HW: Financial Ratio Quantile Strategies

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1 Introduction

Here you will consider a few financial accounting ratios, as an approximation of "quantamental" models that typically take much more numerous and carefully defined financial accounting into consideration. You will then investigate profit opportunity of a quantile-based long-short scheme.

2 Understand Your Data

Read all documentation webpages for Zacks Fundamentals B. You will see they supply 6 related tables, FC, FR, MT, MKTV, SHRC and HDM [1]. The strategy coding for this assignment will be reasonably easy. The data assembly, deliberately, is the difficult part.

3 Define the Universe

Choose at least 200 tickers[2] of US equities such that[3] they satisfy the following:

- end-of-day adjusted closing prices are available , over the entire period Jan 2014 through Jan 2021

[1] It is easiest to download your data through full-table downloads. Use URLs such as *https://www.quandl.com/api/v3/datatables/ZACKS/MT?qopts.export=true*

[2] You can find the full list of available tickers online

[3] We will not concern ourselves with *selection bias* in this exercise.

- debt/market_cap ratio is greater[4] than 0.1 somewhere in the period Jan 2014 through Jan 2021 (preferably more than fleetingly)
- not in the automotive, financial or insurance sector , over the entire period Jan 2014 through Jan 2021[5]
- has feasible calculation of the ratios specified below , over the entire period Jan 2014 through Jan 2021, including for at least one `PER_END_DATE` no more than one year old. Debt ratio of zero is OK.

4 Select Financial Ratios

For this assignment, we will work with the following ratios:

- debt to market cap[6].
- return on investment[7]
- price to earnings[8]

Note that these data items are reported (at best) quarterly. Use annual numbers *only* when quarterly ones do not exist. As the equity price changes day-to-day, each ratio changes accordingly[9], so ultimately the time series you have will be on daily data[10]. Recall that we did not know any of these numbers until the `FC/FILING_DATE` .

[4] This is about 1000-2000 companies, including ASH, VTOL, ISUN and VIVO.

[5] See the Quandl ZFB fields `ZACKS_SECTOR_CODE`, `ZACKS_X_IND_CODE`, and the classification list

[6] `FR/TOT_DEBT_TOT_EQUITY` in Quandl. In this homework we pretend that it is OK to treat market capitalization and book equity as equivalent, though they are not the same thing.

[7] Based on `FR/RET_INVST`, `MKTV/MKT_VAL`, `FC/NET_LTERM_DEBT`, `FC/TOT_LTERM_DEBT`. Investment is defined here as market cap plus long term debt. Use net debt where available, total debt otherwise. Quandl will report debt as NaN if it was 0.0, but be careful about net versus tot debt.

[8] Compute this based on `FC/EPS_DILUTED_NET`, `BASIC_NET_EPS`, `SHRS/SHARES_OUT`, `MKTV/MKT_VAL`, use the basic version (GAAP) if no diluted number is available. Treat negative earnings per share as 0.001.

[9] In many cases `PER_END_DATE` is not a trading day, so go ahead and forward fill equity price from the previous trading day.

[10] If you have memory errors when joining data, you are probably mistakenly creating a combinatorial explosion in your merging code.

As an example, consider V, return on investment. Say that our entity had successive report dates of March 31 and June 30, V^{3-31} and V^{6-30} and those numbers were known on filing dates April 4 and July 7. Our equity price series, which we take (also a bit problematically) as adjusted close prices, will be P^t. We have a debt number D for each report date as well.

We can infer the "return" R for a given report date as the unknown element in

$$V = \frac{R}{D + M}$$

and we assume it doesn't change day-to-day. Rather only the market value element M changes daily, and we estimate the corresponding $\tilde{V}$ values according to the filing dates. So for example our inferred values look like

$$\tilde{V}^{7\text{-}6} = \frac{R^{3\text{-}31}}{D^{3\text{-}31} + M^{7\text{-}6}}$$

but the next day is the filing date so we have

$$\tilde{V}^{7\text{-}7} = \frac{R^{6\text{-}30}}{D^{6\text{-}30} + M^{7\text{-}7}}$$

where

$$M^{7\text{-}6} = M^{3\text{-}31}\frac{P^{7\text{-}6}}{P^{3\text{-}31}}$$

and

$$M^{7\text{-}7} = M^{6\text{-}30}\frac{P^{7\text{-}7}}{P^{6\text{-}30}}.$$

5 Analysis

Study performance of weekly or monthly quantile trading strategies using each of these single ratios as well as your choice of least one nontrivial combination of them[11].

Set initial capital to be 10 times the gross notional of your first month's set of positions. You may assume zero trading costs, that trading fractional shares and arbitrary positions sizes are possible, that all securities are easy to borrow with a repo rate equal to your funding rate minus 100bp[12], and that

[11] That is to say, at least 4 types of scores.

[12] This number may sometimes become negative.

the portfolio capital is equal to the initial capital, adjusted for all realized and unrealized PL to date. Choose either a constant funding rate, or rolling 3-month LIBOR.

Analyze performance of a top-and-bottom decile trading strategy. Now rank based on *changes* in your ratios rather than the ratios themselves. Play with the effects of sizing positions by rank.

6 Data Example

Here is recent sample data for Eli Lilly (ticker LLY):

6.0.1 SEC Reports

per_end_date	2020-06-30	2020-09-30	2020-12-31	2021-03-31	2021-06-30	2021-09-30
filing_date	2020-07-31	2020-10-28	2021-02-17	2021-04-30	2021-08-03	2021-10-27
tot_revnu	5499.4	5740.6	7440.001	6805.6	6740.1	6772.8
eps_diluted_net	1.55	1.33	2.31	1.49	1.53	1.22
basic_net_eps	1.55	1.33	2.32	1.49	1.53	1.22
tot_lterm_debt	15064.4	16334.6	16586.6	16199.6	14736.6	15522.4
net_lterm_debt	712.3	1786.0	1785.8	NaN	NaN	505.5
net_curr_debt	-235.4	-914.3	-1494.2	-3.7	196.3	-1.5
zacks_x_ind_code	225.0	225.0	225.0	225.0	225.0	225.0
zacks_sector_code	4.0	4.0	4.0	4.0	4.0	4.0
zacks_metrics_ind_code	13.0	13.0	13.0	13.0	13.0	13.0
tot_debt_tot_equity	3.8221	3.3871	2.8489	2.2825	2.4784	2.148
ret_invst	7.3023	5.6651	9.445	5.817	6.4962	4.7286
free_cash_flow_per_share	2.5664	4.1159	5.6018	1.5312	3.066	4.4859
shares_out	956.47	956.58	956.58	959.03	959.03	956.59
per_type	Q	Q	Q	Q	Q	Q
mkt_val	157033.3	141593.2	161509.22	179165.14	220115.53	221020.67

6.0.2 Ratios On Key Dates

(Using `MKTV/MKT_VAL, FC/NET_LTERM_DEBT` to infer operating income)

Date	Debt_To_Mkt_Cap	Return_On_Inv	Price_To_Earnings
2019-10-25	5.554480	8.048674	73.467766
2019-10-28	4.352354	7.249701	79.176659
2019-12-31	3.720165	6.227653	92.631604
2020-01-02	3.698217	6.191987	93.181347
2020-02-19	3.453830	5.794008	99.774689
2020-02-20	5.225211	8.356740	77.868328
2020-03-31	5.348760	8.549034	76.069679
2020-04-01	5.438939	8.689238	74.808431
2020-05-01	4.829656	7.739485	84.245853
2020-05-04	4.877282	7.671248	92.984654
2020-06-30	4.532301	7.127691	100.062297
2020-07-01	4.556724	7.166169	99.525966
2020-07-31	4.951182	7.787704	91.596800
2020-08-03	4.105682	7.841469	96.155810
2020-09-30	4.218627	8.056110	93.581421
2020-10-01	4.327682	8.263302	91.223235
2020-10-28	4.755473	9.075546	83.017001
2020-10-29	3.782411	6.317094	97.662767
2020-12-31	2.953930	4.948484	125.053966
2021-01-04	3.013544	5.047243	122.580143
2021-02-17	2.405588	4.038046	153.559427
2021-02-18	2.381655	7.910124	86.126239
2021-03-31	2.563957	8.509632	80.002505
2021-04-01	2.585826	8.581494	79.325897
2021-04-30	2.620772	8.696299	78.268161
2021-05-03	2.293549	5.842814	123.433215
2021-06-30	1.849797	4.789536	153.043896
2021-07-01	1.836912	4.758436	154.117443
2021-08-03	1.658523	4.324818	170.694087
2021-08-04	2.167266	5.725783	170.439396