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Backtesting a Long/Short Strategy by Exploiting Mispricing Opportunities from Long-Run IPO Underperformance

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Abstract

A cash- and market-neutral long/short strategy of shorting a recently IPO-ed stock and longing an offsetting ETF was backtested with daily data over 2010-2019. Excess returns from the strategy was observed to be statistically significant. However, after adjustments to short-selling fees, the excess return vanishes and the strategy becomes unprofitable. This is not entirely unexpected given insights from the efficient market hypothesis.

1. Introduction

This report considers the profitability of an enhanced long/short strategy in the U.S. equity market. A long/short trading strategy involves buying stocks that are expected to have exceptional performance while shorting stocks that are expected to underperform. When their relative prices are expected to diverge, a short position on the loser and a long position on the winner is opened. The pair is closed out once the divergence diminishes, hopefully giving the arbitrageur a cash-neutral profit.

This strategy is improved on by giving empirical reasoning to back-up the price divergence between securities.[1] The strategy hopes to use the empirical evidence of long-run underperformance of initial public offerings (IPO) to potentially exploit arbitrage opportunities (Ritter, 1998). A short position in the IPO-ed stock and a long position in an offsetting portfolio that should theoretically move together with the IPO-ed stock are taken. Due to the underperformance effect, the short position should perform relatively worse than the long position. The pair is then closed out after a certain time, hopefully allowing the arbitrageur to obtain a cash-neutral profit by selling the higher valued long position and buying the lower valued short position.

[1] Potential theoretical reasons given by Ritter (1998) are: the divergence of opinion hypothesis, the impresario hypothesis, and the windows of opportunity hypothesis.

The remainder of this report is organized as follows. Section 2 provides guidance into the methodology used for testing this strategy. Section 3 provides the statistics from the backtest. Section 4 discusses these results and any discrepancies between the backtest to the real-world. Sections 5 and 6 presents limitations and suggests potential improvements to the strategy. Section 7 provides conclusions and presents areas for future research.

2. Methodology

The chosen strategy improves on the base long/short strategy by exploiting potential relative pricing arbitrage opportunities due to long-run underperformance of IPOs. The strategy attempts to create a market-neutral, zero-cost portfolio by shorting the recently IPO-ed company's shares and investing its proceeds in an offsetting ETF (Exchange Traded Fund). The methodology used is broadly consistent with Ritter's methodology to calculate historical evidence for IPO underperformance (Ritter, 1998).

2.1 Pairs formation

For each recently IPO-ed company within the past quarter, a short-position equivalent to 2.5% of the initial cash allocation is taken.[2] The proceeds are invested in an ETF of the same Morningstar sector code as the IPO-ed company (Appendix 1). This broadly ensures the strategy is market-neutral and only depends on the relative mispricing of the two securities. A short-position with an offsetting long-position also ensures the strategy is generally cost-free in setting up, with the exception of any commission fees and margin requirements.

Pairs are aggregated and opened at the end of every quarter as there is a lag on Quantopian from IPO-date to trading-date. Pairs are normally closed at the end of the first quarter on the 4th year

[2] The percentage chosen was arbitrary as the zero-cost strategy is generally insensitive to this parameter and can be altered depending on the risk-preferences of the arbitrageur.

after IPO.[3] The holding period ranges from 3.25 to 4.25 years, broadly consistent with the holding period used in Ritter (1998).

2.2 Market neutrality and alpha capture

The alpha capture strategy sums up our strategy pretty well. The strategy aims to construct a positive-alpha portfolio with systematic-risk hedged away (Bodie, Drew, Basu, Kane & Marcus, 2017). Suppose the IPO-ed security is relatively underpriced compared to a benchmark. We have chosen the ETF with the same Morningstar sector code as the appropriate benchmark and a proxy for approximating the same systematic-risk as the IPO-ed security (i.e. $\beta_{IPO} = \beta_{ETF}$). So, the expected excess returns, $\mathbb{E}(R)$, of the individual securities are:

$$\mathbb{E}(R_{IPO}) = -\alpha_{IPO} + \beta_{IPO} R_{Market}$$

$$\mathbb{E}(R_{ETF}) = \beta_{ETF} R_{Market}$$

A short-position in the IPO-ed security and a long-position in the ETF will yield:

$$\mathbb{E}\left(R_{Portfolio}\right) = -\mathbb{E}(R_{IPO}) + \mathbb{E}(R_{ETF})$$

$$\mathbb{E}\left(R_{Portfolio}\right) = \alpha_{IPO}$$

In theory, the strategy is market-neutral and only depends on the relative-mispricing of IPO-ed companies.

2.3 Backtesting Parameters

The backtesting period is from January 1st 2010 to December 31st 2019. A relatively long time-horizon of 10 years was chosen as the strategy involves pairing securities for an extended period of time. A similar backtest was conducted for January 1st 2007 to December 31st 2019 to

[3] With the exception of delisted securities.

ensure robustness for high-volatility periods during the GFC.[4] The backtest uses the Q3000US universe that incorporates the largest 3000 stocks in the United States. This was chosen so that the IPO-ed firms are not too big so that underperformance is not seen empirically, nor are the firms too small so that shorting-fees are extortionate (Ritter, 1998).

2.4 Robustness

2.4.1 Dividends

Dividends paid are automatically added to the algorithm's cash position for ETFs longed and automatically deducted for securities held short.

2.4.2 Commission and Slippage

A commission of $0.001 per dollar traded was used. A slippage model was included but not used due to the relatively small positions held in each security. For larger positions, the slippage model should be incorporated.

2.4.3 Delisting

For any shorted securities delisted during the paired period, Quantopian automatically deducts the positions held times the last known traded price from the algorithm's cash holdings.[5] To ensure a cash-neutral position, the algorithm sells the corresponding longed ETF at the end of that month. No long ETF positions were delisted over the period.

2.4.4 Risk-free rate

Quantopian assumes a risk-free rate of 0% for cash holdings and for calculating summary statistics.[6]

[4] The findings are generally consistent with the findings for the period January 1st 2010 to December 31st 2019, albeit with higher volatility. Since the findings are broadly similar, it would not be discussed further. The backtesting results are available on Quantopian under Backtest ID '5f93ef1450bb1f47025e1685'.
[5] This may artificially overstate returns for the strategy. Adjustments for this are discussed under Appendix 2.2.
[6] This rate is not very realistic and will be discussed further in the limitations section.

3. Backtesting statistics

Summary statistics[7]	
Backtesting period	January 1st 2010 to December 31st 2019
Initial cash allocation	$100,000
Ending cash allocation	$140,614
Total returns	181.33%[8]
Breakeven annualized short-selling rate	1.84%
Sharpe ratio	0.62
Max drawdown	-42.75%
Volatility (standard deviation of portfolio returns)	0.19
Beta to SPY	0.02
Leverage	4.22 times
Minimum cash position over backtesting period	$92,487
Daily returns single sample t-test (null=0):	
t-statistic	1.9641
p-value	0.0496

Table 1: Summary statistics

[7] Calculations, explanations, adjustments, and appropriate ways of interpretation are provided under Appendix 2. Access to more statistics are available on Quantopian under Backtest ID '5f8ef3db97608e4697d5c231'.
[8] Total returns differ from the percentage change in cash allocation as not all pairs were closed at the end of the backtesting period.

Figure 1: Strategy performance relative to SPY

Figure 2: Cash position over backtesting period

Figure 3: Number of open pairs over backtesting period

4. Discussion

4.1 Experimental results

The backtest results above indicates that the strategy is able to generate a positive return at the 5% confidence level. The strategy was able to generate an excess cash return of $40,614.[9] Consistent with our strategy of being mostly cash-neutral, the cash position over the period is almost always above initial cash allocation and never fell below $92,487.[10] Consistent with our market-neutral methodology, the beta of the portfolio relative to SPY is 0.02. The leverage of the portfolio is 4.22 times. However, this can be increased/decreased depending on the risk-preferences of the investor by adjusting the cash allocation to each pair opened. Maximum drawdown is also relatively high at -42.75%. Risk management strategies to reduce this will be discussed later. Implications of a breakeven annualized short-selling rate at 1.84% will be discussed below.

4.2 Discrepancies between backtesting returns and actual returns

Quantopian assumes a short-selling fee of 0%. Obviously, this is not very realistic as stocks cannot be borrowed for free. Thus, the backtesting returns would almost certainly overstate actual returns. It is advised for the reader to interpret the backtesting returns as a "maximum bound" for profitability. Actual profitability would almost certainly be lower and would be a decreasing function of shorting-fees. At an annualized shorting-fee of approximately 1.84%, the strategy would fail to earn any profits. This shorting-fee benchmark of 1.84% gives us an insight on picking shorting stocks. If the real-world short-selling fee obtained is lower than the benchmark, then it is a potentially profitable opportunity. However, if the fee is higher than the benchmark, then it is most likely unprofitable.

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[9] As explained in the Appendix, the total returns percentage and Sharpe ratio is not very informative. Thus, we have decided to largely ignore them in the discussion section.

[10] There are, however, periods in which cash allocation falls below initial cash allocation. Risk management strategies such as the one discussed in section 5.3 or implementing a cash buffer can be used to mitigate this shortfall.

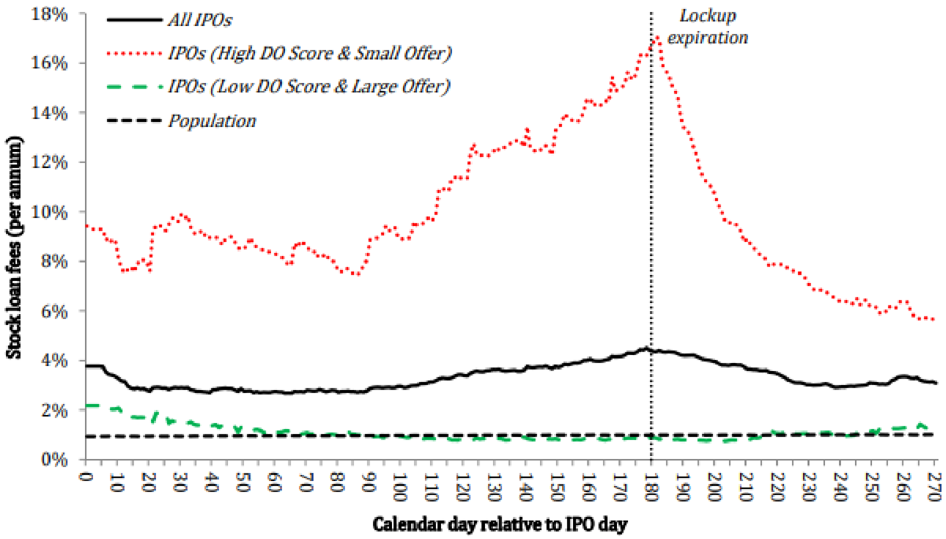

Figure 4: Average stock loan fees for IPO stocks[11]

Figure 4 depicts the average stock-lending fees for IPOs. In section 2.3, it was established that the IPO-ed firms were neither too small nor too big. Thus, "All IPOs", which ranges between 3-4%, can be used as a proxy for the shorting-fees of recently IPO-ed firms. IPO shorting fees are significantly higher than average stock loan fees for the general population (around 1%).

Comparing the benchmark of 1.84% to the real-world average of 3-4%, this strategy would most likely lose money in general. This is contradictory to the profitability indicated by the backtesting result. This result is not entirely unexpected. Since long-run IPO underperformance is a well-known phenomenon, market efficiency and arbitrage pricing theory dictates that this mispricing should be arbitraged away given that the market is rational.[12] The persistence of this underperformance phenomenon in the real-world indicates that market participants are unwilling to profit from this relative mispricing. The high shorting costs could be one explanation to why rational market participants are unwilling to take advantage of this opportunity.

[11] Patatoukas, Sloan & Wang (2020)
[12] Assuming that the market is at least weak-form efficient.

There is also a trade-off between the profit from shorting a certain stock and its shorting fees. Larger IPO-ed firms generally exhibit lower shorting fees, yet these stocks are probably not ideal for shorting. Empirical evidence suggests that larger IPOs do not exhibit underperformance (Ritter, 1998). Thus, shorting larger IPO-ed stocks while longing an ETF would most likely generate very low or even negative returns.

5. Potential improvements

At the current stage, the real-world average shorting fee for IPO firms (3-4%) is significantly greater than the benchmark shorting fee (1.84%). To make the strategy profitable, we have to improve the performance of the strategy by pushing the benchmark shorting fee up or by pushing the real-world average shorting fee down.

5.1 Lowering shorting fees

Achieving lower shorting fees is vital in keeping the strategy profitable. For securities lending, the borrower and lender can negotiate a fee that deviates from the average shorting fee (Duffle, Garleanu & Pedersen, 2002). Given that the long/short nature of our strategy has a promising return over the backtesting period, there is a potential to borrow these IPOs to short-sell at a lower rate compared to the general population. Moreover, as one of the top “Quant” firms, the possibility of achieving this lower cost is greater. Similarly, additional fees such as margin fees could also potentially be negotiated and lowered (Cohen, Diether & Malloy, 2007).

5.2 Not shorting large IPO companies

The First Trust US Equity Opportunities (FPX) ETF consists of the 100 largest, typically best performing and most liquid U.S. public offerings in the IPOX Global Composite Index. Since empirical evidence suggests that large IPOs do not exhibit underperformance, pairs generated by these IPOs will tend to have negative returns and go against the fundamentals of our strategy (Ibbotson & Ritter, 1995).

By consistently tracking FPX ETF's constituents and reconstitution, our strategy should reject creating pairs that involves shorting of its constituents and closing out an existing pair early if the shorted IPO is in the ETF. This eliminates the IPOs that are likely to outperform the long position, leaving us with a greater proportion of pairs with IPOs that are likely to underperform, hence improving the performance of our strategy.[13]

5.3 Risk management

Performance can also be improved if we can lower the risk associated with the strategy. Despite the strategy being mostly market-neutral ($\beta = 0.02$), Maximum drawdown is still relatively high at -42.75%. This mainly results from the high idiosyncratic risk among IPO firms (Fink, Grullon, Fink & Weston, 2005).

Since the strategy aims to earn a profit by shorting the IPO-ed stock, its potential downside risk is unlimited. If an IPO-ed stock is deemed to be having a strong upward momentum, that specific pair would continuously lose money. A stop-loss condition could be set in a way that we do not allow a pair to lose beyond a certain percentage of its value.

For example, as of 27th October 2020, Zoom Video Communications and Livongo Health have had 678% and 503% one-year trailing returns respectively (Verizon Media, n.d.-a, n.d.-b). Not setting a stop-loss would result in a huge loss for the specific pairs involving these shorts. However, for some pairs, the stop-loss strategy would work adversely as the positions are closed out early and potential profits are lost.

[13] This strategy may, however, increase the strategy's shorting fees as explained in the tradeoff in section 4.2.

We may see improvement in performance to some extent, especially for the technology IPOs as there seemed to be a significant momentum effect beyond the initial run-up (Jaggia & Thosar, 2005). This implies that by closing out a pair with high run-up early, we avoid potential losses due to the momentum induced gain in the price of the IPO.

Overall, the value of the stop-loss implementation largely comes from risk reduction rather than return improvement (Lei & Li, 2009). Following the implementation, maximum drawdown should significantly drop from the current level of -42.75%.

6. Limitations

6.1 Shorting constraints

In addition to the short-selling fees discussed in section 4.2, other shorting constraints needs to be taken into consideration if the strategy were to be implemented in real life. The Securities and Exchange Commission (SEC) prohibits the underwriters of the IPO to lend out shares for short sales for the first 30 days after the IPO (Norris, 2020). While it is not entirely easy, it is still possible to get shares from institutional investors or private equity owners. However, the amount of stocks available for short selling is limited and it also relies on the willingness of investors to lend the stocks out for short selling. The short-selling fees charged are also likely to be exorbitantly high.

6.2 Margin requirements

Despite the strategy remaining mostly cash-neutral, there may be margin requirements proportional to the cash amount shorted by the strategy. This proportion may be dictated by regulation, the exchange, and/or the firm. Thus, margin requirements are a necessary consideration if the strategy is to be implemented in real life.

6.3 Stock delisting

Cash flows for delisted stocks on Quantopian are calculated based on the last traded price of the stock. This is inconsistent with the actual market, in which stocks are either traded at a delisting price or the stock continues to be held by the shareholder, albeit with no market to trade the security. Therefore, the backtesting results may artificially overstate the actual returns generated by the strategy. Investors needs to take this into consideration if the strategy were to be implemented in the real world.

6.4 Short recalls

The lender of the stock may recall the shorted security prematurely. Thus, the pairs position must be forcefully closed out ahead of the time dictated by the methodology. As short recalls are more common as stock prices decline, this may negatively impact the profitability of the strategy (D'Avolio, 2002). Thus, investors need to take into consideration of the likelihood of short recalls in implementing this strategy.

7. Conclusion

A market- and cash-neutral long/short strategy of shorting an IPO-ed stock while longing an offsetting ETF was examined in a backtesting environment. The strategy crucially relies on the notion of alpha capture to remove any correlation with the overall market so that the strategy can focus on relative mispricing between securities. We found that, subject to conservative adjustments to dividends, commission, and delisting, the backtested strategy generated statistically significant excess returns at the 5% level. However, the reader must be cautious when inferencing this return, and should interpret it as a "maximum bound" for returns, with returns decreasing as the short-selling rate increases. At an annualized short-selling rate at 1.84%, the strategy will breakeven and excess returns will not be earned.

Empirical findings show that real-world stock-lending fees tend to be around 3-4%. Thus, this strategy is highly unlikely to be profitable in the real-world. This suggests that one reason that this mispricing is not arbitraged away in a rational market is due to the high costs in implementing this strategy. Potential improvements such as lowering shorting fees and/or not shorting large IPO companies were suggested to increase the profitability of the strategy. However, the reader must be careful to assess the trade-off between shorting fees and the strategy's profitability. Risk management strategies are also presented to reduce the idiosyncratic risk of the strategy.

Overall, our long/short strategy acts as a potential candidate for future refinement and research. Limitations such as shorting constraints, margin requirements, stock delisting, and short recalls must be taken into consideration before real-world implementation. Incorporation of these limitations into future backtests and/or live implementations could be a potential area of future research.

References

Bodie, Z., Drew, M., Basu, A., Kane, A., & Marcus, A. (2017). *Principles of Investments* (pp. 533-536). McGraw-Hill Education.

Cohen, L., Diether, K. B., & Malloy, C. J. (2007). Supply and demand shifts in the shorting market. *The Journal of Finance*, *62*(5), 2061-2096.

D'Avolio, G. (2002). The Market for Borrowing Stock. *Journal Of Financial Economics*, *66*, 271-306.

Duffie, D., Garleanu, N., & Pedersen, L. H. (2002). Securities lending, shorting, and pricing. *Journal of Financial Economics*, *66*(2-3), 307-339.

Fink, J., Grullon, G., Fink, K., & Weston, J. (2005). IPO vintage and the rise of idiosyncratic risk. *7th Annual Texas Finance Festival Paper*.

Ibbotson, R. G., & Ritter, J. R. (1995). Initial public offerings. *Handbooks in Operations Research and Management Science*, *9*, 993-1016.

Jaggia, S., & Thosar, S. (2005). Momentum Investing: The Case of High-Tech IPOs. *Finance Letters*, *3*(6).

Lei, A. Y., & Li, H. (2009). The value of stop loss strategies. *Financial Services Review*, *18*(1), 23-51.

Norris, E. (2020). When Are Short Sales Accepted for IPOs?. Retrieved 28 October 2020, from https://www.investopedia.com/ask/answers/05/062905.asp

Patatoukas, P., Sloan, R., & Wang, A. (2020). Valuation Uncertainty and Short-Sales Constraints: Evidence from the IPO Aftermarket. *27Th Annual Conference On Financial Economics And Accounting Paper*.

Ritter, J. (1998). Initial Public Offerings. *Contemporary Finance Digest*, *2*(1), 5-30.

Verizon Media. Livongo Health, Inc. (LVGO). Retrieved 28 October 2020, from https://finance.yahoo.com/quote/lvgo

Verizon Media. Zoom Video Communications, Inc. (ZM). Retrieved 28 October 2020, from https://finance.yahoo.com/quote/ZM/

Appendix

A.1 Morningstar sector code to ETF mappings

Sector Code	ETF	Ticker Symbol
101	Materials Select Sector SPDR Fund	XLB
102	Consumer Discretionary Select Sector SPDR Fund	XLY
103	Financial Select Sector SPDR Fund	XLF
206	Health Care Select Sector SPDR Fund	XLV
207	Utilities Select Sector SPDR Fund	XLU
309	Energy Select Sector SPDR Fund	XLE
310	Industrial Select Sector SPDR Fund	XLI
311	Technology Select Sector SPDR Fund	XLK
205	Consumer Staples Select Sector SPDR Fund	XLP
308[14]	Communication Services Select Sector SPDR Fund	XLC
104[15]	Real Estate Select Sector SPDR Fund	XLRE

Table 2: Morningstar sector code to ETF mappings

A.2 Calculations for Table 1: Summary statistics

A.2.1 Total returns

The total percentage return of the portfolio from the start to the end of the backtest. Quantopian calculates the return based on the initial cash allocation of the algorithm. However, due to the nature of the strategy being cash-neutral, this statistic can be highly manipulative. The strategy can start off with any arbitrary value for its initial cash allocation, thus yielding very different results for total returns. We recommend the reader to put less emphasis on inferencing this result and instead focus on the breakeven annualized short-selling rate.

[14] XLC commenced trading on 2018-06-19. Companies with Morningstar sector code 101 that IPO-ed before this date did not have a suitable offsetting position, thus pair formation did not occur

[15] XLRE commenced trading on 2015-10-12. Companies with Morningstar sector code 104 that IPO-ed before this date did not have a suitable offsetting position, thus pair formation did not occur

A.2.2 Breakeven annualized short-selling rate

The annualized short-selling rate that would make the strategy breakeven. It is calculated as the arithmetic average of the annualized return generated by each pair during the period it is open, based on an initial cash outflow equal to the initially shorted amount. To arrive at a conservative figure, delisted pairs are excluded from this calculation.

A more intuitive explanation is to use the analogy of zero-coupon bonds. Consider at $t = 0$ a pair is opened at zero-cost. Analogously, a bond is purchased for the par-value of the short-position.[16] When the pair is closed, the pair would have generated a positive/negative cash-flow at $t = T$. This cash-flow can be thought of the coupon-payment for the bond at maturity. The breakeven annualized short-selling rate is then the annualized coupon yield of the bond. Equivalently, it is the rate that a lender would charge to the investor for borrowing the funds to buy the bond that would leave the investor with zero profits at $t = T$. Analogously, this rate is the short-selling rate at which this strategy yields zero profits.

This custom statistic is calculated by considering the arithmetic average per-day breakeven short-selling rates of 181 pairs opened and closed during the backtesting period.[17] This rate is then annualized according to the equation:

$$r_{year} = \left(1 + r_{day}\right)^{365} - 1$$

Which gives us an annualized rate of 1.84%.[18] Lines 266 and 267 of the code under Appendix 2.8 can be uncommented out to check this calculation. We suggest more emphasis should be put on this statistic as this rate is less manipulative in interpretation.

[16] The long position here is not considered as they do not incur short-selling fees
[17] Excludes pairs closed due to delisting
[18] More specifically, 0.0183795

A.2.3 Sharpe ratio

A measure of risk-adjusted performance, equal to the portfolio's excess return over the risk-free rate divided by its standard deviation. Quantopian uses a risk-free rate of 0% to calculate the Sharpe ratio. Due to the manipulative nature of total returns explained earlier, the Sharpe ratio is also highly subject to manipulation. Thus, we recommend the reader to put less emphasis on inferencing this result.

A.2.4 Max drawdown

Maximum observed loss from a peak to a trough of a portfolio. An indicator of downside risk of the algorithm.

A.2.5 Beta to SPY

A proxy for the systematic-risk of the portfolio. The SPDR S&P 500 Trust ETF was used as the benchmark. A beta of 0.02 is expected as the strategy aims to be market-neutral.

A.2.6 Leverage

Position value to capital base.

A.2.7 Daily returns single sample t-test (null=0)

Single sample hypothesis test to check if excess returns is statistically significant from 0%. The code for this test is presented below:

```
bt = get_backtest('5f8ef3db97608e4697d5c231')
bt.create_full_tear_sheet()
daily_returns = bt.daily_performance.returns

from scipy import stats
stats.ttest_1samp(daily_returns,0)
```

A.3 Quantopian backtesting code

The code for the backtesting strategy is presented below. The backtesting results are also available on Quantopian under Backtest ID '5f8ef3db97608e4697d5c231'.

```
"""
This is a template algorithm on Quantopian for you to adapt and fill in.
"""

import quantopian.algorithm as algo
from quantopian.pipeline import Pipeline
from quantopian.pipeline.data.builtin import USEquityPricing
from quantopian.pipeline.filters import Q3000US, StaticAssets
from quantopian.pipeline.data.morningstar import Fundamentals
from quantopian.pipeline.data.factset import EquityMetadata
from datetime import date

MONTH_STARTS = [3, 6, 9, 12]

MAX_POSITION = 0.025

ETF_SECTOR_TICKER = {101: symbol('XLB'), 102: symbol('XLY'), 103: symbol('XLF'), 206: symbol('XLV'), 207: symbol('XLU'), 309: symbol('XLE'), 310: symbol('XLI'), 311: symbol('XLK'), 205: symbol('XLP'), 308: symbol('XLC'), 104: symbol('XLRE')}


def initialize(context):
    """
    Called once at the start of the algorithm.
    """
    # Rebalance every 3 months, 1 hour after market open.
    algo.schedule_function(
        rebalance,
        algo.date_rules.month_end(),
        algo.time_rules.market_open(hours=1),
    )

    # Record tracking variables at the end of each day.
    algo.schedule_function(
        record_vars,
        algo.date_rules.every_day(),
        algo.time_rules.market_close(),
    )

    # Create our dynamic stock selector.
    algo.attach_pipeline(make_pipeline(), 'pipeline')

    # Include slippage when positions taken are large, can be ignored for smaller positions
    # set_slippage(slippage.FixedBasisPointsSlippage())

    set_commission(commission.PerDollar(cost=0.0010))

    context.positions_taken = {}
    context.pairs_taken = 0
    context.pairs_return = 0


def make_pipeline():
    """
```

```
    A function to create our dynamic stock selector (pipeline). Documentation
    on pipeline can be found here:
    https://www.quantopian.com/help#pipeline-title
    """

    # Find IPO dates for stocks
    ipo_date = Fundamentals.ipo_date.latest

    # Base universe set to the QTradableStocksUS
    base_universe = Q3000US()

    # Add ETFs to the base universe
    etf_universe = StaticAssets(symbols('XLB', 'XLY', 'XLF', 'XLV', 'XLU', 'XLE', 'XLI', 'XLK', 'XLP', 'XLC', 'XLRE'))

    # Combine the two universe
    combined_universe = base_universe | etf_universe

    # Factor of yesterday's close price.
    yesterday_close = USEquityPricing.close.latest

    # Morningstar sector codes for each stock
    sector_code = Fundamentals.morningstar_sector_code.latest

    pipe = Pipeline(
        columns={
            'close': yesterday_close,
            'ipo_date': ipo_date,
            'sector_code': sector_code
        },
        screen=(combined_universe)
    )
    return pipe


def before_trading_start(context, data):
    """
    Called every day before market open.
    """
    context.output = algo.pipeline_output('pipeline')

    # These are the securities that we are interested in trading each day.
    context.security_list = context.output.index


def rebalance(context, data):
    """
    Execute orders according to our schedule_function() timing.
    """

    # To close out ETF positions if the shorted stock gets delisted
    client_side_securities = set(context.positions_taken.keys())

    server_side_all_securities = set([sec.sid for sec in context.portfolio.positions.keys()])

    ETF_securities = set([etf.sid for etf in ETF_SECTOR_TICKER.values()])

    server_side_securities = server_side_all_securities - ETF_securities

```

```
    delisted_securities = client_side_securities.difference(server_side_securities)

    for security in delisted_securities:

            ETF_amount = context.positions_taken[security][1]
            sector_code = context.positions_taken[security][2]
            ETF_ticker = ETF_SECTOR_TICKER.get(sector_code)
            ETF_price = context.output.at[ETF_ticker, 'close']
            context.positions_taken.pop(security)

            order(ETF_ticker, -ETF_amount)

            log.info("Security with SID {} was delisted, closing offsetting ETF {} for {} ETFs @ ${}".format(security, ETF_ticker.symbol, ETF_amount, ETF_price))

    # Early return if current month is not in QUARTER_STARTS
    month_number = get_datetime().date().month
    if month_number not in MONTH_STARTS:
        return None

    order_price = context.portfolio.starting_cash * MAX_POSITION

    for security in context.security_list:

        ipo_date = context.output.at[security, 'ipo_date']

        # Remove securities that do not have data on IPO dates and removes intraday information on
        # IPO time
        if str(ipo_date) is not "NaT":

            ipo_year = int(str(ipo_date)[:4])
            ipo_month = int(str(ipo_date)[5:7])

            backtesting_year = int(get_datetime().date().year)
            backtesting_month = int(get_datetime().date().month)
            backtesting_day = int(get_datetime().date().day)

            # Find all IPOs of companies within the last 3 months
            if ipo_year == backtesting_year:
                if ipo_month >= backtesting_month - 2:

                    # Find the ETF sid for the offsetting portfolio
                    sector_code = context.output.at[security, 'sector_code']
                    ETF_ticker = ETF_SECTOR_TICKER.get(sector_code)

                    # Extra conditioning for XLRE and XLC ETFs as they started trading on
                    # 2015-10-12 and 2018-06-19 respectively
                    if sector_code == 104:
                        if (backtesting_year >= 2015) and (backtesting_month >= 10) and (backtesting_day >= 12):
                            True

                        else:
                            log.info("Failed to form pairs for security {} due to non-existing XLRE ETF".format(security.symbol))
                            continue

                    if sector_code == 308:
```

```
                        if (backtesting_year >= 2018) and (backtesting_month >= 6) and (backtesting_day >= 19):
                            True

                        else:
                            log.info("Failed to form pairs for security {} due to non-existing XLC ETF".format(security.symbol))
                            continue

                    if ETF_ticker is not None:

                        # Short the IPO company's stocks
                        share_price = context.output.at[security, 'close']
                        share_amount = order_price // share_price
                        order(security, -share_amount)

                        # Long the offsetting ETF
                        ETF_price = context.output.at[ETF_ticker, 'close']
                        ETF_amount = order_price // ETF_price
                        order(ETF_ticker, ETF_amount)

                        context.positions_taken[security.sid] = [share_amount, ETF_amount, sector_code, share_amount * share_price]

                        log.info("Opening position. Shorting security {} for {} shares @ ${}. Longing ETF {} for {} ETFs @ ${}".format(security.symbol, share_amount, share_price, ETF_ticker.symbol, ETF_amount, ETF_price))

    for security in context.portfolio.positions.keys():

        # Get IPO date if the current security is not an ETF
        try:

            ipo_date = context.output.at[security, 'ipo_date']

            # Close out positions on the 4th year after IPO
            ipo_year = int(str(ipo_date)[:4])
            backtesting_year = int(get_datetime().date().year)

            if (ipo_year + 4) == backtesting_year:

                share_amount = context.positions_taken[security.sid][0]
                share_price = context.output.at[security, 'close']

                order(security, share_amount)

                # Close out the offseting ETF
                ETF_amount = context.positions_taken[security.sid][1]
                sector_code = context.positions_taken[security.sid][2]
                ETF_ticker = ETF_SECTOR_TICKER.get(sector_code)

                ETF_price = context.output.at[ETF_ticker, 'close']

                order(ETF_ticker, -ETF_amount)

                log.info("Closing position. Longing security {} for {} shares @ ${}. Shorting ETF {} for {} ETFs @ ${}".format(security.symbol, share_amount, share_price, ETF_ticker.symbol, ETF_amount, ETF_price))

                # Calculate the return generate by each pair
```

```
                closing_profit = (ETF_amount * ETF_price) - (share_amount * share_price)
                initial_borrowing = context.positions_taken[security.sid][3]
                context.positions_taken.pop(security.sid)
                closing_return = closing_profit / initial_borrowing

                # Calculate the number of days the pair was open
                ipo_year = int(str(ipo_date)[:4])
                ipo_month = int(str(ipo_date)[5:7])
                ipo_day = int(str(ipo_date)[8:10])

                backtesting_year = int(get_datetime().date().year)
                backtesting_month = int(get_datetime().date().month)
                backtesting_day = int(get_datetime().date().day)

                d0 = date(ipo_year, ipo_month, ipo_day)
                d1 = date(backtesting_year, backtesting_month, backtesting_day)

                time_open = (d1 - d0)
                days_open = time_open.days

                # Calculate the breakeven per day return
                breakeven_return = (1 + closing_return) ** (1 / days_open) - 1

                # Add cumulative return times 100 million to context.pairs_return. The 100 million
                # is due to Quantopian not having sufficient accuracy for decimal places
                if str(breakeven_return) is not 'nan':

                    int_return = int(breakeven_return * 100000000)

                    context.pairs_return += int_return
                    context.pairs_taken += 1

        except (KeyError, ValueError):
            continue


def record_vars(context, data):
    """
    Plot variables at the end of each day.
    """

    record("Cash", context.portfolio.cash)
    record("Positions", len(context.portfolio.positions))
    # log.info(context.portfolio.positions.keys())

    # Uncomment out this section and comment out all other loggings to calculate the breakeven
    # shorting fees
    # log.info(context.pairs_taken)
    # log.info(context.pairs_return)


def handle_data(context, data):
    """
    Called every minute.
    """
    pass
```