of the Great Recession, then we would have a rise in systematic risk since now the market is at a low point, and everyone is inherent to that risk. As a result, the average weighted equity risk premium should be higher. A potential reason for this positive change is the fact that after the market crisis of 2008, the equity risk premia are of higher value than those before as equity investors would want to be compensated more for taking on more systematic risk.

3 Methodology

Our data for the U.S. stock portfolio returns are sorted into 25 portfolios according to size and momentum. Therefore there is no need to re-balance the portfolios using a rolling window. We implement the Fama-MacBeth regression as follows:

First, we run time series regression to estimate betas for each portfolio from excess returns regressed on to factor returns. Here we obtain a beta corresponding to each factor within the model for every portfolio. Then we apply cross-sectional regression at each period where we regress excess returns on our estimated betas. From this, we end up with a gamma for each factor for each month within the sample. For each sample, we take the arithmetic average across the period and denote this by

$$\lambda_i = \frac{1}{T}\sum_{t=1}^{T}\gamma_{i,t}$$

for ease of interpretation and comparison. We will fit the following models:

Factor model:

$$\textbf{Time Series Regression}: \quad R_{i,t} - r^f = \alpha_{0,t} + \beta_{1,i}[r_{M,t} - r^f_t] + \beta_{2,i}Factor_{2,t} + \epsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the return for portfolio i at the time period t, r^f is the corresponding risk free rate. Excess market return $r_{M,t} - r^f_t$ is the risk factor premium for this model, with $\alpha_{0,t}$ corresponding to the intercept, $Factor_{2,t}$ the risk factor premium according to a liquidity factor. $\beta_{1,i}$ is the sensitivity of portfolio i to the respective factor, found through conducting the time series regression.

At each time t we conduct a cross sectional regression,

$$R_{i,t} - r^f = \gamma_{0,t} + \gamma_{1,t}\beta_{1,i} + \gamma_{2,t}\beta_{2,i} + u_{i,t} \tag{2}$$

where $R_{i,t}$ is the return for portfolio i at the time period t, r^f is the corresponding risk free rate. $\beta_{1,i}$ is the sensitivity of portfolio i to the respective factor, found through conducting the initial time series regression. The $\gamma_{1,t}$ corresponds to excess market return $\mathbb{E}[r_{M,t} - r^f_t]$ risk factor premium, $\gamma_{2,t}$ the risk premium corresponding to a liquidity factor, with $\gamma_{0,t}$ corresponding to the intercept.

We then average the time series of $\gamma_{0,t}$, $\gamma_{1,t}$ and $\gamma_{2,t}$ as $\lambda_i = \frac{1}{T}\sum_{t=1}^{T}\gamma_{i,t}$

Note for the CAPM model we fit, we assume there to be no additional $Factor_2$ and its corresponding $\beta_{2,i}$

The above was implemented in Matlab, and details of this can be found in the appendix. We test the statistical significance of the parameters found by calculating the corresponding t-statistic using the Newey West estimator, which accounts for heteroscedasticity and autocorrelation using the default Bartlett method. In Matlab, we used the `hac.m` function to get an adjusted covariance matrix to calculate t-statistics. As the statistics behind our methodology is beyond the scope of this project, we will not discuss the validity of this approach but acknowledge that this method is necessary in order to have valid t-statistic comparisons.

It is worth noting that we run OLS at each stage in Fama Macbeth, and so we are assuming that the errors are normally distributed with a conditional mean of 0.

One would anticipate for the CAPM model to find that the term corresponding to the intercept $\lambda_0 = 0$ if the CAPM model holds. Also, we would expect to observe a positive return-risk trade-off within the market. These are all confirmed by conducting the following hypothesis test at a 5% significance level.

$$H_0 : \lambda_i = 0 \qquad\qquad H_1 : \lambda_i \neq 0$$

4 Data and Empirical Results

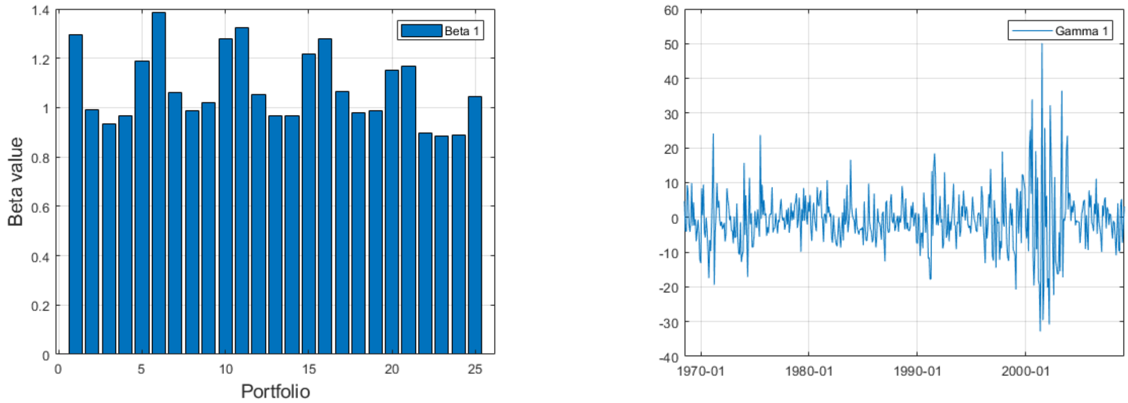
4.1 Data Description

For this study, we observe monthly returns of US stock portfolios sorted by size and momentum and obtain data for excess market return and risk-free rate from Kenneth R. French's website. We compare the models built with liquidity factors from Pastor and Stambaugh using data from 1962 to 2018. The dates in the raw data were misaligned, so the start and end dates of our periods were synchronised before running the regressions. After adjusting for null values, we consider only the periods between January 1968 and December 2018.

4.2 Testing CAPM

In order to test the validity of CAPM, we follow the methodology described above.

Using our in-sample data from 1968 to 2008, we obtain an average of γ_0 (averaged over the whole period) $\lambda_0 = 1.3541$. From table 1, we find this to be significant, implying that there is sufficient evidence to reject our null hypothesis that $\lambda_0 = 0$ and so we can conclude that the CAPM model does not hold within the market we are studying. For completeness, we also obtain a factor value for excess market return (equity risk premium) of -0.761, which tests insignificant at a 95% confidence level. Therefore as the t-test is insignificant, nothing can be said about the null hypothesis and so it is inconclusive as to whether the factor has a positive risk premium, as one should expect.



(a) Measure of exposure to excess market return risk for portfolios sorted by size and momentum.

(b) Excess market return premia as a function of time.

Figure 4.1: In sample CAPM β and excess market return risk premia estimates

Table 1: In sample t-test at 5% significance level

Model	λ_0	λ_1	λ_2
CAPM	1.3541 (2.33)	-0.761 (-1.3295)	
Aggregate liquidity	0.8662 (1.3630)	-0.3977 (-0.6283)	0.0616 (2.5152)
Innovation liquidity	1.4658 (2.2684)	-0.7817 (-1.3279)	-0.0261 (-1.0216)
Traded liquidity	0.8800 (1.8419)	-0.3549 (-0.8617)	-0.0748 (-6.2689)

In terms of the validity of the CAPM model, one can observe from the residual plot (figure 4.2) that the residual values are predominantly centered around zero. We witness large deviations mostly at notable dates such as 2000 and 2008, where it can be assumed that this is driven by global economic shocks.

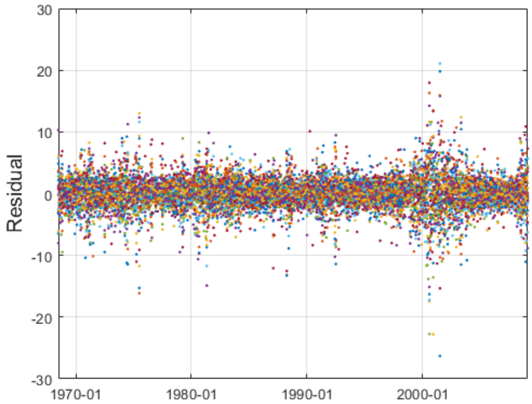


Figure 4.2: Resiudal plot of CAPM model

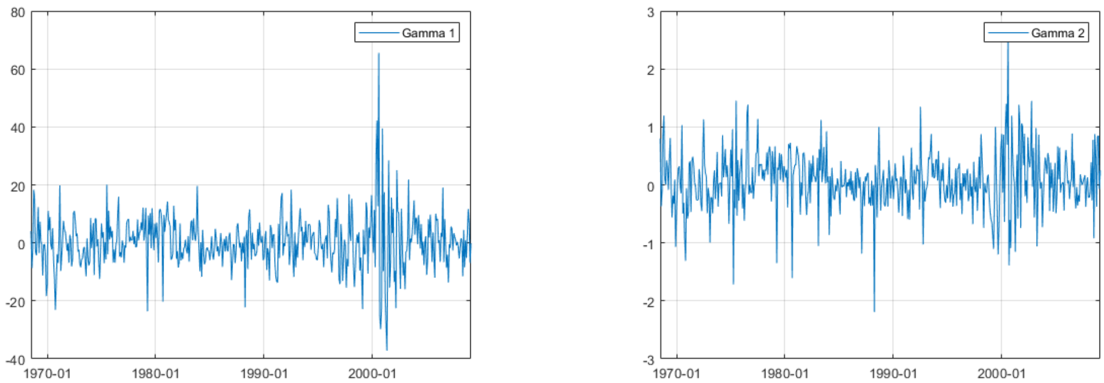
Therefore it can be said that this model fits the data well despite not being successful at explaining the cross-section of returns.

Overall we find that the CAPM model with only one factor fails to explain the cross-section of stock returns that are sorted by size and momentum.

4.3 Testing CAPM - Multi-Factor Models 1968 - 2008

We now conduct the same procedure for liquidity factors as an additional factor on the CAPM model using in sample data.

Aggregate liquidity



(a) Excess market return premia as a function of time.

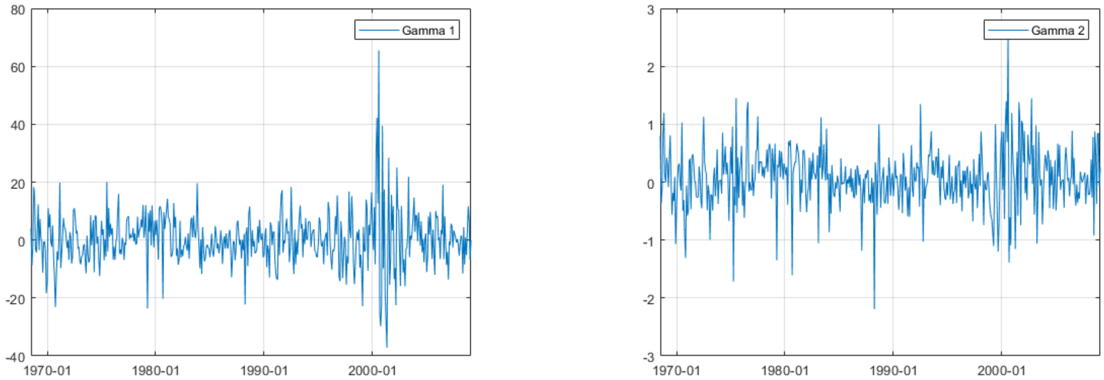
(b) Aggregate liquidity premia as a function of time.

Figure 4.3: In sample factor risk premia - aggregate liquidity

Using our in-sample data from 1968 to 2008 we obtain an average of γ_0, $\lambda_0 = 0.8662$. From table 1, we find this to be insignificant. Also, we obtain a factor value for the excess market return of $\lambda_1 = -0.3977$, which tests insignificant at a 95% confidence level. Therefore as the t-test is insignificant, nothing can be said about the null hypothesis and so it is inconclusive as to whether the factor has a positive risk premium, as one should expect. However, the risk premium for aggregate liquidity with a value of $\lambda_2 = 0.061$ tests significant. Therefore as the value is positive, then investors are compensated for the additional risk, and so the liquidity risk is priced.

Innovation in liquidity

For an additional factor of innovation in liquidity observe that $\lambda_0 = 1.4658$. From table 1, we find this to be significant, implying that there is sufficient evidence to reject our null hypothesis that $\lambda_0 = 0$. For completeness, we also obtain a factor value for excess market return (equity risk premium) of -0.7817, not too dissimilar from the CAPM model built above, which also tests insignificant at a 95% confidence level. Therefore as the t-test is insignificant, nothing can be said about the null hypothesis and so it is inconclusive as to whether the factor has a positive risk premium, as one should expect. Similarly, the risk premium for innovations in liquidity with a value of -0.0261 also tests insignificant.
Overall we find that the CAPM model with an additional factor of innovations in liquidity fails to explain the cross-section of stock returns that are sorted by size and momentum.



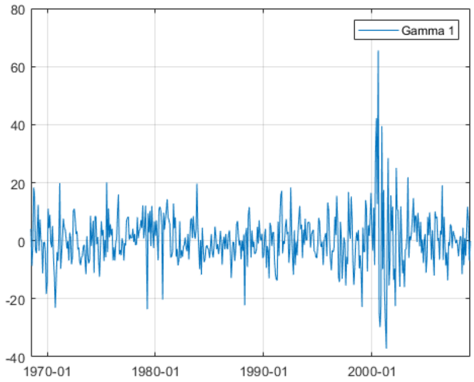
(a) Excess market return premia as a function of time. (b) Innovation in liquidity premia as a function of time.

Figure 4.4: In sample factor risk premia - innovation in liquidity

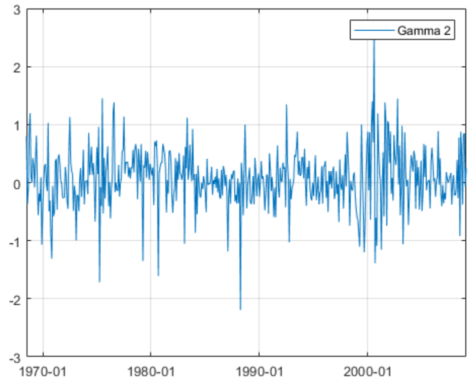
Traded liquidity

Using in-sample data from 1968 to 2008 we find that $\lambda_0 = 0.8800$. From table 1, we find this to be insignificant, and so no conclusions can be made about the value of λ_0. We also obtain a factor value for the excess market return of -0.3549, not too dissimilar from the model containing aggregate liquidity built above, which also tests insignificant at a 95% confidence level. Therefore as the t-test is insignificant, nothing can be said about the null hypothesis and so it is inconclusive as to whether the factor has a positive risk premium, as one should expect. However, we find that the risk premium for traded liquidity with a value of -0.0748 tests significant, and so we have evidence to suggest that this value is non-zero. As this value is negative, we conclude that traded liquidity is not priced.

In the CAPM model, the liquidity factors are not included. Hence, it is assumed in the CAPM that the only determinant of excess returns is the exposure to systematic risk. However, from an economic point of view, other factors like liquidity may predict the changes in excess returns. For example, a portfolio with high exposure to liquidity risk can be undesirable by investors. That is because investors prefer more liquid assets to those that are less liquid. Hence, the demand for portfolios with high liquidity risk may be low. Therefore, the market will offer the investor a higher return to compensate them for the added risk.



(a) Excess market return premia as a function of time.



(b) Traded liquidity premia as a function of time.

Figure 4.5: In sample factor risk premia - traded liquidity

The extended factor model makes a more realistic assumption about the determinants of the excess returns. By omitting the liquidity factor from the CAPM model, the model may suffer from the omitted variable problem. The fact that liquidity is correlated with the excess market returns (liquidity falls when the market declines), leads the CAPM to perform worse than the extended factor model. (Hameed, Kang and Viswanathan, 2010)[13].

4.4 Testing CAPM - MultiFactor Models 2008 - 2019

Now we refit the models using out of sample data.

CAPM

With out-of-sample data from 2008 to 2019 we obtain a $\lambda_0 = 0.9266$. From table 2, we find this to be significant, implying that there is sufficient evidence to reject our null hypothesis that $\lambda_0 = 0$. Also, we obtain a factor value for the excess market return of $\lambda_1 = -0.0043$, which tests insignificant at a 95% confidence level. Therefore as the t-test is insignificant, nothing can be said about the null hypothesis and so it is inconclusive as to whether the factor has a positive risk premium, as one should expect. Compared to our in-sample estimates, we find the intercept to be much lower post-crisis.

Table 2: Out of sample t-test at 5% significance level

Model	λ_0	λ_1	λ_2
CAPM	0.9266 (4.3343)	-0.0043 (-0.0230)	
Aggregate liquidity	1.2887 (6.1620)	-0.3456 (-1.9401)	-0.0146 (-2.8181)
Innovation liquidity	1.1337 (5.8912)	-0.2408 (-1.4178)	-0.0240 (-2.8202)
Traded liquidity	0.9527 (4.7396)	-0.0130 (-0.0705)	-0.0023 (-0.6057)

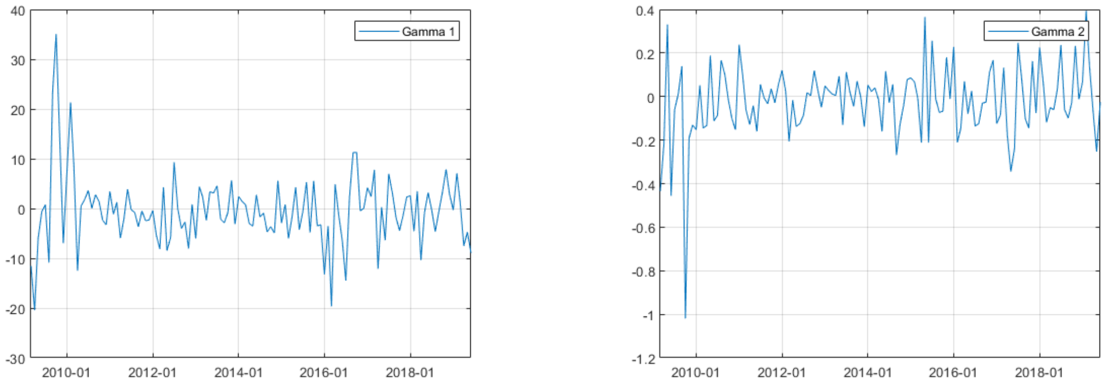
Aggregate liquidity

Using our out of sample data from 2008 to 2019, we obtain an average of γ_0, $\lambda_0 = 1.2887$. From table 2, we find this to be significant, implying that there is sufficient evidence to reject our null hypothesis that

$\lambda_0 = 0$. Also, we obtain a factor value for the excess market return of $\lambda_1 = -0.3456$, which also tests insignificant at a 95% confidence level. Therefore as the t-test is insignificant, nothing can be said about the null hypothesis and so it is inconclusive as to whether the factor has a positive risk premium, as one should expect. However, the risk premium for aggregate liquidity with a value of $\lambda_2 = -0.0146$ tests significant. Therefore as the value is negative, then investors are not compensated for the additional risk, and so the liquidity risk is not priced.

Innovation in liquidity

We now conduct the same procedure for the innovation in liquidity factor as an additional factor on the CAPM model for the out of sample data.



(a) Excess market return premia as a function of time. (b) Innovation in liquidity premia as a function of time.

Figure 4.6: Out-of-sample factor risk premia - innovation in liquidity

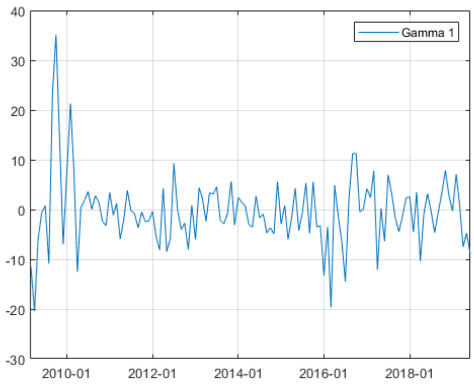
Using our out-of-sample data from 2008 to 2018 we obtain an average of γ_0, $\lambda_0 = 1.1337$. From table 2, we find this to be significant, implying that there is sufficient evidence to reject our null hypothesis that $\lambda_0 = 0$ For completeness, we also obtain a factor value for excess market return (equity risk premium) of -0.2408, not too dissimilar from the value obtained from the in-sample data, which also tests insignificant at a 95% confidence level. Therefore as the t-test is insignificant, nothing can be said about the null hypothesis and so it is inconclusive as to whether the factor has a positive risk premium, as one should expect. Surprisingly, the risk premium for innovations in liquidity with a value of -0.0240 also tests significant, and so there is evidence to suggest this value is non-zero, which is opposite to what was found in the in-sample case.

Overall we find that the CAPM model with an additional factor of innovations in liquidity appears to explain the cross-section of stock returns that are sorted by size and momentum.

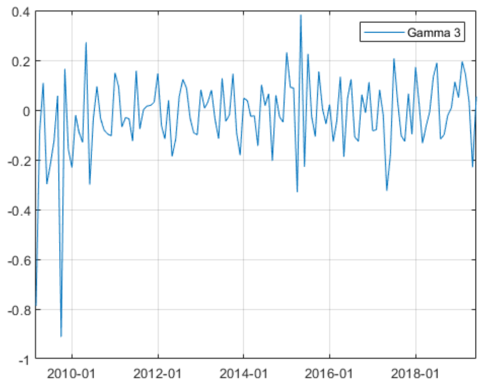
Traded liquidity

We now conduct the same procedure for the traded liquidity factor as an additional factor on the CAPM model using out-of-sample data.

Using our out-of-sample data from 2008 to 2018, we obtain an average of γ_0 (averaged over the whole period) $\lambda_0 = 0.9527$. From table 2, we find this to be significant, and so we can conclude that λ_0 is non-zero, which is opposite to the in-sample case. For completeness, we also obtain a factor value for excess market return (equity risk premium) of -0.013, which also tests insignificant at a 95% confidence level. Therefore as the t-test is insignificant, nothing can be said about the null hypothesis and so it is inconclusive as to whether the factor has a positive risk premium, as one should expect. We find that



(a) Excess market return premia as a function of time.



(b) Traded liquidity premia as a function of time.

Figure 4.7: Out-of-sample factor risk premia - traded liquidity

the risk premium for traded liquidity with a value of -0.0023 also tests insignificant.

In the out-of-sample data, all of the three liquidity factors seem to have a negative lambda value. The out-of-sample estimation shows that both the aggregate liquidity and innovation in aggregate liquidity do predict changes in excess returns. However, it does not provide evidence for where the traded liquidity predicts the changes in excess returns or not.

Similar to the in-sample estimation, the out-of-sample provides negative lambda value for the innovation in liquidity and the traded liquidity. Unlike in the out-of-sample, the in-sample three-factor model provides positive lambda value for the aggregate liquidity factor. The out-of-sample extended factor model implies that the liquidity risk is not priced. Since all of the liquidity factors gammas are negative, this implies that higher exposure to liquidity risk leads to lower returns. However, in the in-sample estimation of the risk premium of the aggregate liquidity was positive. The downward spike (figure 4.7(b)) may explain the change in the gamma relating to aggregate liquidity in the out-of-sample data in 2009. The downward spike coincides with the credit crunch caused by the Financial crisis. In the Financial crisis, portfolios with higher sensitivity to liquidity suffered lower returns.

5 Conclusion

In conclusion, in this project, we estimated the CAPM and the extended factor model with liquidity factor for the cross-section of stock returns. Both models provided a positive intercept. This suggests that there exists a factor not included in our model that can explain some of the variations in excess returns.

When looking at the liquidity factors, the evidence shows that they do explain the movement in the excess returns of the portfolios in both the out-of-sample and in-sample partially. However, the out-of-sample results suggest that the liquidity factors are not priced. Compared to the out-of-sample, where the in-sample estimates provide mixed results.

The λ_1 in all the estimations are not significant. The theory of asset pricing tells us that the λ_1 must be positive in expectation only. The fact that λ_1 takes both positive and negative values is driven by the volatility of the portfolios whose betas are greater than 1. Portfolios whose betas are greater than 1 exhibit higher fluctuations in their returns. These fluctuations make it difficult to pin down the relationship between the betas and excess return of the portfolios.

Further research might investigate the reason why liquidity risk is not priced. Also, whether it is possible to create an arbitrage strategy to take advantage of such mispricing. Other interesting areas to explore is whether such mispricing is found in other financial markets.

One of the main limitations of our study is that size and momentum were not controlled for. This is something that Pastor and Stambaugh (2003) did using the Fama-French 3 factor model and found liquidity to be a priced factor. Another limitation is that, since liquidity is not a traded factor, the way the liquidity measure is constructed may affect our estimation.

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A Matlab Code

The code was written with re-usability in mind and should work for comparable files for historical factors and returns other than the ones used in this study.

The raw data was processed into datatables using `data_processing.m` and `download_data.m`, and the matching dates in the tables were found with the function `index_tables.m`. All of the regressions discussed above were performed in `main.m`, where `run_regression`, `Fama_Macbeth.m` and several plotting functions were called. For further information, refer to the code.

List of Figures

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