DEMOS

Volume 1 Article 7

2018

Market-Neutral Strategy for Quantitative Trading: Long Positive Beta and Shorting Negative Beta Stocks

Charmaine Chung
Lake Forest College

Alina Kotlova
Lake Forest College

Grant Zimmerman
Lake Forest College

MARKET-NEUTRAL STRATEGY FOR QUANTITATIVE TRADING: LONG POSITIVE BETA AND SHORTING NEGATIVE BETA STOCKS

Charmaine Chung, Alina Kotlova, and Grant Zimmerman

Lake Forest College
Class of 2018

This was originally submitted to FIN 485: Quantative Finance with Dr. Muris Hadzic in the fall of 2017. This is a Senior Seminar final project.

Executive Summary

Our investment idea is a long-short strategy that aims to neutralize or minimize our beta as much as possible, to create a market-neutral portfolio. We base our investment theory off the Security Market Line model, which demonstrates using the capital asset pricing model that you can gain from only residual returns (the returns not explainable by market returns) by minimizing beta. By doing so, we aim to identify and exploit market inefficiencies that are present in human biases, which are reflected in market prices. In our algorithm, we set thresholds to accounting factors that are used as conditions of adding stocks to our long and short positions from the universe of stocks. The metrics are momentum, value, and quality (profitability) --- which are determined using book-to-price ratio and return on equity, respectively.

Investment Philosophy

As the project guidelines assert, an investment philosophy is the theory before which we implement our trading strategy. It is rooted in our view of market efficiency, and how it affects security prices.

What causes an inefficient market? We cite multiple reasons that market prices tend to deviate from the "true discounted value of their future cash flows" ("Inefficient Market", Investopedia). When exploited in investing strategies, some of these "anomalies" in pricing behavior generate "abnormal" returns, or returns that are not explainable by the market. In times when the price of securities accurately reflects the demand for it, the security can reach market equilibrium. This happens when all buyers and sellers in the market have the same information. However, this is difficult to ascertain - there is both public and privately shared information on publicly traded securities, which makes it impossible for all investors to be able to determine the same willingness to trade on a security that they might otherwise have had, with access to all the private and public information on the security. Put another way, because everyone evaluates a security with a different perception of future cash flows, they valuate the security to have different present value than they might otherwise have, had everyone had the exact same information in mind. Thus, it is virtually impossible for the pricing of a security to exactly reflect this demand, when everyone has considered their willingness to buy with different parameters in mind (p. 2).

Even with universal structural knowledge, Khan asserts that investors would still have psychological biases that are unique to the individual. The commonality of these behavioral biases, including loss aversion, overconfidence, limited attention, representativeness, gambler's fallacy, mental accounting, conservatism, disposition effect, and narrow framing biases, result in distortions of logic between each investor, that are separate of the differences in informational access each investor has. This idea of psychological bias in making risky decisions is stressed in the academic realm of behavioral economics and finance as well. Filc (2007) references economists such as Hyman Minsky, who believed that capitalism inherently “[tended] towards instability” (p. 1). In times of long-term economic growth and low interest rates, Minsky points out businesses’ tendencies to take on greater risk.

Thus, the market price of publicly traded securities is not an unbiased estimate of the true value of the investment, because psychological biases result in no true unbiased estimate of the market price. Furthermore, psychological (including informational) biases are random, in such a way that the deviations from any true value of an investment cannot be predetermined. By using studies of human bias and foundations of behavioral economics, we gathered our assertion on market inefficiency that would be at the core of our investment strategy.

Fama and French, the theorists of the efficient market hypothesis, also created a revised version of the capital asset pricing model, a core model of investment theory. The capital asset pricing model is used as a model of governing a stock’s returns. In such a way, it is the foundation of the security market line, the function used to graphically illustrate how market returns and the security’s correlation to the market, or beta, result in residual returns (the returns not explainable by market returns). As Vidyamurthy (2004) shows, the security market line is modeled with CAPM:

Security Market Line: $E(R) = Rf + \beta i[E(Rm) - Rf]$

Where θp is the residual return, and can be modeled by: $\theta p = R - Rf - \beta i[E(Rm) - Rf]$

We quantify our strategy by seeking to maximize our residual returns, and minimize our market returns. This is because the returns are directly correlated with risk, and increasing beta increases not only returns from the market but also its risks. Selecting stocks from different sectors, based off accounting measures (fundamental analysis), aims to maximize this residual return. By using accounting data, including earnings before income tax (EBIT), enterprise value, and return on equity, to determine value and quality (profitability) of the stock, we are developing an algorithm that disregards human biases, which we believe distort the values of securities. Thus, we are implementing in our strategy an inefficient market approach. A Harvard study on investment styles and market anomalies found that the long-short strategy in combination with certain valuation factors can produce returns beating market returns. In Michaud (1999) writes in his publication that Lakonishok, Shleifer, and Vishny (1994) assert that “a long-short portfolio framework and multifactor valuation” lead to 7-8 percent above- market returns ... and “generally substantially increases residual risk” (8). This is exactly our approach as we utilize fundamental analyses to valuate against market prices that are reflective of human biases in trading.

Investment Strategy

Sophisticated investors have used long-short strategies, such as institutions, for years. They became increasingly popular among individual investors as traditional strategies struggled in the most recent market, and stressed the need for investors to consider expanding their portfolios into innovative financial ideas.

According to historical data, total hedge fund assets set a record of $2.7 trillion, in the first quarter of 2014. The demand was strongest within the long short equity strategy, with investors allocating over $16.3 billion in new capital during the quarter. Overall assets in the long short equity space reached $761 billion, the largest area of hedge fund capital. This data inspired us to create our portfolio based on innovated and profitable financial strategies. Consequently, we build our portfolio using long-short strategy, in which we use beta as our main factor. We create a market-neutral portfolio by having one set of stocks that have a positive beta, and the other set of stocks with a negative beta that makes the net beta of the portfolio zero. Besides, the goal of our long-short strategy is to minimize exposure to the market in general, and profit from a change in the difference, or spread, between two stocks. Thus, we are trying to diversify market risk by ensuring that each stock of our portfolio is in different sectors.

Theoretically speaking, a long-short strategy involves having one set of securities in the long position, that we anticipate will increase in value, and another set of securities in the short position, that we anticipate will decrease in value. Hence, we buy the long position securities prior to this anticipated market increase, and short the short position securities at the same time. Thus, we assume the long-short strategy will leads to the capital gains of buying low and selling high the long-position security. While, selling short the short-position security allowed us to profit from selling high and rebuying it at lower future price.

Our idea is mainly consisting of buying an undervalued stock and shorting an overvalued stock as we assume that the long position will increase in value, and the short position will decline in value. Ideally our strategy will be profitable even if the long position declines in value because. since we have market neutral portfolio, the long position will outperform the short position. According to this theory, we decided to invest a $100,000 thousand in long position security and a $100,000 thousand in short position security. With these position, any circumstances that can cause the long position securities to decline will lead to a loss on the long position and a profit on the short position. In like manner, an event which can causes both, long and short position securities, to rise will have minor effect on portfolio profit, since the positions of our securities balance each other out. Thus, this will lead to minimal market risk.

Algorithm

To minimize the exposure to the market, rebalancing the stocks every month is essential and written into our algorithm. The algorithm will automatically boot out the underperforming stocks and purchase the over-performing stocks based on the previous month's market beta. This code allows our strategy to constantly stay on top of market trends and maximize potential value.

Here is a breakdown of the algorithm:

We start by importing pipeline and pull statistics such as simple moving average, average dollar volume, and the rolling linear regression of returns. We created a universe of the top 15000 U.S stocks based on these factors and coded the algorithm to take the top 300 performing stocks from the list and the bottom 300 stocks from the list. These listings are based on the variables momentum, value, and quality. The stocks also must have a max exposure of .1 in the sector and a max beta of .2. The algorithm short sells the bottom 300 performing stocks and long buys the 300 best performing stocks. Variables such as momentum are being calculated by pulling statistics from the previous 252-day time span. We chose to pick stocks that are already well-established and have a market cap of over $5,000,000,000. Beta is calculated from the regression from the last two years of trading days, also pulled from the universe of 15,000 US stock. Every month, the betas are recalculated by plugging in the last 30 trading days into the equations and removing the oldest month. Based on the new betas, the algorithm rebalances its stock portfolio by removing the underperforming stocks and adding to our over-performing stock portfolio. The main objective of this maneuver is to maximize the alpha. The rebalancing portion has two key components, the objectives and the constraints. Its objective consists of using the pipeline's "combined rank" in this "alpha" or active trading strategy. It asks to maximize the combined rank of momentum (which was a Custom Factor), quality (EBIT/EV from Morningstar), value (ROE from Morningstar), and beta (calculated in pipeline) in our portfolio, while minimizing the constraints --- this includes ensuring that the portfolio is within the parameters of the magnitude of beta that was prior defined. You can see this where it says the

following code:

```
neutralize_risk_factors = opt.FactorExposure(

loadings=risk_factor_exposures, min_
exposures={'market_beta':-MAX_BETA_EXPOSURE},
max_exposures={'market_beta':MAX_BETA_
EXPOSURE} )

constraints.append(neutralize_risk_factors

from quantopian.algorithm import attach_pipeline,
pipeline_output, order_optimal_portfolio from
quantopian.pipeline import Pipeline from
quantopian.pipeline.factors import CustomFactor,
SimpleMovingAverage, AverageDollarVolume, Rolling
LinearRegressionOfReturns from quantopian.pipeline.
data.builtin import USEquityPricing from quantopian.
pipeline.data import morningstar from quantopian.
pipeline.filters.morningstar import IsPrimaryShare from
quantopian.pipeline.classifiers.morningstar import Sector

import numpy as np import pandas as pd

from quantopian.pipeline.filters import Q1500US import
quantopian.optimize as opt

MAX_GROSS_LEVERAGE = 1.0 NUM_LONG_
POSITIONS = 300 NUM_SHORT_POSITIONS = 300

MAX_SHORT_POSITION_SIZE = 2*1.0/(NUM_
LONG_POSITIONS + NUM_SHORT_POSITIONS)
MAX_LONG_POSITION_SIZE = 2*1.0/(NUM_
LONG_POSITIONS + NUM_SHORT_POSITIONS)

MAX_SECTOR_EXPOSURE = 0.10 MAX_BETA_
EXPOSURE = 0.20

class Momentum(CustomFactor): inputs =
[USEquityPricing.close] window_length = 252

def compute(self, today, assets, out, prices): out[:] =
((prices[-21] - prices[-252])/prices[-252] -

(prices[-1] - prices[-21])/prices[-21])

def make_pipeline(): momentum = Momentum() value =
morningstar.income_statement.ebit.latest / morningstar.
valuation.enterprise_value.latest quality = morningstar.
operation_ratios.roe.latest sector = Sector()

mkt_cap_filter = morningstar.valuation.market_cap.
```

latest >= 500000000 price_filter = USEquityPricing. close.latest >= 5 universe = Q1500US() & price_filter & mkt_cap_filter

beta = 0.66*RollingLinearRegressionOfReturns(target=sid(8554),

returns_length=5, regression_length=504, mask=universe).beta + 0.33*1.0

combined_rank = (

beta.rank(mask=universe).zscore() + momentum. rank(mask=universe).zscore() + value. rank(mask=universe).zscore() + quality. rank(mask=universe).zscore()

)

longs = combined_rank.top(NUM_LONG_POSITIONS) shorts = combined_rank.bottom(NUM_SHORT_POSITIONS)

long_short_screen = (longs | shorts)

pipe = Pipeline(columns = { 'longs':longs, 'shorts':shorts, 'combined_rank':combined_rank, 'quality':quality,

'value':value, 'momentum':momentum, 'sector':sector, 'market_beta':beta

}, screen = long_short_screen) return pipe

def initialize(context): set_commission(commission. PerShare(cost=0.0, min_trade_cost=0)) set_slippage(slippage.VolumeShareSlippage(volume_limit=1, price_impact=0)) context.spy = sid(8554)

attach_pipeline(make_pipeline(), 'long_short_equity_template')

schedule_function(func=rebalance, date_rule=date_rules. month_start(),

time_rule=time_rules.market_open(hours=0,minutes=30),

half_days=True) schedule_function(func=recording_statements,

date_rule=date_rules.every_day(), time_rule=time_rules. market_close(), half_days=True)

def before_trading_start(context, data): context.pipeline_data = pipeline_output('long_short_equity_template')

def recording_statements(context, data): record(num_positions=len(context.portfolio.positions))

def rebalance(context, data): pipeline_data = context. pipeline_data risk_factor_exposures = pd.DataFrame({

'market_beta':pipeline_data.market_beta.fillna(1.0) })

objective = opt.MaximizeAlpha(pipeline_data. combined_rank)

constraints = [] constraints.append(opt. MaxGrossExposure(MAX_GROSS_LEVERAGE))

constraints.append(opt.NetGroupExposure.with_equal_bounds(

labels=pipeline_data.sector, min=-MAX_SECTOR_EXPOSURE, max=MAX_SECTOR_EXPOSURE,

))

neutralize_risk_factors = opt.FactorExposure(loadings=risk_factor_exposures, min_exposures={'market_beta':-MAX_BETA_EXPOSURE}, max_exposures={'market_beta':MAX_BETA_EXPOSURE})

constraints.append(neutralize_risk_factors)

constraints.append(opt.PositionConcentration.with_equal_bounds(

min=-MAX_SHORT_POSITION_SIZE,

max=MAX_LONG_POSITION_SIZE))

order_optimal_portfolio(objective=objective, constraints=constraints

)

Conclusion

Our portfolio is developed using long short strategy and positive-negative beta neutralization. We base our investment theory off of the Security Market Line model. In our portfolio we have two sets of securities, one set of securities that have positive beta (which is sold high when the value of the stock in proportion to invested capital reaches a certain amount) and another with negative (which is bought low at a certain proportion of gross leverage as well). The neutralize_risk_factors function ensures that the portfolio consists of positive and negative beta stocks up to a certain magnitude. This makes us have a market neutral portfolio, which will be profitable even if the long position declines in value: since we have a market neutral portfolio, the long position will outperform the short position. By creating such a portfolio, we aim to exploit inefficiencies in the market that can make a stock's market price reflect psychological and informational biases in the individual buyers' judgments of that security. As the Security Market Line shows, we are using the CAPM model to valuate our stocks' expected returns (neutralizing our complete portfolio's beta in the constraints of the algorithm), but using accounting measures to determine what stocks go into the long and short positions of the algorithm from the universe of stocks.

References

Vidyamurthy, Ganapathy. (2004) Pairs Trading: Quantitative Methods and Analysis. Hoboken, New Jersey: John Wiley & Sons, Inc.

Zacks, Leonard, and Khan, Mozaffar. (2011) The Handbook of Equity Market Anomalies: Translating Market Inefficiencies into Effective Trading Strategies. Hoboken, New Jerskey: John Wiley & Sons, Inc.

Filc, Wolfgang. (2007, October 26). Inefficient Markets: Causes and Consequences. Boeckler.de. Retrieved from https://www.boeckler.de/pdf/v_2007_10_26_filc.pdf.

Michaud, Richard O. (1999, January). Investment Styles, Market Anomalies, and Global Stock Selection. The Research Foundation of the Institute of Chartered Financial Analysts. Retrieved from https://www.cfapubs.org/doi/pdf/10.2470/rf.v1999.n1.4467.

How to cite this journal article:

Chung, Kotlova, and Zimmerman. (2018, April). Market-Neutral Strategy for Quantitative Trading: Long Positive Beta and Shorting Negative Beta Stocks. *Demos 1*, 38-42.

Find the online version at:

https://publications.lakeforest.edu/demos/vol1/7/