Informational Value of Daily Firm-Specific Twitter Sentiment

Analysis on Short-Term Returns of Large-Cap U.S. Companies

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Proposal Overview

Research Objectives

Research Question

- Can firm-level Twitter sentiment and volume explain daily returns and trading volumes of large-cap U.S. stocks?
- If so, could they contain fundamental information which is not incorporated into the stock prices?

The intention was to implement the methodology of Gu et al. [1] (also applied by Duz Tan et al. [2])

→ using a more transparent sentiment classification approach

→ for a different company sample and period.

Research Design

1. Extract all Tweets for the stocks constituting *S&P500* during the period starting on *June 1* and ending on *November 30* (*2021*)
2. Train a *supervised* sentiment polarity classification model using available labelled data
3. Construct daily sentiment scores for every stock-trading-day combination
4. Run controlled *Fama-MacBeth*-type regressions to analyse the effects of interest
5. Compute *time-series averages* of the coefficient estimates and the corresponding t-statistics
6. Analyse the findings and check their consistency with related results

Data Retrieval

Data Retrieval

- **Tweets:**
  - ∼ 20,000,000 Tweets[1] retrieved via the Academic Research track
  - CRAN package `academictwitteR` (Barrie et al. [3])
- **Labelled data:**
  - Sanders-Twitter Sentiment Corpus [4]
  - Sentiment140 [5]
  - Stock Market Tweets [6]
  - Financial PhraseBank [7]
  - BTC tweets sentiment [8]
  - Coronavirus tweets NLP [9]
  - StockTwits sample [10]
- **Prices and trading volumes:** Yahoo Finance, Alpha Vantage
- **Dividends and ex-dates:** Yahoo Finance, S&P Capital IQ
- **Numbers of shares outstanding:** S&P Capital IQ

[1] Containing one or more of the applicable ticker cashtags.

Sentiment Classifier

Classification Algorithm

- Multinomial and Bernoulli Naive Bayes (MNB & BNB, resp.) algorithms were considered
- 2 classes - positive and negative
- Features considered include:
  - Unigrams & bigrams[2]:
    - counts for MNB
    - Boolean values for BNB
  - Miscellaneous:
    - lexicon features
    - total word count
    - negated word count
    - negating word count
    - exclamation mark count
    - question mark count

[2] The bigram features were selected via likelihood ratio tests.

Strategy

The method was largely influenced by Renault [11].

→ Balanced train set of $\sim$ 200,000 texts
→ Validation set = Sanders Corpus + Stock Market Tweets
→ 5-fold CV to compare models

1. Fix **sparsity**[3] $= 0.9999$ and **Laplace smoothing parameter** $\alpha = 1$.
2. Compare the effect of the "optional" pre-processing methods on performance (relative to the benchmark).
3. For those with a positive effect, identify optimal combinations.
4. For the optimal combination(s), consider the effect of adding bigrams and miscellaneous features.
5. Use grid-search CV to tune the hyperparameters for the final candidate.

[3] As defined in `tm` (a CRAN package focused on text mining).

Pre-Processing

Some pre-processing methods were applied for all models, eg. converting all letters to lowercase and removing user handles, hashtags, cashtags and links.

The following were optional:

Keep/remove:

- Punctuation
- Emojis
- Emoticons
- Stopwords[4]
- Stemming
- Lemmatisation
- Negation handling

[4] From a pre-compiled list.

Optimal Model

Let "+" correspond to "keep/apply" and "-" to "remove/do not apply".

Benchmark	Optimal
- Punctuation	- Punctuation
- Emojis	+ Emojis
- Emoticons	+ Emoticons
+ Stopwords	+ Stopwords
- Stemming	+ Stemming
- Lemmatisation	- Lemmatisation
- Negation handling	+ Negation handling[5]
- Extra features	+ Extra features[6]

Table 1: Pre-processing steps applied during the training phase.

[5]The two words following "no", "n't", "not", "never", "without" were given the prefix "neg_" under certain conditions.

[6]Namely, two lexicon features based on Renault [12], exclamation mark and negated word counts.

Performance Comparison

	Benchmark ($\alpha = 1$, sparsity $= 0.9999$)	**Optimal** ($\alpha = 0.1$, sparsity $= 0.99993$[7])
5-fold CV		
Accuracy	76.13	77.00
Sensitivity	74.48	75.71
Specificity	77.73	78.26
Validation		
Accuracy	71.55	74.79
Sensitivity	71.70	76.05
Specificity	71.38	73.39

Table 2: Performance metric values for the two models (in %).

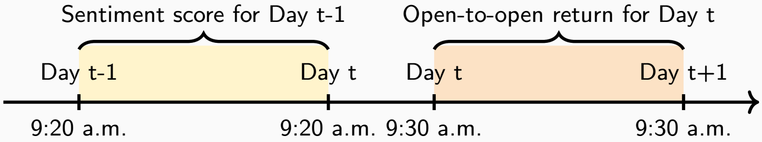
[7] Corresponds to approx. 7500 terms in the document-term matrix.

Sentiment Scores

Sentiment Score Construction (1/2)

All of the stocks considered are traded on either NASDAQ, NYSE or BATS (1 stock only). Hence, the Eastern Time (ET) Zone was used[8].

The return and sentiment score[9] values are computed as in [1] and [2]:



[8] Either Eastern Daylight Time (EDT) or Eastern Standard Time (EST), depending on the time of the year.

[9] The minimum number of Tweets required was set to 10.

Sentiment Score Construction (2/2)

For a given stock, denote the number of Tweets classified as positive (negative) on day t by N_t^+ (N_t^-).

Multiple sentiment measures were used in the experiments, specifically:

- Average Sentiment Score (Renault [11]):

$$AVG_t = \frac{1 \cdot N_t^+ + (-1) \cdot N_t^-}{N_t^+ + N_t^-}$$

- Average Weighted Sentiment Score (Bloomberg [13]):

$$AVGw_t = \frac{\sum_{i=1}^{N_t^+} 1 \cdot C_{i,t}^+ + \sum_{j=1}^{N_t^-} (-1) \cdot C_{j,t}^-}{N_t^+ + N_t^-}$$

- Agreement (Antweiler et al. [14], Sprenger et al. [15]):

$$AG_t = 1 - \sqrt{1 - \left(\frac{N_t^+ - N_t^-}{N_t^+ + N_t^-} \right)^2}$$

Experiments

Experiments: Set-Up

Method (Gu et al. [1], Duz Tan et al. [2], Tetlock [16]):

Use daily cross-sectional regressions, similar to those in Fama et al. [17]:

1. Run cross-sectional regressions for each trading day.
2. Report the time-series averages of the daily coefficient estimates and the corresponding (robust[10]) t-statistics.

Controls (Duz Tan et al. [2]):

- $Size_{t-1}$, log of market capitalisation
- $Ret_{[t-5,t-1]}$, cumulative returns
- $AbTurn_{t-1}$, abnormal turnover[11] (Tetlock [16])
- $Vola_{[t-5,t-1]}$, Park volatility measure (Parkinson [19])
- $Illiq_{[t-5,t-1]}$, Amihud's illiquidity measure (Amihud [20])

[10] Standard errors are Newey-West ([18]) adjusted up to four lags for heteroskedasticity and autocorrelation.
[11] Excluded from the regressions where abnormal turnover is the response variable.

Holding Period Return (HPR) & Twitter Sentiment (1/2)

	AVG		$AVGw$		AG	
$SentScore_t$	0.0055	(16.00)	0.0063	(15.22)	0.0048	(5.61)
$Size_{t-1}$	0.0002	(1.30)	0.0002	(1.30)	0.0003	(1.94)
$Ret_{[t-5,t-1]}$	0.0135	(1.48)	0.0140	(1.53)	0.0166	(1.77)
$AbTurn_{t-1}$	0.0009	(1.69)	0.0009	(1.71)	0.0009	(1.61)
$Vola_{[t-5,t-1]}$	-0.0213	(-0.28)	-0.0213	(-0.28)	-0.0214	(-0.28)
$Illiq_{[t-5,t-1]}$	0.0124	(3.27)	0.0125	(3.30)	0.0099	(2.75)
$Const.$	-0.0071	(-1.57)	-0.0071	(-1.55)	-0.0087	(-1.92)
R^2	0.0102		0.0096		0.0038	
N	30162		30162		30162	
Time periods	128		128		128	

Table 3: Results of contemporaneous regressions of HPR on Twitter sentiment, constant and controls.

Holding Period Return (HPR) & Twitter Sentiment (2/2)

	AVG		$AVGw$		AG	
$SentScore_{t-1}$	-0.0004	(-1.41)	-0.0004	(-1.30)	-0.0004	(-0.63)
$Size_{t-1}$	0.0004	(2.39)	0.0004	(2.42)	0.0004	(2.31)
$Ret_{[t-5,t-1]}$	0.0086	(0.99)	0.0084	(0.98)	0.0083	(0.95)
$AbTurn_{t-1}$	0.0008	(1.49)	0.0008	(1.48)	0.0008	(1.52)
$Vola_{[t-5,t-1]}$	-0.0013	(-0.02)	-0.0015	(-0.02)	0.0010	(0.01)
$Illiq_{[t-5,t-1]}$	0.0046	(1.21)	0.0047	(1.23)	0.0044	(1.17)
$Const.$	-0.0110	(-2.33)	-0.0112	(-2.36)	-0.0109	(-2.25)
R^2	0.0018		0.0018		0.0018	
N	30115		30115		30115	
Time periods	128		128		128	

Table 4: Results of predictive regressions of HPR on Twitter sentiment, constant and controls.

Holding Period Return (HPR) & Tweet Count (1/2)

	$N_{OG+RT+RE}$[12]		N_{OG+RE}		N_{OG}	
$TweetCount_t$	0.000002	(3.31)	0.000003	(3.84)	-0.000009	(-2.71)
$Size_{t-1}$	0.000096	(0.77)	-0.000005	(-0.04)	0.000112	(0.91)
$Ret_{[t-5,t-1]}$	0.004837	(0.60)	0.004881	(0.61)	0.004870	(0.60)
$AbTurn_{t-1}$	0.000627	(1.88)	0.000590	(1.81)	0.000613	(1.87)
$Vola_{[t-5,t-1]}$	-0.027839	(-0.38)	-0.037472	(-0.51)	-0.026472	(-0.36)
$Illiq_{[t-5,t-1]}$	-0.001445	(-1.30)	-0.001698	(-1.50)	-0.001312	(-1.17)
$Const.$	-0.002186	(-0.69)	0.000400	(0.12)	-0.002220	(-0.69)
R^2	0.002161		0.002224		0.001819	
N	63744		63744		63744	
Time periods	128		128		128	

Table 5: Results of contemporaneous regressions of HPR on Tweet count, constant and controls.

[12] Number of original Tweets (OG), Retweets (RT) and Replies (RE).

Holding Period Return (HPR) & Tweet Count (2/2)

	$N_{OG+RT+RE}$		N_{OG+RE}		N_{OG}	
$TweetCount_{t-1}$	0.0000004	(1.01)	0.0000007	(1.22)	-0.0000027	(-1.07)
$Size_{t-1}$	0.0001950	(1.66)	0.0001630	(1.30)	0.0001836	(1.48)
$Ret_{[t-5,t-1]}$	0.0050200	(0.62)	0.0052380	(0.65)	0.0050908	(0.63)
$AbTurn_{t-1}$	0.0006635	(2.01)	0.0006357	(1.93)	0.0006418	(1.93)
$Vola_{[t-5,t-1]}$	-0.0179252	(-0.24)	-0.0206711	(-0.28)	-0.0188605	(-0.26)
$Illiq_{[t-5,t-1]}$	-0.0009990	(-0.89)	-0.0011575	(-1.01)	-0.0010726	(-0.95)
$Const.$	-0.0046585	(-1.55)	-0.0038303	(-1.19)	-0.0042448	(-1.34)
R^2	0.0014154		0.0014089		0.0014012	
N	63744		63744		63744	
Time periods	128		128		128	

Table 6: Results of predictive regressions of HPR on Tweet count, constant and controls.

Abnormal Turnover & Twitter Sentiment (1/2)

	AVG		$AVGw$		AG	
$SentScore_t$	-0.0714	(-9.10)	-0.1039	(-10.95)	-0.2181	(-14.63)
$Size_{t-1}$	-0.0134	(-2.45)	-0.0133	(-2.44)	-0.0166	(-3.00)
$Ret_{[t-5,t-1]}$	-0.1766	(-1.33)	-0.1686	(-1.28)	-0.1799	(-1.35)
$Vola_{[t-5,t-1]}$	-10.1481	(-11.67)	-10.2003	(-11.81)	-10.5689	(-12.20)
$Illiq_{[t-5,t-1]}$	0.9716	(8.46)	0.9664	(8.45)	1.0427	(8.82)
$Const.$	0.4952	(3.55)	0.4992	(3.60)	0.5800	(4.11)
R^2	0.0395		0.0414		0.0434	
N	30162		30162		30162	
Time periods	128		128		128	

Table 7: Results of contemporaneous regressions of abnormal turnover on Twitter sentiment, constant and controls.

Abnormal Turnover & Twitter Sentiment (2/2)

	AVG		$AVGw$		AG	
$SentScore_{t-1}$	-0.0028	(-0.49)	-0.0119	(-1.56)	-0.0754	(-5.44)
$Size_{t-1}$	-0.0058	(-1.08)	-0.0058	(-1.09)	-0.0068	(-1.28)
$Ret_{[t-5,t-1]}$	-0.2419	(-1.82)	-0.2351	(-1.78)	-0.2311	(-1.71)
$Vola_{[t-5,t-1]}$	-9.017	(-11.91)	-9.0401	(-11.90)	-9.2432	(-12.33)
$Illiq_{[t-5,t-1]}$	0.6687	(6.89)	0.6664	(6.89)	0.6814	(6.98)
$Const.$	0.2593	(1.89)	0.2630	(1.91)	0.2954	(2.13)
R^2	0.0241		0.0241		0.0249	
N	30115		30115		30115	
Time periods	128		128		128	

Table 8: Results of predictive regressions of abnormal turnover on Twitter sentiment, constant and controls.

Abnormal Turnover & Tweet Count (1/2)

	$N_{OG+RT+RE}$		N_{OG+RE}		N_{OG}	
$TweetCount_t$	0.00009	(8.23)	0.00022	(11.76)	-0.00060	(-7.16)
$Size_{t-1}$	-0.00184	(-0.52)	-0.01321	(-3.16)	-0.00403	(-1.03)
$Ret_{[t-5,t-1]}$	-0.25065	(-1.89)	-0.26742	(-2.05)	-0.25198	(-1.91)
$Vola_{[t-5,t-1]}$	8.69094	(-11.45)	-9.66331	(-12.77)	-8.87359	(-11.76)
$Illiq_{[t-5,t-1]}$	0.24398	(5.69)	0.20822	(5.08)	0.23771	(5.73)
$Const.$	0.13883	(1.52)	0.42746	(4.05)	0.22055	(2.20)
R^2	0.0186		0.0246		0.0193	
N	63744		63744		63744	
Time periods	128		128		128	

Table 9: Results of contemporaneous regressions of abnormal turnover on Tweet count, constant and controls.

Abnormal Turnover & Tweet Count (2/2)

	$N_{OG+RT+RE}$		N_{OG+RE}		N_{OG}	
$TweetCount_{t-1}$	0.00006	(4.88)	0.00013	(6.22)	-0.00036	(-3.79)
$Size_{t-1}$	-0.00034	(-0.10)	-0.00646	(-1.57)	-0.00104	(-0.27)
$Ret_{[t-5,t-1]}$	-0.25201	(-1.89)	-0.25548	(-1.95)	0.24268	(-1.85)
$Vola_{[t-5,t-1]}$	-8.58515	(-11.34)	-9.17434	(-12.19)	-8.66398	(-11.51)
$Illiq_{[t-5,t-1]}$	0.25096	(5.91)	0.23225	(5.60)	0.24907	(5.96)
$Const.$	0.10224	(1.12)	0.25888	(2.53)	0.13625	(1.41)
R^2	0.01684		0.01826		0.01652	
N	63744		63744		63744	
Time periods	128		128		128	

Table 10: Results of predictive regressions of abnormal turnover on Tweet count, constant and controls.

Experiments: Discussion of Results

Contemporaneous:

- For all regressions, the estimates of the coefficients of interest are significant at 1% level:
  - all positive for "return-sentiment" regressions,
  - all negative for "turnover-sentiment" regressions,
  - positive (incl. Retweets + Replies / Replies only) and negative (excl. both) for "return-count" and "turnover-count" regressions.

Predictive:

- No evidence in support of Twitter sentiment and Tweet count being significant predictors of HPR is observed (at any common level).
- The agreement (AG) measure seems to have a significant (1%) negative linear association with abnormal turnover.
- All of the Tweet count measures are found to be significant (1%) predictors[13] of abnormal turnover.

[13] The direction of association is the same as for the contemporaneous regressions.

Case Study

Case Study: Set-Up

- We explore whether (aggregated) firm-level Twitter sentiment provides information not already reflected in the value of S&P500.
- More precisely, we analyse if it is a significant predictor when it comes to the daily returns and abnormal volumes of:
  - SPDR SP 500 ETF Trust (SPY),
  - iShares Core SP 500 ETF (IVV),
  - Vanguard 500 Index Fund (VOO).
- In each case[14], a single regression with 128[15] observations is run.

$\rightarrow$ Twitter sentiment = equal- or value-weighted average of individual sentiment scores

[14] In essence, for every combination of model specification and predictor of interest.
[15] The number of trading days in the sample period.

Case Study: Results of Regressions on Twitter Sentiment

Response	Predictor	SPY		IVV		VOO	
HPR_t	AVG_t	0.0203	(1.55)	0.0206	(1.67)	0.0202	(1.60)
HPR_t	$AVGw_t$	0.0241	(1.77)	0.0237	(1.80)	0.0265	(1.99)
HPR_t	AG_t	0.0339	(0.82)	0.0374	(1.01)	0.0313	(0.83)
HPR_t	AVG_{t-1}	0.0334	(2.32)	0.0397	(2.62)	0.0383	(2.73)
HPR_t	$AVGw_{t-1}$	0.0369	(2.16)	0.0435	(2.38)	0.0445	(2.65)
HPR_t	AG_{t-1}	0.0836	(2.23)	0.1014	(2.63)	0.0927	(2.61)
$AbTurn_t$	AVG_t	-1.0823	(-2.08)	-1.0491	(-1.91)	-1.7527	(-3.10)
$AbTurn_t$	$AVGw_t$	-1.3422	(-2.17)	-1.2570	(-1.92)	-3.7502	(-2.86)
$AbTurn_t$	AG_t	-2.2424	(-1.61)	-3.7502	(-2.31)	-3.2284	(-2.05)
$AbTurn_t$	AVG_{t-1}	-1.0311	(-1.69)	-0.2792	(-0.52)	-1.2677	(-2.08)
$AbTurn_t$	$AVGw_{t-1}$	-1.2576	(-1.70)	-0.3203	(-0.48)	-1.4093	(-1.93)
$AbTurn_t$	AG_{t-1}	-1.5384	(-0.81)	-1.3039	(-0.72)	-2.1011	(-0.99)

Table 11: Results of controlled regressions on value-weighted sentiment.

Case Study: Discussion of Results

The results of regressions on equal-weighted sentiment scores are similar to the ones demonstrated.

Predictive "return-sentiment" regressions:

- All coefficients are positive and significant at 5% level.
- Further inclusion of sentiment lags showed that there were no subsequent *reversals* during the week offsetting the price increases.
- This supports the view that Twitter sentiment contains valuable private signals about firms' prospects, which upon aggregation can become a valuable signal about performance of the corresponding ETFs / index.

Contemporaneous "turnover-sentiment" regressions:

- We have evidence (5%) for a negative linear association between abnormal turnover and Twitter sentiment.

Conclusion

Conclusion

Research Question Revisited

- Can firm-level Twitter sentiment and volume explain daily returns and trading volumes of large-cap U.S. stocks?
  - → Yes, given that Twitter predictors are contemporaneous.
  - → For one-day ahead predictions, the agreement measure and Tweet counts have significant explanatory power when it comes to abnormal turnover.
- If so, could they contain fundamental information which is not incorporated into the stock prices?
  - → Possibly if one considers intra-day returns and sentiment, but not at daily frequency.

Thank you for your attention!
Any questions?

References

[1] Chen Gu and Alexander Kurov. "Informational role of social media: Evidence from Twitter sentiment". In: *Journal of Banking Finance* 121 (2020), p. 105969. issn: 0378-4266. doi: https://doi.org/10.1016/j.jbankfin.2020.105969. url: https://www.sciencedirect.com/science/article/pii/S0378426620302314.

[2] Selin Duz Tan and Oktay Tas. "Social Media Sentiment in International Stock Returns and Trading Activity". In: *Journal of Behavioral Finance* 22.2 (2021), pp. 221–234. url: https://EconPapers.repec.org/RePEc:taf:hbhfxx:v:22:y:2021:i:2:p:221-234.

[3] Christopher Barrie and Justin Chun-ting Ho. "academictwitteR: an R package to access the Twitter Academic Research Product Track v2 API endpoint". In: *Journal of Open Source Software* 6.62 (2021), p. 3272. doi: 10.21105/joss.03272. url: https://github.com/cjbarrie/academictwitteR.

[4] Sanders Analytics. *Sanders Twitter Corpus*. https://github.com/zfz/twitter_corpus. 2013.

[5] Alec Go, Richa Bhayani, and Lei Huang. "Twitter sentiment classification using distant supervision". In: *CS224N project report, Stanford* 1.12 (2009), p. 2009.

[6] Bruno Taborda, Ana de Almeida, José Carlos Dias, Fernando Batista, and Ricardo Ribeiro. *Stock Market Tweets Data*. 2021. doi: 10.21227/g8vy-5w61. url: https://dx.doi.org/10.21227/g8vy-5w61.

[7] P. Malo, A. Sinha, P. Korhonen, J. Wallenius, and P. Takala. "Good debt or bad debt: Detecting semantic orientations in economic texts". In: *Journal of the Association for Information Science and Technology* 65 (2014).

[8] Al Mercado. *BTC tweets sentiment*. https://data.world/mercal/btc-tweets-sentiment. 2018.

[9] Aman Miglani. *Coronavirus tweets NLP - Text Classification*. https://www.kaggle.com/datasets/datatattle/covid-19-nlp-text-classification. 2019.

[10] Sean Bryan Trace Russell. *Project for CMU course 15-388, Practical Data Science*. https://github.com/tdrussell/stocktwits_analysis. 2016.

[11] Thomas Renault. "Sentiment analysis and machine learning in finance: a comparison of methods and models on one million messages". In: *Digital Finance* 2.1 (Sept. 2020), pp. 1–13. doi: 10.1007/s42521-019-00014-. url: https://ideas.repec.org/a/spr/digfin/v2y2020i1d10.1007_s42521-019-00014-x.html.

[12] Thomas Renault. "Intraday online investor sentiment and return patterns in the U.S. stock market". In: *Journal of Banking Finance* 84 (2017), pp. 25–40. issn: 0378-4266. doi: https://doi.org/10.1016/j.jbankfin.2017.07.002. url:

https://www.sciencedirect.com/science/article/pii/S0378426617301589.

[13] Bloomberg. *Embedded value in Bloomberg News amp; social sentiment data - twitter*. url: https://developer.twitter.com/content/dam/developer-twitter/pdfs-and-files/Bloomberg-Twitter-Data-Research-Report.pdf.

[14] Werner Antweiler and Murray Z. Frank. "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards". In: *The Journal of Finance* 59.3 (2004), pp. 1259–1294. doi: https://doi.org/10.1111/j.1540-6261.2004.00662.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2004.00662.x. url: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2004.00662.x.

[15] Timm O. Sprenger, Andranik Tumasjan, Philipp G. Sandner, and Isabell M. Welpe. "Tweets and Trades: the Information Content of Stock Microblogs". In: *European Financial Management* 20.5 (2014), pp. 926–957. doi: https://doi.org/10.1111/j.1468-036X.2013.12007.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-036X.2013.12007.x. url: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-036X.2013.12007.x.

[16] Paul C. Tetlock. "All the News That's Fit to Reprint: Do Investors React to Stale Information?" In: *The Review of Financial Studies* 24.5 (Jan. 2011), pp. 1481–1512. issn: 0893-9454. doi: 10.1093/rfs/hhq141. eprint: https://academic.oup.com/rfs/article-

pdf/24/5/1481/24430733/hhq141.pdf. url: https://doi.org/10.1093/rfs/hhq141.

[17] Eugene F Fama and James D MacBeth. "Risk, return, and equilibrium: Empirical tests". In: *Journal of political economy* 81.3 (1973), pp. 607–636.

[18] Whitney K. Newey and Kenneth D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix". In: *Econometrica* 55.3 (1987), pp. 703–708. issn: 00129682, 14680262. url: http://www.jstor.org/stable/1913610 (visited on 06/10/2022).

[19] Michael H. Parkinson. "The Extreme Value Method for Estimating the Variance of the Rate of Return". In: *The Journal of Business* 53 (1980), pp. 61–65.

[20] Yakov Amihud. "Illiquidity and stock returns: cross-section and time-series effects". In: *Journal of Financial Markets* 5.1 (2002),

pp. 31–56. issn: 1386-4181. doi:
https://doi.org/10.1016/S1386-4181(01)00024-6. url:
https://www.sciencedirect.com/science/article/pii/S1386418101000246.