WARWICK BUSINESS SCHOOL
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Asset Pricing

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

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Abstract

This project investigates the ability of both CAPM as presented by Sharpe (1964) and Lintner (1965) and the liquidity factor as in Pastor and Stambaugh (2003, Journal of Political Economy) 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 the 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, just as Pastor and Stambaugh did, that liquidity risk is, in fact, a priced factor.

1 Introduction

In economic and asset pricing theory it seems reasonable that investors require higher returns on investments that have higher risk. [Measured by either volatility, Glosten Jagannathan and Runkle (1993 journal of finance) or sensitivity to risk factors as presented by Chan, Karceski and Lakonishok (1998, Journal of Financial and Quantitative Analysis)]. 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 loop:

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 explained by its sensitivity of its return to these factors ... This model captures the cross-sectional variation of average stock returns

1.1 Something...

1.2 Something else...

2 Literature Review (*Optional*)

https://faculty.chicagobooth.edu/john.cochrane/research/papers/cochrane_fall_2004_ap_review.pdf:
Lubos Pastor and Robert F. Stambaugh "Liquidity Risk and Expected Stock Returns" (NBER WP 8462 and Journal of Political Economy 111, 642-685) find that stocks whose prices decline when the market gets more illiquid receive a compensation in expected returns.

Viral V. Acharya, Lasse H. Pedersen 2004 "Asset Pricing with Liquidity Risk" (NBER WP10814) perform a similar but more general investigation. They examine all four channels for a liquidity premium. A the security might have to pay a premium simply to compensate for its particular illiquidity or transactions cost, but this is the least interesting (and, as we will see in the theory discussion, least likely) effect. Second, a security might have to pay a premium because it becomes more illiquid in bad times, i.e. when the market goes down. If you have to sell it, (and sellers are the marginal investor) this tendency amounts to a larger beta than would be measured by the midpoint of a bid-asked spread. Third, the security's price (the midpoint) might decline when markets as a whole become less liquid. If "market liquidity" is a state variable, an event that drives up the marginal utility of a marginal investor, then this tendency will also result in a return premium. This is the mechanism that Pastor and Stambaugh investigated. Fourth, the security could become more illiquid when the market becomes more illiquid. Of course these characteristics are correlated in the data, which makes sorting out their relative importance more difficult.

2.1 Something...

2.2 Something else...

3 Methodology

As our data for stock portfolio returns is already sorted into 25 portfolios according to size and momentum there is no need to re-balance the portfolio using a rolling window. And so we can implement Fama-Macbeth regression as follows:

First we run time series regression where we estimate betas from excess returns regressed on to factor returns. So for each portfolio we obtain a beta. Then we apply cross-sectional regression at each time 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 for ease of interpretation and comparison.

The Fama Macbeth regression takes the form of:

$$R_{i,t} - r_t^f = \gamma_0 + \beta_{1,i}\gamma_1 + \beta_{2,i}\gamma_2 + \beta_{3,i}\gamma_3 + \beta_{4,i}\gamma_4 + \epsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the return for portfolio i at time t, r_t^f is the risk free rate corresponding to the time period. The γ_{factor} is the risk factor premium, with γ_0 corresponding to the intercept. $\beta_{factor,i}$ is the sensitivity of portfolio i to the respective factor, found through conducting the initial time series regression.

The above has been 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 which uses the Newey West estimator. This is done to account for Heteroscedasticity and auto correlation using default Bartlett method. In Matlab this is performed using the HAC function giving us an adjusted covariance matrix used 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 conditional mean of 0.

We perform Fama Macbeth regressions on the following models:

CAPM:
Running time series regression of excess returns $(R_{i,t} - r_t^f)$ on the factor $\gamma_{1,i} = \mathbb{E}[r_{M,t} - r_t^f]$ and we obtain estimates for the exposure (β_1) of the excess returns on each of our 25 portfolios to those two factors.
Now running cross-sectional regression across the 25 portfolios at each time period of excess returns $(R_{i,t} - r_t^f)$ on our betas $\beta_0 = 1$ and β_1 we obtain estimates for $\gamma_{0,i}$ and $\gamma_{1,i} = \mathbb{E}[r_{M,t} - r_t^f]$ for each time t.

If we fit the model

$$R_{i,t} - r_t^f = \gamma_{0,t} + \beta_{1,i}\gamma_{1,t} + \epsilon_{i,t}$$

where the parameters are as described above and $\gamma_{1,t}$ corresponds to excess market return $\mathbb{E}[r_{M,t} - r_t^f]$

(+) $\lambda_i = \frac{1}{T}\sum_{t=1}^{T}\gamma_{i,t}$
one would anticipate to find that the term corresponding to the intercept $\lambda_0 = 0$ if the CAPM model holds true.

For completeness, if the CAPM model were to hold true we would also expect to observe a positive return-risk trade off within the market (i.e $\gamma_{1,i} = \mathbb{E}[r_{M,t} - r_t^f] > 0$).

$$H_0 : \gamma_1 = \mathbb{E}[r_M - r^f] = 0 \qquad\qquad H_1 : \gamma_1 = \mathbb{E}[r_M - r^f] \neq 0$$

Running time series regression of excess returns $(R_{i,t} - r_t^f)$ on factors $\gamma_{0,i}$ and $\gamma_{1,i} = \mathbb{E}[r_{M,t} - r_t^f]$ we obtain estimates for the exposure (β_1) of the excess returns on each of our 25 portfolios to those two factors.

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 effects (???) of the liquidity factors of 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 Decemember 2018.

4.2 Testing CAPM

In order to test the validity of CAPM, we follow the methodology described above.
From the time series regression we obtain estimates for the exposure (β_1) of the excess returns of the 25 portfolios to excess market returns and we see that average value of β_1 across the 25 portfolios is 1.079. It is worth noting that the variation of these betas (**figure**) is 0.0222 and so the sensitivity of each portfolio to the excess market return does not differ greatly. We observe that the betas do not change much with size, however there is a notable pattern that emerges as momentum varies. We observe that the betas corresponding to the smallest and largest momentum for each size group have larger betas than those of medium momentum for each size group. Intriguingly the lowest momentum group corresponding to the past losers is higher than that of the past winners (high momentum). This is something that Jagadeesh and Titman found in their study (Jegadeesh and Titman, 1993). **does this mean its failed at explaining the cross section**

Now running cross-sectional regression across the 25 portfolios at each time period of excess returns $(R_{i,t} - r_t^f)$ on our betas $\beta_0 = 1$ and β_1 we obtain estimates for $\gamma_{0,i}$ and $\gamma_{1,i} = \mathbb{E}[r_{M,t} - r_t^f]$ for each time t. The outputs are displayed in **figure x and y**, which shows how much the gammas vary over time. Here $\gamma_{1,i}$ can be interpreted as the risk premium of being exposed to excess market return. It is worth noting that the variance of this risk premium is 71.0945, with major fluctuations occurring in the early 2000s. **bring in Kyrillos and knowledge of systematic risk for market risk premium around dot com bubble? refer back to figure y** Big boy spike at 2000 where equity risk premium goes from

50 to -30!

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

Model	λ_0	λ_1	λ_2	λ_3	λ_4
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)		
Saturated	0.2181 (0.6054)	0.3069 (0.9631)	0.0720 (4.6196)	0.0256 (2.4805)	-0.0549 (-6.0122)

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.

In terms of the validity of the CAPM model, one can observe from the residual plot **big dot plot** that the residual values are predominantly centred 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 shock/event. Therefore it can be said that this model performs well in explaining returns 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 and so we proceed to introduce additional factors corresponding to liquidity and compare their performance.

4.3 Testing CAPM - MultiFactor Models 1968 - 2008

Abdullah - All factor (saturated) model
Abdullah - market return + liquidityfactor1
Neel - market return + liquidityfactor2

Innovation in liquidity

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

From the time series regression we obtain estimates for the exposure (β_1) of the excess returns of the 25 portfolios to excess market returns and we see that average value of β_1 across the 25 portfolios is 1.0624. It is worth noting that the variation of these betas (**figure**) is once again quite small 0.0226. We observe that the beta1s follow an identical pattern to that described for the CAPM case where there is not much difference in size, yet an anomaly corresponding to the smallest and largest momentum for each size group. We also obtain an estimate for the sensitivity (β_2) of excess returns on the innovations in liquidity factor, which has an average value of 3.93 across the 25 portfolios. Surprisingly there is a large variance of 10.2 associated with these beta2s which is attributed to the fact that the highest size stocks exhibit

varying beta2 values as momentum increases with large negative beta2 value for the largest momentum portfolio.
This suggests that as liquidity decreases one would expect high momentum stocks of large sizes to exhibit excess returns
Now running cross-sectional regression across the 25 portfolios at each time period of excess returns $(R_{i,t} - r_t^f)$ on our betas $\beta_0 = 1$, β_1 and β_2 we obtain estimates for $\gamma_{0,i}$, $\gamma_{1,i} = \mathbb{E}[r_{M,t} - r_t^f]$ and $\gamma_{2,i}$ for each time t. The outputs are displayed in **figure x and y**, which shows how much these gammas vary over time. As for the CAPM case, $\gamma_{1,i}$ can be interpreted as the risk premium of being exposed to excess market return. Similarly the variance of this risk premium is 73.5907, with major fluctuations occurring in the early 2000s. $\gamma_{2,i}$ can be interpreted as the risk premium of being exposed to innovations in liquidity. This appears to be much less volatile with a variance of this risk premium being 0.1357. **bring in Kyrillos and knowledge of systematic risk for market risk premium**

Using our in-sample data from 1968 to 2008 we obtain an average of γ_0 (averaged over the whole period) $\lambda_0 = 1.4658$. From table 1, we find this to be significant, implying that there is sufficient evidence to reject our null hypothesis that $\lambda_0 = 0$ **and so we can conclude that the intercept of this model is not 0. As liquidity factor is not an excess return factor - this may be a plausible outcome**. For completeness, we also obtain a factor value for excess market return (equity risk premium) of -0.7817, not to 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.

Neel - market return + liquidityfactor3

Traded liquidity

We now conduct the same procedure for the traded liquidity factor as an additional factor on the CAPM model.

From the time series regression we obtain estimates for the exposure (β_1) of the excess returns of the 25 portfolios to excess market returns and we see that average value of β_1 across the 25 portfolios is 1.0791. It is worth noting that the variation of these betas (**figure**) is once again quite small 0.0223. We observe that the beta1s follow an identical pattern to that described for the CAPM case where there is not much difference in size, yet an anomaly corresponding to the smallest and largest momentum for each size group. We also obtain an estimate for the sensitivity (β_2) of excess returns on the traded liquidity factor, which has an average value of -0.4782 across the 25 portfolios. This negative value can be interpreted as the stocks being negatively related to liquidity. Surprisingly there is a large variance of 16.0269 associated with these beta2s which is attributed to the fact that the smallest momentum portfolios exhibit large beta2 values and high momentum portfolios have large negative beta2 value for all apart from the largest size group.
This suggests that as liquidity decreases one would expect high momentum stocks sizes to exhibit excess returns - something similar to what innovations in liquidity suggests
Now running cross-sectional regression across the 25 portfolios at each time period of excess returns $(R_{i,t} - r_t^f)$ on our betas $\beta_0 = 1$, β_1 and β_2 we obtain estimates for $\gamma_{0,i}$, $\gamma_{1,i} = \mathbb{E}[r_{M,t} - r_t^f]$ and $\gamma_{2,i}$ for each time t. The outputs are displayed in **figure x and y**, which shows how much these gammas vary over time. As for the CAPM case, $\gamma_{1,i}$ can be interpreted as the risk premium of being exposed to excess market return. Similarly the variance of this risk premium is 66.8651, with major fluctuations occurring in the early 2000s. $\gamma_{2,i}$ can be interpreted as the risk premium of being exposed to traded liquidity. This appears to be much less volatile with a variance of this risk premium being 0.0815. **bring in Kyrillos and knowledge of systematic risk for market risk premium**

Using our in-sample data from 1968 to 2008 we obtain an average of γ_0 (averaged over the whole period) $\lambda_0 = 0.8800$. From table 1, we find this to be insignificant, and so no conclusions can be made about the value of λ_0 **and so we can conclude anything about the intercept of this model**. For completeness, we also obtain a factor value for excess market return (equity risk premium) of -0.3549, not to 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. **And so we can conclude that this factor is able to explain the cross section of stock returns that are sorted by size and momentum???**

4.4 Testing CAPM - MultiFactor Models 2008 - 2019

Now if we re-estimate the model using out of sample data

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

Model	γ_0	γ_1	γ_2	γ_3	γ_4
CAPM	0.9266 (4.3343)	-0.0043 (-0.0230)			
Factor1 Aggregate liquidity	1.2887 (6.1620)	-0.3456 (-1.9401)	-0.0146 (-2.8181)		
Factor2	1.1337 (5.8912)	-0.2408 (-1.4178)	-0.0240 (-2.8202)		
Factor3	0.9527 (4.7396)	-0.0130 (-0.0705)	-0.0023 (-0.6057)		
Saturated	1.2754 (3.8828)	-0.3863 (-1.2295)	-0.222 (-2.2258)	-0.0255 (-2.7887)	0 (0.0004)

Abdullah - Out of Sample CAPM
Abdullah - All factor (saturated) model
Abdullah - market return + liquidityfactor1
Neel - market return + liquidityfactor2

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.

From the time series regression we obtain estimates for the exposure (β_1) of the excess returns of the 25 portfolios to excess market returns and we see that average value of β_1 across the 25 portfolios is 1.2487, which is not too disimilar to the value obtained prior to 2008. It is worth noting that the variation of these betas (**figure**) is once again quite small 0.0520. We observe that the beta1s follow a similar pattern to that described for the in sample data where there is not much difference in size, yet the smallest momentum portfolio has larger beta than the largest momentum portfolio for each size group. We also obtain an estimate for the sensitivity (β_2) of excess returns on the innovations in liquidity factor, which has an average value of -3.6691 across the 25 portfolios. This is considerably different to the in sample case as we witness an inverse trend, where low momentum portfolios exhibit low beta values and high momentum portfolios have high beta values.
This suggests that the relationship between innovations in liquidity and excess returns in the market have completely reversed after the crisis??
Now running cross-sectional regression across the 25 portfolios at each time period of excess returns ($R_{i,t} - r_t^f$) on our betas $\beta_0 = 1$, β_1 and β_2 we obtain estimates for $\gamma_{0,i}$, $\gamma_{1,i} = \mathbb{E}[r_{M,t} - r_t^f]$ and $\gamma_{2,i}$ for

each time t. The outputs are displayed in **figure x and y**, which shows how much these gammas vary over time. As for the CAPM case, $\gamma_{1,i}$ can be interpreted as the risk premium of being exposed to excess market return. Similarly the variance of this risk premium is 63.5550, with a large spike occurring in the aftermath of the crisis. $\gamma_{2,i}$ can be interpreted as the risk premium of being exposed to innovations in liquidity. This appears to be much less volatile with a variance of this risk premium being 0.0249. (Massive dip at same time $\gamma_1 goesup!$)**bring in Kyrillos and knowledge of systematic risk for market risk premium**

$Usingourout-of-sampledatafrom1968to2008weobtainanaverageof \gamma_0$ (averaged over the whole period) $\lambda_0 = 1.1337$. 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 intercept of this model is not 0. As liquidity factor is not an excess return factor - this may be a plausible outcome**. For completeness, we also obtain a factor value for excess market return (equity risk premium) of -0.2408, not to 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 contradictory/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.

Neel - market return + liquidityfactor3

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.

From the time series regression we obtain estimates for the exposure (β_1) of the excess returns of the 25 portfolios to excess market returns and we see that average value of β_1 across the 25 portfolios is 1.2337. It is worth noting that the variation of these betas (**figure**) is once again quite small 0.0496. We observe that the beta1s follow an identical pattern to that described for the in-sample case where there is not much difference in size, yet the smallest momentum portfolio has larger beta than the largest momentum portfolio for each size group. We also obtain an estimate for the sensitivity (β_2) of excess returns on the traded liquidity factor, which has an average value of 6.8065 across the 25 portfolios. This is once again opposite to what was experienced prior to the crash. Here we find that beta value increases with momentum in each size group, which appears to have positive beta apart from the largest size group. Surprisingly there is a large variance of 101.6502 associated with these beta2s which is attributed to the fact that the smallest momentum portfolios exhibit small beta2 values and high momentum portfolios have large beta2 value for all sizes apart from the largest size group.

This suggests that as liquidity increases one would expect high momentum stocks sizes to exhibit excess returns and those of large size are negatively correlated (with that relationship) - something opposite to pre-crisis?

Now running cross-sectional regression across the 25 portfolios at each time period of excess returns $(R_{i,t} - r_t^f)$ on our betas $\beta_0 = 1$, β_1 and β_2 we obtain estimates for $\gamma_{0,i}$, $\gamma_{1,i} = \mathbb{E}[r_{M,t} - r_t^f]$ and $\gamma_{2,i}$ for each time t. The outputs are displayed in **figure x and y**, which shows how much these gammas vary over time. As for the CAPM case, $\gamma_{1,i}$ can be interpreted as the risk premium of being exposed to excess market return. Similarly the variance of this risk premium is 69.8010, with a large spike post crisis. $\gamma_{2,i}$ can be interpreted as the risk premium of being exposed to traded liquidity. This appears to be much less volatile with a variance of this risk premium being 0.0128. (massive dip when spike occurs) **bring in Kyrillos and knowledge of systematic risk for market risk premium**

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 1, we find this to be significant, and so we can conclude that λ_0 is non-zero, which is opposite to in-sample case. For completeness, we also obtain a factor value for excess market return (equity risk premium) of -0.0705, not to 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. We find that the risk premium for traded liquidity with a value of -0.0023 also tests insignificant **And so we cannot comment on the ability of this factor to explain the cross section of stock returns that are sorted by size and momentum???**

Limitations of the study We acknowledge that the analysis we have conducted may be of poor statistical standards, but for all intents and purposes of this study we can assume this to be sufficient.
We have also excluded analysis of the cross sectional regression using rolling windows. This has been done in order to stop the introduction of serial auto correlation. Instead we adopt the methodology whereby we take the average over the whole time period.

Only looking at certain factors. And so if model is built with additional factors (i.e Fama French 3 factor) then it may be useful - Pastor Stambaugh did something with this and found liquidity to be a factor

low momentum - portfolio has high volatility (riskier which means it has high beta)

gamma tells us that increasing beta by 1 unit of the portfolio, then excess return increases by gamma value

negative gamma - suggests that riskier portfolio (higher beta) should be rewarded with higher excess returns for gamma 1

low momentum has high beta (from graph of beta)

eq8 - innovation in liquidity is unexpected changes in aggregate liquidity (change in aggregate liquidity eq(7)

liquidity risk is priced - gamma positive - investors compensated for risk

liquidity risk is not priced - gamma negative - investors not compensated for risk

5 Conclusion

6 Bibliography

Jegadeesh, N. and Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance, 48(1), p.72.

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.

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