

Not Over Thinking

Post-Earnings Announcement Effect
Algorithmic Trading Strategy with Full Code

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STRATEGY & ECONOMIC RATIONALE

The selection of stocks for investment is based on the NYSE, AMEX, and NASDAQ, excluding financial and utility companies, and stocks that cost less than \$5.

The stocks are divided into quintiles according to their EAR and SUE. To avoid any look-ahead bias, data from the previous quarter are used for sorting the stocks.

All the stocks in each quintile are given equal weightage, and the portfolio is rebalanced every quarter.

The trading strategy only involves the long leg since the research paper suggests that the long leg contributes significantly to the performance of the strategy.

LONG	SHORT
goes long stocks from the intersection of top SUE and EAR quintiles the second day after the actual earnings announcement and holds the portfolio one quarter (or 60 working days).	goes short stocks from the intersection of the bottom SUE and EAR quintiles the second day after the actual earnings announcement and holds the portfolio one quarter (or 60 working days).

PARAMETER & VARIABLES

Two factors are used: EAR (Earnings Announcement Return) and SUE (Standardized Unexpected Earnings).

- SUE is constructed by dividing the earnings surprise (calculated as actual earnings minus expected earnings; expected earnings are computed using a seasonal random walk model with drift) by the standard deviation of earnings surprises.
- EAR is the abnormal return for firms recorded over a three-day window centered on the last announcement date, in excess of the return of a portfolio of firms with similar risk exposures.

PARAMETER	VALUE
MARKETS TRADED	NYSE, AMEX, NASDAQ
FINANCIAL INSTRUMENTS	Stocks
PERIOD OF REBALANCING	Quarterly
NO. OF TRADED INSTRUMENTS	1000
PRICE LIMIT	<\$5
LOOK-AHEAD BIAS AVOIDED?	Yes
WEIGHTING	Equal in each quantile
HOLDING PERIODS	60 working days
LONG/SHORT	Long Only

DATA SOURCE

- Universe consists of stocks, with earnings data from <https://www.nasdaq.com/market-activity/earnings> available.
 - At least 4 years of seasonal earnings data is required to calculate earnings surprise.

- At least 4 years of earnings surprise values are required for SUE calculation.

ALGORITHM

```

from AlgorithmImports import *
import numpy as np
from collections import deque
from pandas.tseries.offsets import BDay
from dateutil.relativedelta import relativedelta

## inherent from parent class QCAAlgorithm
class PostEarningsAnnouncementEffect(QCAAlgorithm):

    def Initialize(self):
        self.SetStartDate(2010, 1, 1) ## did not set end date >will run till today
        self.SetCash(100000)

        self.earnings_surprise = {}
        self.min_seasonal_eps_period = 4 ## 4 years
        self.min_surprise_period = 4 ## 4 years

        self.long = []

        # SUE and EAR history for previous quarter used for statistics.
        self.sue_ear_history_previous = []
        self.sue_ear_history_actual = []
        ## prepared for rolling window, current/newest 3-month data will overwrites in sue_ear_
        history_previous; since SUE and EAR are both calculated in 3-month window, hence can use same s
        et of placeholders

        # EPS data keyed by tickers, which are keyed by dates
        self.eps_by_ticker = {} ## for symbols that do not have EPS data, ignore them

        # daily price data
        self.price_data_with_date = {}
        self.price_period = 63
        ## 60-day holding period + 3-day calculation window after the announcement

        self.market = self.AddEquity('SPY', Resolution.Daily).Symbol
        self.price_data_with_date[self.market] = deque(maxlen=self.price_period)
        ## deque has the methods for adding and removing elements which can be invoked directly
        with arguments > it extract 63 days of data for SPY

        # parse earnings dataset
        self.first_date:datetime.date|None = None
        earnings_data:str = self.Download('data.quantpedia.com/backtesting_data/economic/earnin
        gs_dates_eps.json')
        ## first download data and save in "str"

        earnings_data_json:list[dict] = json.loads(earnings_data)
        ## json.loads parse a valid JSON string and convert it into a Python Dictionary > earni
        ngs_data_json becomes distionary

        for obj in earnings_data_json:
            date:datetime.date = datetime.strptime(obj['date'], "%Y-%m-%d").date()
            ## convert datetime format and save it under key "date"

            if not self.first_date: self.first_date = date
            ## if there is no self.first date, set it to "date"

            for stock_data in obj['stocks']:
                ticker:str = stock_data['ticker']

```


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save ticker under key “ticker”

```
it
    if stock_data['eps'] == '':
        continue
    ## good practice to check if the “eps” column is empty, before storing data in

    # initialize dictionary for dates for specific ticker
    if ticker not in self.eps_by_ticker:
        self.eps_by_ticker[ticker] = {}

    # store EPS value keyed date, which is keyed by ticker
    self.eps_by_ticker[ticker][date] = float(stock_data['eps'])

self.month = 12
self.selection_flag = False
self.UniverseSettings.Resolution = Resolution.Daily
self.AddUniverse(self.CoarseSelectionFunction, self.FineSelectionFunction)
self.Schedule.On(self.DateRules.MonthStart(self.market), self.TimeRules.AfterMarketOpen
(self.market), self.Selection)

def OnSecuritiesChanged(self, changes):
    ## manage (i) AddedSecurities; (ii) RemovedSecurities
    ## if there is any change in the portfolio, the change object is saved in variable “change
s”
    for security in changes.AddedSecurities:
        security.SetFeeModel(CustomFeeModel()) ## calling class defined “CustomFeeModel”
        security.SetLeverage(5) ## for newly added securities, set the leverage to 5x

    # remove earnings surprise data so it remains consecutive
    for security in changes.RemovedSecurities:
        symbol = security.Symbol
        if symbol in self.earnings_surprise:
            del self.earnings_surprise[symbol]
            ## remove the earnings_surprise data for the deleted symbols

def CoarseSelectionFunction(self, coarse):
    # update daily price data
    for stock in coarse:
        symbol = stock.Symbol

        if symbol in self.price_data_with_date:
            ## price_data_with_date saves the securities’ prices by date
            self.price_data_with_date[symbol].append((self.Time.date(), stock.AdjustedPric
e))

    if not self.selection_flag:
        return Universe.Unchanged
    self.selection_flag = False
    ## for securities not selected, they will have no impact on universe

    # filter only symbols, which have earnings data from csv
    selected = [x.Symbol for x in coarse if x.Symbol.Value in self.eps_by_ticker]

    # warmup price data
    for symbol in selected:
        if symbol in self.price_data_with_date:
            ## filter the symbols that have EPS data also have price data by date
            continue

        self.price_data_with_date[symbol] = deque(maxlen=self.price_period)
        history = self.History(symbol, self.price_period, Resolution.Daily)
```

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```
if history.empty:
    self.Log(f"Not enough data for {symbol} yet.")
    continue
## housekeeping check if there is enough history data to warm up

closes = history.loc[symbol].close
for time, close in closes.iteritems():
    self.price_data_with_date[symbol].append((time.date(), close))

# market price data is not ready yet
if len(self.price_data_with_date[self.market]) != self.price_data_with_date[self.marke
t].maxlen:
    return Universe.Unchanged

return [x for x in selected if len(self.price_data_with_date[x]) == self.price_data_wit
h_date[x].maxlen]
## final output from CoarseSelectionFunction function >> securities that have (i) EPS d
ata; (ii) price data by date; (iii) sufficient history data

def FineSelectionFunction(self, fine):
    # SUE and EAR data
    sue_ear = {}

    current_date = self.Time.date()
    prev_three_months = current_date - relativedelta(months=3)

    for stock in fine:
        symbol = stock.Symbol
        ticker = symbol.Value

        recent_eps_data = None ## placeholder

        # store all EPS data since previous three months window
        for date in self.eps_by_ticker[ticker]:
            if date < current_date and date >= prev_three_months:
                EPS_value = self.eps_by_ticker[ticker][date]

                # create tuple (EPS date, EPS value of specific stock)
                recent_eps_data = (date, EPS_value)
                break

        if recent_eps_data: ## if recent_eps_data exists
            last_earnings_date = recent_eps_data[0]

            # get earnings history until previous earnings
            earnings_eps_history = [(x, self.eps_by_ticker[ticker][x]) for x in self.eps_by
_ticker[ticker] if x < last_earnings_date]

            # seasonal earnings for previous years
            # prev_month_date = last_earnings_date - relativedelta(months=1)
            # next_month_date = last_earnings_date + relativedelta(months=1)
            # month_range = [prev_month_date.month, last_earnings_date.month, next_month_da
te.month]

            # seasonal_eps_data = [x for x in earnings_eps_history if x[0].month in month_r
ange]

            seasonal_eps_data = [x for x in earnings_eps_history if x[0].month == last_earn
ings_date.month]

            if len(seasonal_eps_data) >= self.min_seasonal_eps_period:
                ## min_seasonal_eps_period defined as 4
                # make sure we have a consecutive seasonal data. Same months with one year
difference
                year_diff = np.diff([x[0].year for x in seasonal_eps_data])
```

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```
if all(x == 1 for x in year_diff):
    # SUE calculation
    seasonal_eps = [x[1] for x in seasonal_eps_data]
    diff_values = np.diff(seasonal_eps)
    drift = np.average(diff_values)

    last_earnings_eps = seasonal_eps[-1]
    expected_earnings = last_earnings_eps + drift
    actual_earnings = recent_eps_data[1]

    earnings_surprise = actual_earnings - expected_earnings

    # initialize surprise data
    if symbol not in self.earnings_surprise:
        self.earnings_surprise[symbol] = []

    # surprise data is ready.
    elif len(self.earnings_surprise[symbol]) >= self.min_surprise_period:
        earnings_surprise_std = np.std(self.earnings_surprise[symbol])
        sue = earnings_surprise / earnings_surprise_std

        # EAR calculation
        min_day = last_earnings_date - BDay(2)
        max_day = last_earnings_date + BDay(1)
        stock_closes_around_earnings = [x for x in self.price_data_with_date[symbol] if x[0] >= min_day and x[0] <= max_day]
        market_closes_around_earnings = [x for x in self.price_data_with_date[self.market] if x[0] >= min_day and x[0] <= max_day]

        if len(stock_closes_around_earnings) == 4 and len(market_closes_around_earnings) == 4:
            stock_return = stock_closes_around_earnings[-1][1] / stock_closes_around_earnings[0][1] - 1
            market_return = market_closes_around_earnings[-1][1] / market_closes_around_earnings[0][1] - 1

            ear = stock_return - market_return
            sue_ear[symbol] = (sue, ear)

            # store pair in this month's history
            self.sue_ear_history_actual.append((sue, ear))

        self.earnings_surprise[symbol].append(earnings_surprise)

    # wait until we have history data for previous three months.
    if len(sue_ear) != 0 and len(self.sue_ear_history_previous) != 0:
        # Sort by SUE and EAR.
        sue_values = [x[0] for x in self.sue_ear_history_previous]
        ear_values = [x[1] for x in self.sue_ear_history_previous]

        top_sue_quintile = np.percentile(sue_values, 80)
        bottom_sue_quintile = np.percentile(sue_values, 20)

        top_ear_quintile = np.percentile(ear_values, 80)
        bottom_ear_quintile = np.percentile(ear_values, 20)

        self.long = [x[0] for x in sue_ear.items() if x[1][0] >= top_sue_quintile and x[1][1] >= top_ear_quintile]

    return self.long

def OnData(self, data):
    # trade execution
    invested = [x.Key for x in self.Portfolio if x.Value.Invested]
```

##self object has a built-in attribute “.Portfolio”

```
for symbol in invested:
    if symbol not in self.long: ## if not labelled as long, liquidate it
        self.Liquidate(symbol)
```

```
long_count = len(self.long)
```

```
for symbol in self.long:
    if symbol in data and data[symbol]:
        self.SetHoldings(symbol, 1 / long_count) ## equal weighting
        ## buy in the securities labelled “long”
```

```
self.long.clear() ## clear the long list once purchased, so do not purchase again
```

```
def Selection(self):
    self.selection_flag = True
```

```
# store new EAR and SUE values every three months
```

```
if self.month % 3 == 0:
```

```
## ask for remainder > if = 0, means self.month is a multiple of 3
```

```
    # Save previous month history.
```

```
    self.sue_ear_history_previous = self.sue_ear_history_actual
```

```
    self.sue_ear_history_actual.clear() ## prepare for next 3-month period’s input
```

```
self.month += 1
```

```
if self.month > 12: ## when a year is ended, redstart from 1
```

```
    self.month = 1
```

```
# Custom fee model
```

```
class CustomFeeModel(FeeModel):
```

```
    def GetOrderFee(self, parameters):
```

```
        fee = parameters.Security.Price * parameters.Order.AbsoluteQuantity * 0.00005
```

```
        return OrderFee(CashAmount(fee, "USD")) ## denoted in USD
```

BACKTESTING PERFORMANCE



Fig 1. Overall Performance

PSR	0.020%	Sharpe Ratio	0.399
Total Trades	1038	Average Win	0.48%
Average Loss	-0.55%	Compounding Annual Return	7.124%
Drawdown	54.700%	Expectancy	0.435
Net Profit	390.227%	Loss Rate	24%
Win Rate	76%	Profit-Loss Ratio	0.89
Alpha	0.009	Beta	0.891
Annual Standard Deviation	0.153	Annual Variance	0.023
Information Ratio	0.059	Tracking Error	0.053
Treynor Ratio	0.068	Total Fees	\$136.30
Estimated Strategy Capacity	\$92000000.00	Lowest Capacity Asset	NVS RULY784EQ6AT

Fig 2. Performance Metrics

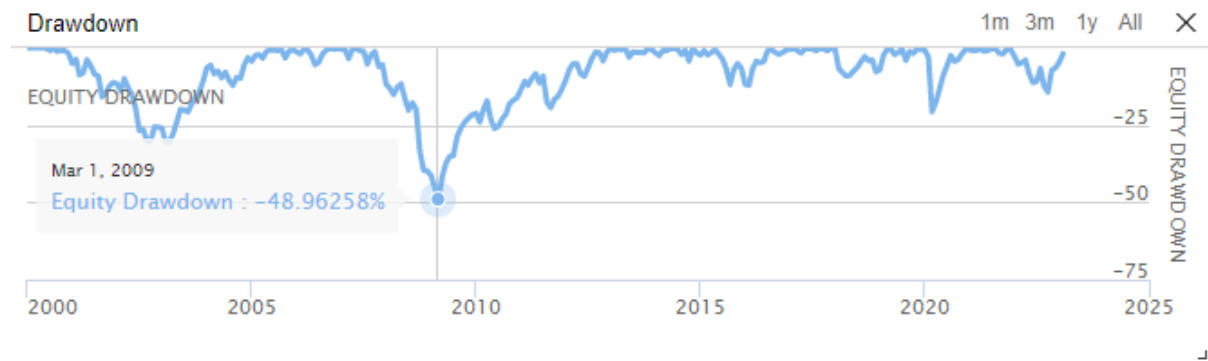


Fig 3. Drawdown

Assets Sales Volume ×

NVS	AXP	SNY	TSM
MO	CHTR	TM	USB
		JCI	MDT UTX
RIO	GM		XOM BEL
		BMJ	D
	INTC		C... SO
KO		IBM	
	AMGN		SLB AIG
		MCD	ABT U...
PEP	ORCL		
		HBC	STD E
WFC	BA		K...
		DIS	BHP D...
BPA	MRK	AAPL	CAT CL
	GS	AZN	KMB CS
QCOM			VOD DB
	TXN	DOW	A...
			ALL
HWP		HD	C
	NFLX		COP MS
		GE	FLS A
MMM	UPS	RY	TRV C...

Fig 4. Assets Sales Volume