Value, Profitability, and the Short Duration Premium

Arizona State University

Prepared by the Undergraduate Student Investment Management Fund – Team A

Under the designation of Dr. Wahal
Friday December 1st, 2023

Team Introduction



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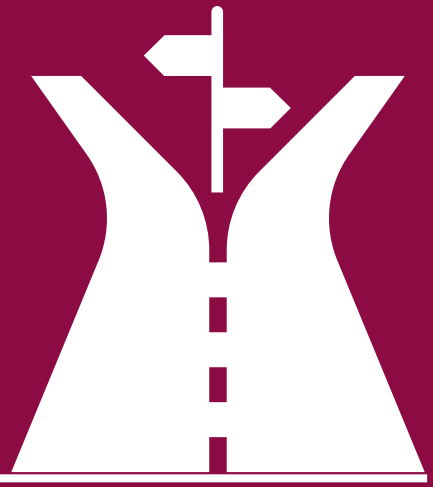
Our Path to an Investment Strategy



Valuation Identity

Expected Profitability

Expected Investment

$$M_t = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})}{(1+r)^{\tau}} \rightarrow \frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})}{B_t(1+r)^{\tau}}$$

Value

Equity Duration

- Macaulay formula for evaluating the duration of bonds
- Equity duration equation derived from bond duration formula
  - Weighted by present value of cash flows divided by investment value

1 $$Macaulay\ Duration = \sum_{i}^{n} t_i \frac{PV}{V}$$

2 $$Equity\ Duration = \sum_{h=1}^{\infty} w_{j,t}^{(h)}\, h$$

3 $$w = \frac{E_t[CF_{j,t+h}] \cdot e^{-h \cdot dr_{j,t}}}{V_{j,t}}$$

Source: Gonçalves (2021)

Cash Flows & Payouts: Clean Surplus Accounting

- Eq. 4 is functionally the same as the valuation equation
- Cash flows a function of value, profit, growth, and leverage
- Vector autoregression predicts future value with previous period
- Rewrite Eq. 5 with VAR (Eq. 6) & substitute into Eq. 3 for final Eq.

4 $$\frac{E_t[PO_{j,t+h}]}{BE_{j,t}} = E_t\left[(1+\frac{CSE_{j,t+h}}{BE_{j,t+h-1}}-\frac{BE_{j,t+h}}{BE_{j,t+h-1}})\cdot\prod_{\tau=1}^{h-1}\frac{BE_{j,t+\tau}}{BE_{j,t+\tau-1}}\right]$$

5 $$\frac{E_t[PO_{j,t+h}]}{BE_{j,t}} = E_t\left[\left(e^{CSprof_{j,t\_h}-BEg_{j,t+h}}-1\right)\cdot e^{\sum_{\tau=1}^{h}BEg_{j,t+\tau}}\right]$$

6 $$s_{j,t} = \Gamma s_{j,t-1} + u_{j,t} \;;\; 1_x' s_{j,t} = x_{j,t}$$

$$\frac{BE_{j,t}}{ME_{j,t}}\cdot\sum_{h=1}^{\infty}h\cdot\left[e^{(1_{CSprof}-1_{BEg})'\Gamma^h s_{j,t}+v_1(h)}-1\right]\cdot e^{1_{BEg}'(\sum_{\tau=1}^{h}\Gamma^\tau)\cdot s_{j,t}+h\cdot v_2(h)-h\cdot dr_{j,t}}$$

Source: Gonçalves (2021)

Alphas & Betas of Duration Deciles

Duration	CAPM		Fama and French (2015) 5-factors					
decile	α_{CAPM}	β_{MKT}	α_{FF}	β_{MKT}	β_{SMB}	β_{HML}	β_{CMA}	β_{RMW}
						Value-weighted portfolios		
Short	5.1%	0.97	0.4%	0.99	0.67	0.33	0.14	0.21
2	4.6%	0.94	1.3%	0.95	0.46	0.19	0.09	0.19
3	5.4%	0.97	1.8%	1.01	0.37	0.17	0.11	0.32
4	4.8%	0.93	2.6%	0.97	0.17	0.14	0.08	0.15
5	4.3%	0.95	2.5%	0.98	0.12	−0.09	0.30	0.14
6	2.2%	0.91	0.6%	0.95	0.08	−0.10	0.22	0.19
7	1.1%	0.95	0.3%	0.97	0.00	−0.08	0.08	0.19
8	−0.2%	1.02	0.2%	1.02	−0.06	−0.16	0.13	−0.02
9	−2.6%	1.10	−3.0%	1.11	0.03	−0.10	0.04	0.14
Long	−4.9%	1.25	−4.1%	1.20	0.13	−0.14	−0.05	−0.04
L-S	−10.0%	0.28	−4.4%	0.21	−0.55	−0.47	−0.19	−0.25
(t_{L-S})	(−3.78)	(4.20)	(−2.49)	(2.98)	(−4.62)	(−2.77)	(−1.20)	(−2.39)

Source: Gonçalves (2021)

Implementing the Value-Profitability Portfolio

Investible Universe

- Started with Russell 3000
- Constraints:
  - Equities require a minimum average daily volume of 5000 shares
  - All companies must have a market capitalization of at least $1 billion at purchase

- We utilized the data from the Short Duration Premium

Measuring Value and Profitability

Value Statistics	Book-to-market	$bm_{j,t} = \log\left(\frac{BE_{j,t}}{ME_{j,t}}\right)$
	Payout yield	$POy_{j,t} = \log\left(\frac{1 + PO_{j,t}}{ME_{j,t}}\right)$
	Sales yield	$Yy_{j,t} = \log\left(\frac{Y_{j,t}}{ME_{j,t}}\right)$
Profitability Statistics	Clean surplus earnings	$CSprof_{j,t} = \log\left(1 + \frac{CSE_{j,t}}{BE_{j,t-1}}\right)$
	Return on equity	$ROE_{j,t} = \log\left(1 + \frac{E_{j,t}}{0.5BE_{j,t} + 0.5BE_{j,t-1}}\right)$
	Gross profitability	$Gprof_{j,t} = \log\left(1 + \frac{GP_{j,t}}{0.5A_{j,t} + 0.5A_{j,t-1}}\right)$

Source: Gonçalves (2021)

Calculating Metrics

Ranking Securities

Security	Value Z-Score	Rank	Profitability Z-Score	Rank	Combined Rank	Security Rank
Security 1	4.5	1	-.01	1600	1601	200
Security 2	.5	300	.6	200	500	1
Security 3	.02	1000	.03	1200	2200	400

Source: SIM Fund analysis

Portfolio Constraints

- No more than 10% of the funds market value may be invested in the stock of any one company
- Minimum of 30 securities must be maintained by portfolio
- Portfolio sector weights cannot deviate more than 7.5% from the sector weights of the Russell 3000

Industries by Value-Profitability Z-score

GICS Sector	Average of Combined Z-Score	Average Top 6 Cap Weighted Z-scores
Energy	0.57	4.68
Consumer Staples	0.26	2.12
Industrials	0.14	1.67
Materials	0.30	1.47
Communication Services	0.03	1.33
Financials	-0.22	1.13
Consumer Discretionary	0.53	0.95
Information Technology	-0.25	0.90
Health Care	-0.52	0.50
Utilities	-0.19	0.46
Real Estate	0.17	0.21

Source: SIM Fund analysis

Sector Weights Determined Through…

1. Russell 3000 GICS sector weights
2. Z-score of sectors' Value-Profitability metrics
3. Underweight sectors with Z-scores of <.9 by 5%
4. Apply a waterfall method to add subtracted weights to the sectors with the best metrics

Value-Profitability Industry Weights

GICS Sector	Russell 3000 Weight	+	Portfolio Tilt	=	Portfolio Weight
Energy	4.71%		5.00%		9.71%
Consumer Staples	6.14%		5.00%		11.14%
Industrials	9.23%		5.00%		14.23%
Materials	2.46%		0.34%		2.80%
Communication Services	8.10%		0.00%		8.10%
Financials	12.66%		0.00%		12.66%
Consumer Discretionary	10.69%		0.00%		10.69%
Information Technology	27.60%		-5.00%		22.60%
Health Care	13.07%		-5.00%		8.07%
Utilities	2.43%		-2.43%		0.00%
Real Estate	2.91%		-2.91%		0.00%

Source: SIM Fund analysis

Security Selection

- # of securities within sector were determined by sector weight
- Sectors that did not meet diversification standards gained a security
- Securities were then market-cap weighted within their sectors

Going Forward

Questions?

Appendix

Vector Autoregression Code Calculations

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```
#### Investible Universe: filtered_df variable ####

filtered_df = pd.read_csv('filtered_securities.csv', index_col=0)

##################################################


def test_stationarity(series):
    if not series.apply(lambda x: isinstance(x, (int, float))).all():
        print(f"Skipping column '{series.name}' as it is not numeric.")
        return False

    # Skip columns with all missing values
    if series.isna().all():
        print(f"Skipping column '{series.name}' as it contains only missing values.")
        return False

    # Drop missing values and test for stationarity
    series = series.dropna()
    result = adfuller(series)
    return result[1] <= 0.05

# List of columns that could not be tested for stationarity
columns_to_difference = []

# List of columns to test stationarity for (last 13 columns)
columns_to_test = filtered_df.columns[-13:-1]

```

```
# Iterate through the last 13 columns
for column in columns_to_test:
    if test_stationarity(filtered_df[column]):
        print(f'{column} is stationary')
    else:
        print(f'{column} could not be tested for stationarity')
        columns_to_difference.append(column)

# Difference the columns that could not be tested and retest for stationarity
for column in columns_to_difference:
    filtered_df[column + '_diff'] = filtered_df[column].diff()
    if test_stationarity(filtered_df[column + '_diff']):
        print(f'{column}_diff is stationary after differencing')
    else:
        print(f'{column}_diff is still not stationary after differencing')

# Drop the original columns
data1 = filtered_df.drop(columns=columns_to_difference)


# this is the gamma matrix
gamma_matrix = results.params
cov_matrix = results.resid.cov()


print(gamma_matrix)
print(cov_matrix)

```

Source: SIM Fund analysis

Equation 6 Code Calculations

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```python
###### Import Data ########
filtered_df = pd.read_csv('filtered_securities.csv', index_col=0)
gamma_matrix = pd.read_csv('gamma_matrix.csv', index_col=0)
cov_matrix = pd.read_csv('cov_matrix.csv', index_col=0)

##########################


grouped = filtered_df.groupby(filtered_df.index)

# Create a dictionary to store the separated DataFrames
separated_dfs = {}

# Iterate through the groups
for index, group_df in grouped:
    separated_dfs[index] = group_df


for i in separated_dfs:
    separated_dfs[i] = separated_dfs[i].drop(columns=['FYEAR'])
    separated_dfs[i] = separated_dfs[i].reset_index(drop = True)


def test_and_difference(df):
    def is_stationary(column):
        try:
            result = adfuller(column)
            return result[1] <= 0.05  # Assuming 5% significance level
        except:
            return False  # Return False if an exception occurs

    def difference_column(column):
        return column.diff().dropna()

    # Check if DataFrame is large enough for processing
    if len(df) < 2:
        print("DataFrame is too small for processing.")
        return df

    for column in df.columns:
        if not is_stationary(df[column]):
            df[column] = difference_column(df[column])

    return df
```

```python
# Assuming 'company_data' is your dictionary
keys_to_remove = []

for company, df in separated_dfs.items():
    if not isinstance(test_and_difference(df), pd.DataFrame):
        keys_to_remove.append(company)

for key in keys_to_remove:
    del separated_dfs[key]


forecasts = {}  # Create an empty dictionary to store forecasts

for company, df in separated_dfs.items():
    try:
        # Assuming 'df' has a suitable time series data for VAR analysis

        # Perform VAR modeling
        model = VAR(df[-13:])
        results = model.fit(1)

        # Forecast a certain number of steps ahead (change 'steps' to your desired foreca
        # Adjust as needed
        forecast = results.forecast(df.values[-13:], steps=1)

        # Store the forecast in the dictionary
        forecasts[company] = forecast

    except Exception as e:
        print(f"Error processing {company}: {e}")
        continue  # Continue with the next iteration


print(len(forecasts))
```

```python
file_path = 'forecasts.csv'

# Assuming 'forecasts' is your dictionary
with open(file_path, mode='w', newline='') as file:
    writer = csv.writer(file)

    column_headings = ["PERMNO","BM","POy","Yy","BE_g","A_g","Y_g","CSprof","ROE","Gprof"

    writer.writerow(column_headings)

    for company, matrix in forecasts.items():
        # Write company name
        writer.writerow([company])

        # Write the first 12 values from the matrix in separate cells

        # Write each value in the matrix as a separate cell
        for row in matrix[:12]:
            writer.writerow(row)

        # Write an empty row
        writer.writerow([])
```

Source: SIM Fund analysis

Gonçalves Deriving $v_1(h)$

$$
\begin{aligned}
Cov_1(2) &= Cov_t[po_{t+2}, BEg_{t+1} + BEg_{t+2}] \\
&= \theta \cdot Cov_t[po_{t+2}, BEg_{t+1}] + Cov_t[po_{t+2}, BEg_{t+2}] \\
&= \theta \cdot Cov_t\left[\mathbf{1}'_{po}(\Gamma u_{t+1} + u_{t+2}), \mathbf{1}'_{BEg} u_{t+1}\right] + Cov_t\left[\mathbf{1}'_{po}(\Gamma u_{t+1} + u_{t+2}), \mathbf{1}'_{BEg}(\Gamma u_{t+1} + u_{t+2})\right] \\
&= \theta \cdot \mathbf{1}'_{po}\Gamma\Sigma\mathbf{1}_{BEg} + \mathbf{1}'_{po}\Gamma\Sigma\Gamma'\mathbf{1}_{BEg} + \mathbf{1}'_{po}\Sigma\mathbf{1}_{BEg} \\
&= \mathbf{1}'_{po}\Gamma\Sigma(\Gamma + \theta \cdot \mathrm{I})'\mathbf{1}_{BEg} + Cov_1(1)
\end{aligned}
$$

and

$$
\begin{aligned}
Cov_1(3) &= Cov_t[po_{t+3}, BEg_{t+1} + BEg_{t+2} + BEg_{t+3}] \\
&= \theta^2 \cdot Cov_t[po_{t+3}, BEg_{t+1}] + \theta \cdot Cov_t[po_{t+3}, BEg_{t+2}] + Cov_t[po_{t+3}, BEg_{t+3}] \\
&= \theta^2 \cdot Cov_t\left[\mathbf{1}'_{po}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3}), \mathbf{1}'_{BEg} u_{t+1}\right] \\
&\quad + \theta \cdot Cov_t\left[\mathbf{1}'_{po}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3}), \mathbf{1}'_{BEg}(\Gamma u_{t+1} + u_{t+2})\right] \\
&\quad + Cov_t\left[\mathbf{1}'_{po}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3}), \mathbf{1}'_{BEg}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3})\right] \\
&= \mathbf{1}'_{po}\Gamma^2\Sigma(\Gamma^2 + \theta \cdot \Gamma + \theta^2 \cdot \mathrm{I})'\mathbf{1}_{BEg} + \mathbf{1}'_{po}\Gamma\Sigma(\Gamma + \theta \cdot \mathrm{I})'\mathbf{1}_{BEg} + \mathbf{1}'_{po}\Sigma\mathbf{1}_{BEg} \\
&= \mathbf{1}'_{po}\Gamma^2\Sigma(\Gamma^2 + \theta \cdot \Gamma + \theta^2 \cdot \mathrm{I})'\mathbf{1}_{BEg} + Cov_1(2)
\end{aligned}
$$

which generalizes to:

$$Cov_1(h) = \mathbf{1}'_{po}\Gamma^{h-1}\Sigma F(h)'\mathbf{1}_{BEg} + Cov_1(h-1) \tag{IA.2}$$

where $F(h) = F(h-1)\Gamma + \mathrm{I} \cdot \theta^{h-1}$ with I representing an identity matrix and θ capturing a scalar shrinkage factor I introduce (see below).

Putting all terms together, we have:

$$v_1(h) = v_1(h-1) + 0.5 \cdot \mathbf{1}'_{po}\Gamma^{h-1}\Sigma\Gamma'^{h-1}\mathbf{1}_{po} + \mathbf{1}'_{po}\Gamma^{h-1}\Sigma F(h)'\mathbf{1}_{BEg} \tag{IA.3}$$

with boundary condition $v_1(1) = 0.5 \cdot \mathbf{1}'_{po}\Sigma\mathbf{1}_{po} + \mathbf{1}'_{po}\Sigma\mathbf{1}_{BEg}$.

Source: Gonçalves (2021)

Gonçalves Deriving $v_2(h)$

Letting $Cov_t\left(BEg_{t+\tau}, BEg_{t+h}\right) = Cov_{\tau,h}^{BEg}$, we have $1 \cdot v_2(1) = 0.5 \cdot Cov_{1,1}^{BEg}$ and then:

$$\begin{aligned} 2 \cdot v_2(2) &= 0.5 \cdot Cov_t\left[BEg_{t+1} + BEg_{t+2}, BEg_{t+1} + BEg_{t+2}\right] \\ &= 0.5 \cdot (Cov_{1,1}^{BEg} + Cov_{2,2}^{BEg}) + \theta \cdot Cov_{1,2}^{BEg} \end{aligned}$$

and

$$\begin{aligned} 3 \cdot v_2(3) &= 0.5 \cdot Cov_t\left[BEg_{t+1} + BEg_{t+2} + BEg_{t+3}, BEg_{t+1} + BEg_{t+2} + BEg_{t+3}\right] \\ &= 0.5 \cdot (Cov_{1,1}^{BEg} + Cov_{2,2}^{BEg} + Cov_{3,3}^{BEg}) + \left[\theta \cdot Cov_{1,2}^{BEg} + \theta \cdot Cov_{2,3}^{BEg} + \theta^2 \cdot Cov_{1,3}^{BEg}\right] \end{aligned}$$

which generalizes to:

$$h \cdot v_2(h) = (h-1) \cdot v_2(h-1) + 0.5 \cdot Cov_{h,h}^{BEg} + \sum_{i=1}^{h-1} \theta^i \cdot Cov_{h-i,h}^{BEg} \qquad \text{(IA.4)}$$

with boundary condition $v_2(1) = 0.5 \cdot Cov_{1,1}^{BEg}$

Hence, all we need is an expression for $Cov_{\tau,h}^{BEg}$ with $\tau = 1, 2, ..., h$. However, note that $BEg_{t+h} = u_{t+h} + \Gamma u_{t+h-1} + \Gamma^2 u_{t+h-2} + ... + \Gamma^{h-1} u_{t+1} + \Gamma^h s_t$, and thus:

$$\begin{aligned} Cov_{\tau,h}^{BEg} &= Cov_t\left(u_{t+\tau} + \Gamma u_{t+\tau-1} + ... + \Gamma^{\tau-1} u_{t+1}, u_{t+h} + \Gamma u_{t+h-1} + \Gamma^2 u_{t+h-2} + ... + \Gamma^{h-1} u_{t+1}\right) \\ &= Cov_t\left(u_{t+\tau} + \Gamma u_{t+\tau-1} + ... + \Gamma^{\tau-1} u_{t+1}, \Gamma^{h-\tau} u_{t+\tau} + \Gamma^{h-\tau+1} u_{t+\tau-1} + ... + \Gamma^{h-1} u_{t+1}\right) \\ &= \mathbf{1}_{BEg}' \left[\Sigma \Gamma'^{h-\tau} + \Gamma \Sigma \Gamma'^{h-\tau+1} + \Gamma^2 \Sigma \Gamma'^{h-\tau+2} + ... + \Gamma^{\tau-1} \Sigma \Gamma'^{h-1}\right] \mathbf{1}_{BEg} \qquad \text{(IA.5)} \end{aligned}$$

which concludes the derivation of $v_2(h)$.

Source: Gonçalves (2021)

Short-Duration Subsumes Value and Profitability Premia

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Sorting variable	Decile portfolios based on included covariates							
	[1.1]	[1.2]	[1.3]	[1.4]	[1.5]	[1.6]	[1.7]	[1.8]
Dur	−8.6%	−9.7%	−12.3%	−10.1%	−9.7%		−12.7%	−14.4%
	(−3.85)	(−4.22)	(−4.28)	(−3.98)	(−4.26)		(−2.87)	(−2.44)
BE/ME	4.9%	0.9%				12.7%	−0.4%	−2.5%
	(2.06)	(0.32)				(3.33)	(−0.09)	(−0.37)
Gprof	1.5%		−2.1%			10.0%	−1.6%	−1.8%
	(0.70)		(−0.81)			(2.84)	(−0.34)	(−0.31)
Ag	−3.8%			−2.9%				−3.3%
	(−2.06)			(−1.29)				(−0.94)
Size	−4.4%				−2.7%			−2.8%
	(−1.89)				(−1.08)			(−0.97)

Source: Gonçalves (2021)

Value-Profitability Portfolio Investments

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Communication Services	Portfolio Weight	Position	shares
NEWS CORPORATION (XNAS:NWS)	6.83%	$42,596.08	1829.728719
CARGURUS, INC. (XNAS:CARG)	1.27%	$7,940.39	367.440359
Consumer Discretionary			
AUTONATION, INC. (XNYS:AN)	3.87%	$24,145.51	182.120342
LEVI STRAUSS & CO. (XNYS:LEVI)	4.16%	$25,956.91	1700.977055
GROUP 1 AUTOMOTIVE, INC. (XNYS:GPI)	2.66%	$16,593.24	59.20447579
Consumer Staples			
INGLES MARKETS, INCORPORATED (XNAS:IMKTA)	0.38%	$2,348.81	29.30146076
PERFORMANCE FOOD GROUP COMPANY (XNYS:PFGC)	2.46%	$15,359.90	240.03593
CENTRAL GARDEN & PET COMPANY (XNAS:CENT)	0.49%	$3,058.97	76.24544333
THE KROGER CO. (XNYS:KR)	7.81%	$48,735.57	1109.644205
Energy			
PBF ENERGY INC. (XNYS:PBF)	0.74%	$4,641.39	102.5381756
HF SINCLAIR CORPORATION (XNYS:DINO)	1.31%	$8,152.93	150.7567802
MARATHON PETROLEUM CORPORATION (XNYS:MPC)	7.66%	$47,787.06	318.60162
Financials			
PROG Holdings, Inc (XNYS:PRG)	0.37%	$2,303.43	84.09732126
FIRST CITIZENS BANCSHARES, INC. (XNAS:FCNCA)	6.28%	$39,190.27	27.51468553
ROCKET COMPANIES, INC. (XNYS:RKT)	5.57%	$34,777.98	3727.543862
MERCHANTS BANCORP (XNAS:MBIN)	0.44%	$2,714.95	81.31042194

Health Care	Portfolio Weight	Position	Shares
SURGERY PARTNERS, INC. (XNAS:SGRY)	5.05%	$31,499.12	983.4255127
GOODRX HOLDINGS, INC. (XNAS:GDRX)	3.02%	$18,850.18	3157.483996
Industrials			
AVIS BUDGET GROUP, INC. (XNAS:CAR)	3.21%	$20,002.84	111.8164178
BUILDERS FIRSTSOURCE, INC. (XNYS:BLDR)	8.12%	$50,691.64	380.939688
Matson, Inc. (XNYS:MATX)	1.64%	$10,229.11	107.8450753
HERTZ GLOBAL HOLDINGS, INC. (XNAS:HTZ)	1.26%	$7,858.38	950.2278121
Information Technology			
ARROW ELECTRONICS, INC. (XNYS:ARW)	2.80%	$17,459.79	146.5362314
AVNET, INC. (XNAS:AVT)	1.82%	$11,384.20	244.8214649
JABIL INC. (XNYS:JBL)	7.25%	$45,238.06	346.1743072
SUPER MICRO COMPUTER, INC. (XNAS:SMCI)	6.60%	$41,198.57	144.2476326
PC CONNECTION, INC. (XNAS:CNXN)	0.68%	$4,240.72	71.08146568
VISHAY INTERTECHNOLOGY, INC. (XNYS:VSH)	1.34%	$8,365.33	374.287876
INSIGHT ENTERPRISES, INC. (XNAS:NSIT)	2.10%	$13,116.32	88.14141031
Materials			
ALPHA METALLURGICAL RESOURCES, INC. (XNYS:AMR)	2.80%	$17,469.40	63.26511894
Real Estate			
EXP WORLD HOLDINGS, INC. (XNAS:EXPI)	0.00%	$0.00	0
FORESTAR GROUP INC. (XNYS:FOR)	0.00%	$0.00	0
NEWMARK GROUP, INC. (XNAS:NMRK)	0.00%	$0.00	0
Utilities			
CLEARWAY ENERGY, INC. (XNYS:CWEN)	0.00%	$0.00	0
NRG ENERGY, INC. (XNYS:NRG)	0.00%	$0.00	0
NORTHWEST NATURAL HOLDING COMPANY (XNYS:NWN)	0.00%	$0.00	0

Source: SIM Fund analysis

Investment Thesis and Implementation - Fall 2023

Arizona State University

Prepared by the Undergraduate Student Investment Management Fund - Team B

Under the designation of Dr. Wahal
Friday December 1st, 2023

Team Introduction

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Agenda

Investment Thesis

By Brendan Weinberg

Strategy Implementation

By Cameron Ulreich-Power

Investment Thesis

Post-Earnings Announcement Drift

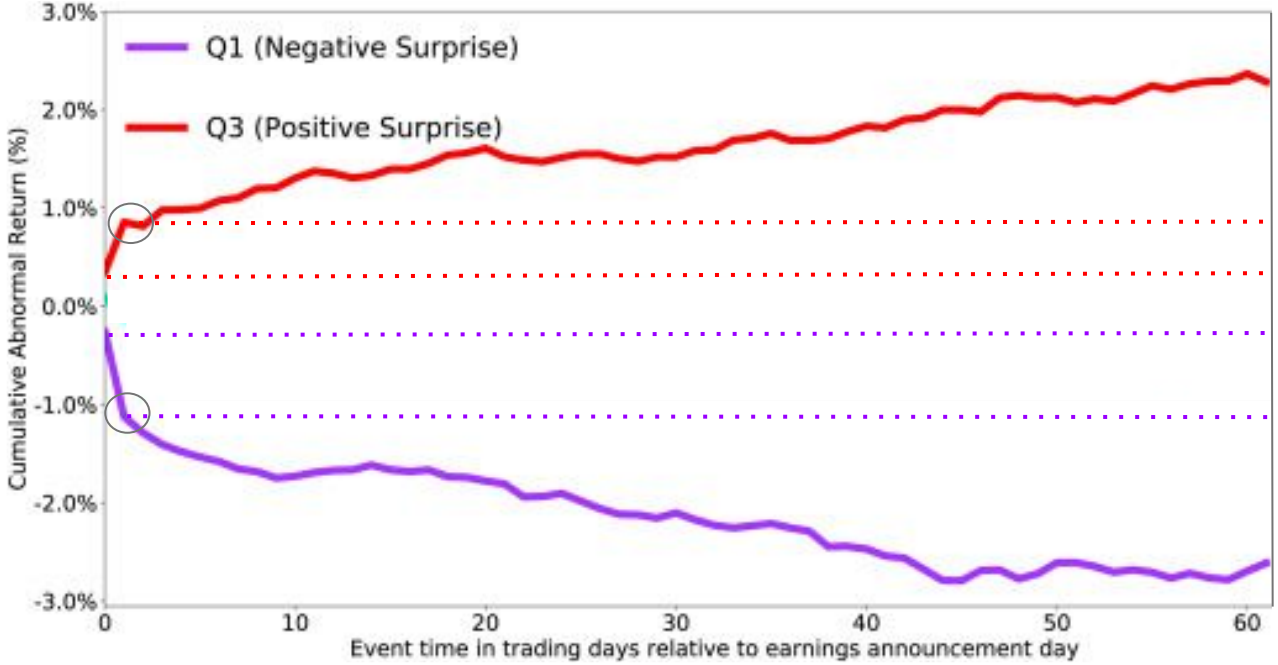
Earnings Announcement

Surpasses Expectations

Stock Price Increase

- PEAD contradicts the efficient market hypothesis.
- This anomaly has been studied for over 50 years, yet there is **no definitive explanation.**

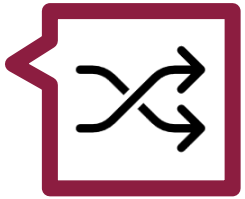
Post-Earnings Announcement Drift



Potential Explanations for PEAD

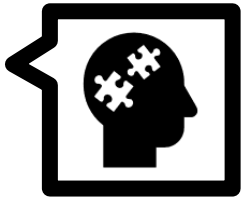
Insufficient Risk Adjustment and Information Uncertainty

- Weak correlation with beta
- Uncertainty leads to under reactions



Cross Sectional Drivers

- Firm characteristics (Liquidity and Arbitrage)
- Inflation

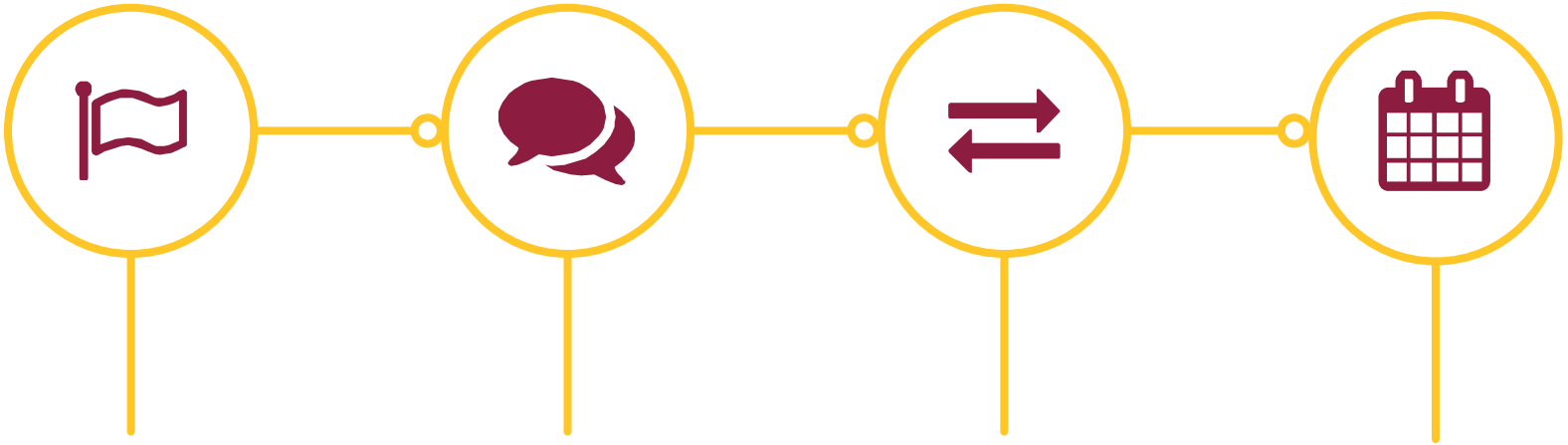


Inattention and Behavioral Biases

- Disposition effect
- Anchoring and recency bias

Strategy Implementation

Implementation steps



Data

Investable Universe
Earning Release Dates

Process

Gantt Charts
Checks and Balances

Strategy Rules

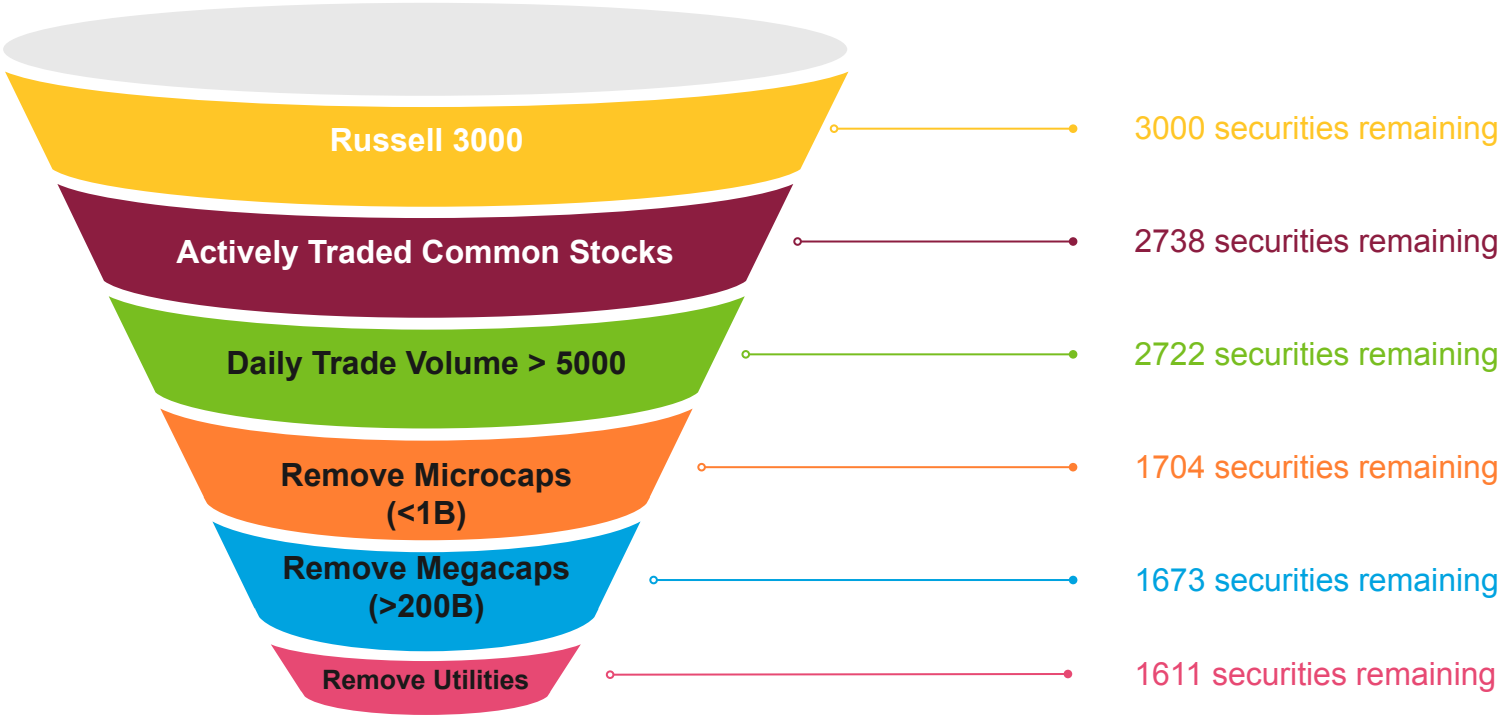
Trading Issues
Solutions

Implementation

Current Portfolio
Major Calendar Events

Data

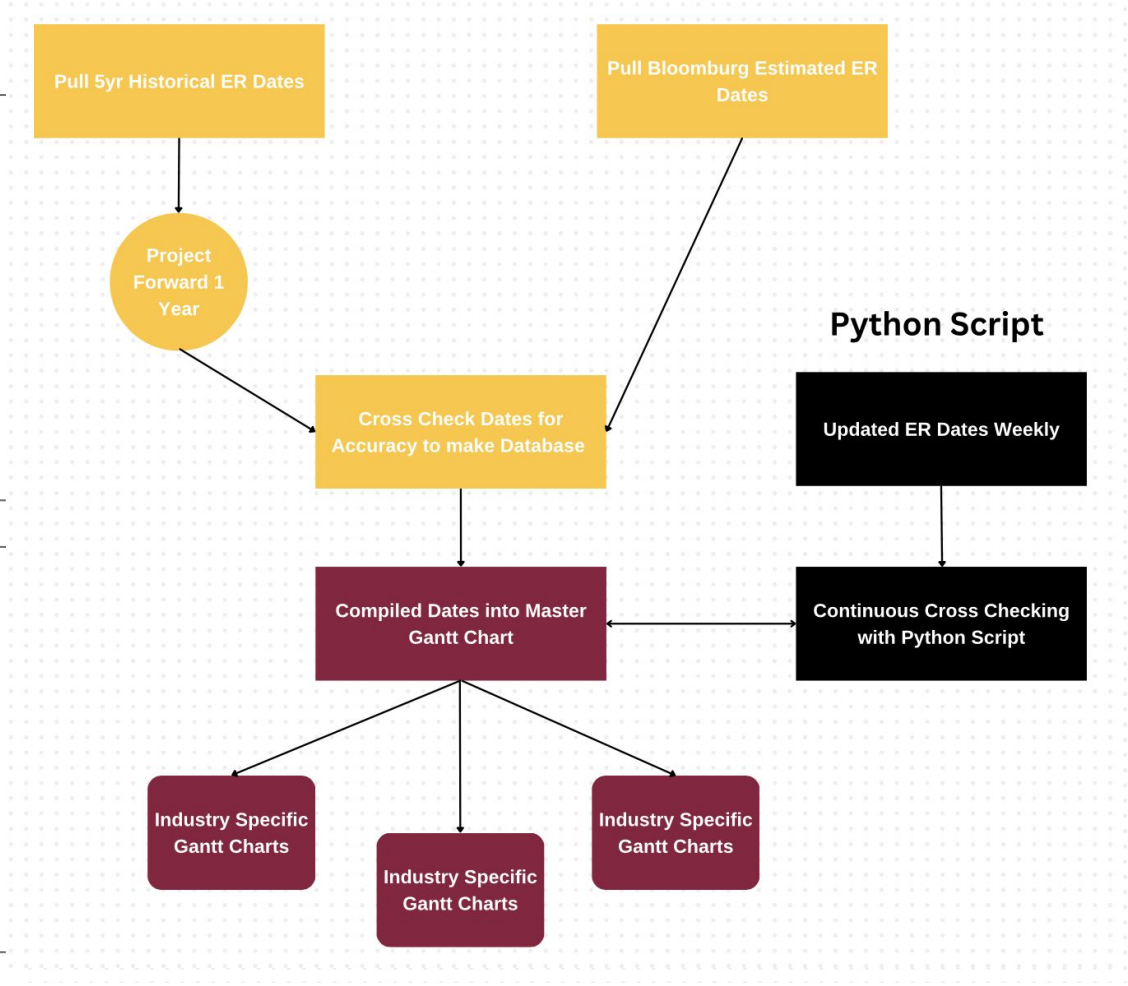
Investable Universe



Flow Chart

Data

Process



Earning Release Information

Source: Bloomberg Finance L.P.

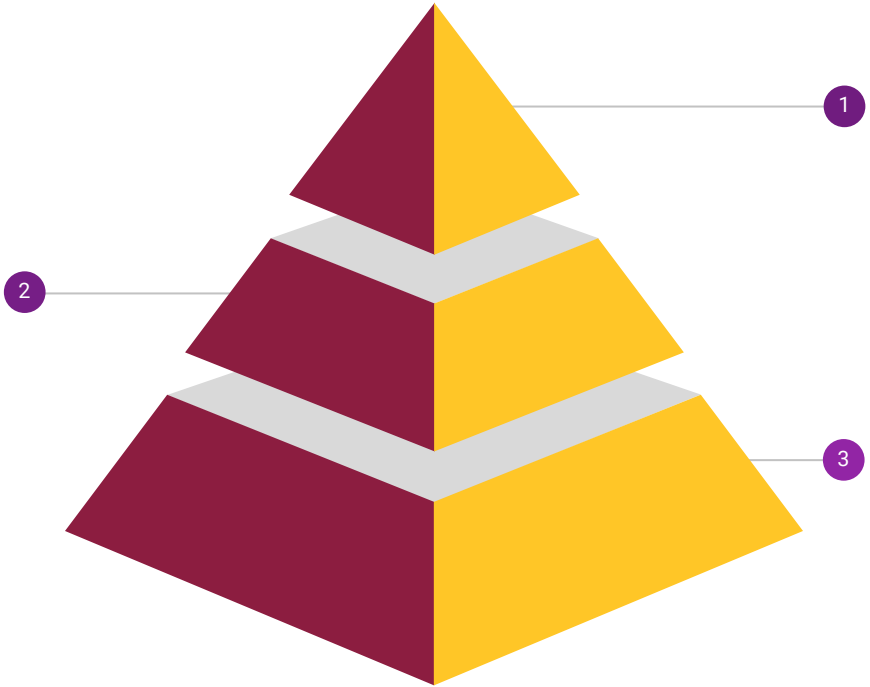
Name	Estimated ER Date	Date Type	Estimate	Guidance	Sector
EQRx Inc	11/27/23	E	(0.16)		Healthcare
Waldencast plc	11/27/23	E	0.03		Consumer Staples
Seadrill Ltd	11/27/23	C	0.846		Energy
Zscaler Inc	11/27/23	C	0.492	0.49	Information Technologies
AZEK Co Inc/The	11/28/23	C	0.286		Industrials
Crowdstrike Holdings Inc	11/28/23	C	0.743	0.74	Information Technologies
Fluence Energy Inc	11/28/23	C	(0.059)		Industrials
Hewlett Packard Enterprise Co	11/28/23	T	0.499	0.50	Information Technologies
Intuit Inc	11/28/23	C	1.983	1.97	Information Technologies
NetApp Inc	11/28/23	C	1.393	1.40	Information Technologies
Splunk Inc	11/28/23	C	1.162		Information Technologies
Workday Inc	11/28/23	C	1.403		Information Technologies
Construction Partners Inc	11/29/23	C	0.519		Industrials
Dollar Tree Inc	11/29/23	C	1.007	0.99	Consumer Staples
Donaldson Co Inc	11/29/23	T	0.723		Industrials
Foot Locker Inc	11/29/23	C	0.228		Consumer Discretionary
Hormel Foods Corp	11/29/23	C	0.441		Consumer Staples
Patterson Cos Inc	11/29/23	C	0.585		Healthcare

Process

Master Gantt Chart

SECTOR	Company Name	47	48	49	50	51	52	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Communication Services	TEGNA Inc															ER									
Communication Services	Telephone and Data Systems Inc													ER											
Communication Services	TKO Group Holdings Inc											ER													
Communication Services	Trade Desk Inc/The													ER											
Communication Services	TripAdvisor Inc													ER											
Communication Services	Verizon Communications Inc										ER													ER	
Communication Services	Vivid Seats Inc																ER								
Communication Services	Walt Disney Co/The												ER												
Communication Services	Warner Bros Discovery Inc														ER										
Communication Services	Yelp Inc												ER												
Communication Services	Ziff Davis Inc													ER											
Communication Services	ZipRecruiter Inc														ER										
Communication Services	ZoomInfo Technologies Inc												ER												ER
Consumer Discretionary	Advance Auto Parts Inc															ER									
Consumer Discretionary	Asbury Automotive Group Inc											ER												ER	
Consumer Discretionary	Airbnb Inc													ER											
Consumer Discretionary	Adient PLC												ER												
Consumer Discretionary	ADT Inc															ER									
Consumer Discretionary	American Eagle Outfitters Inc	ER														ER									

Checks and Balances



Python Script
Instantly cross-references the weekly ER data with our original database, updating any outdated information

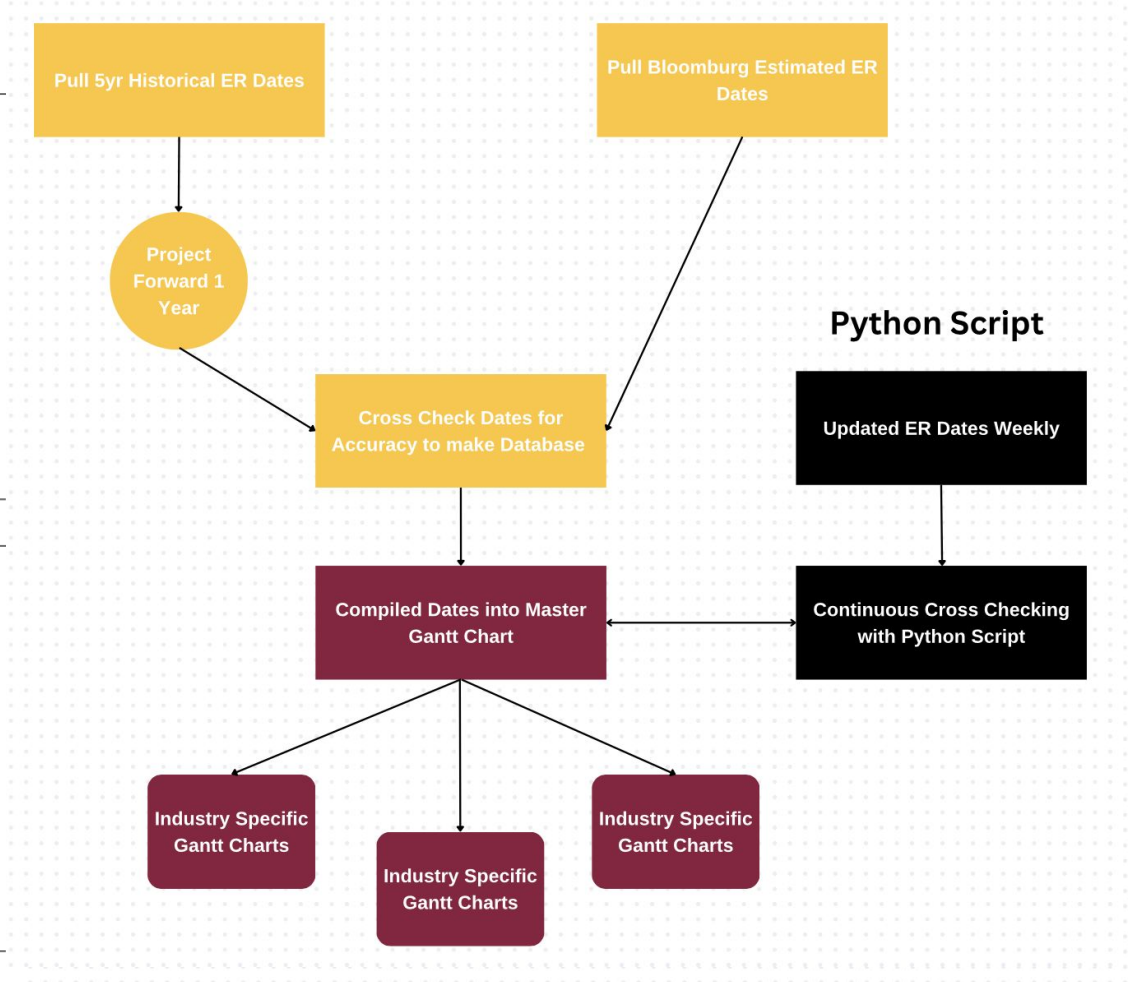
Automatic Alerts
Bloomberg Alerts set up to send team members a notification of any changes to earning releases in their Sector

Accurate Charts
Utilizing these checks and balances, the Gantt Chart is updated weekly to account for every earning release

Flow Chart

Data

Process

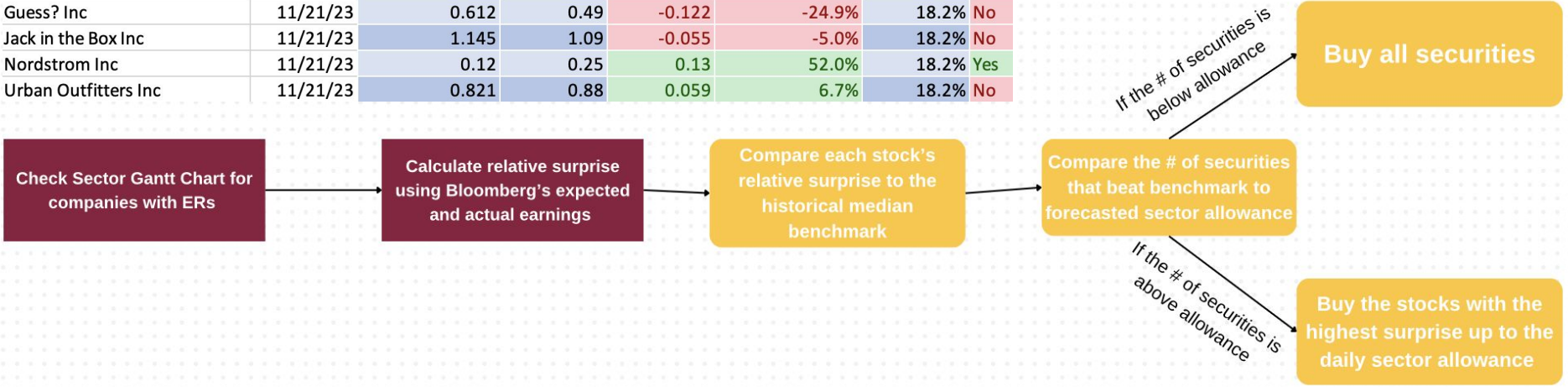


Strategy Rules

Trading Issues

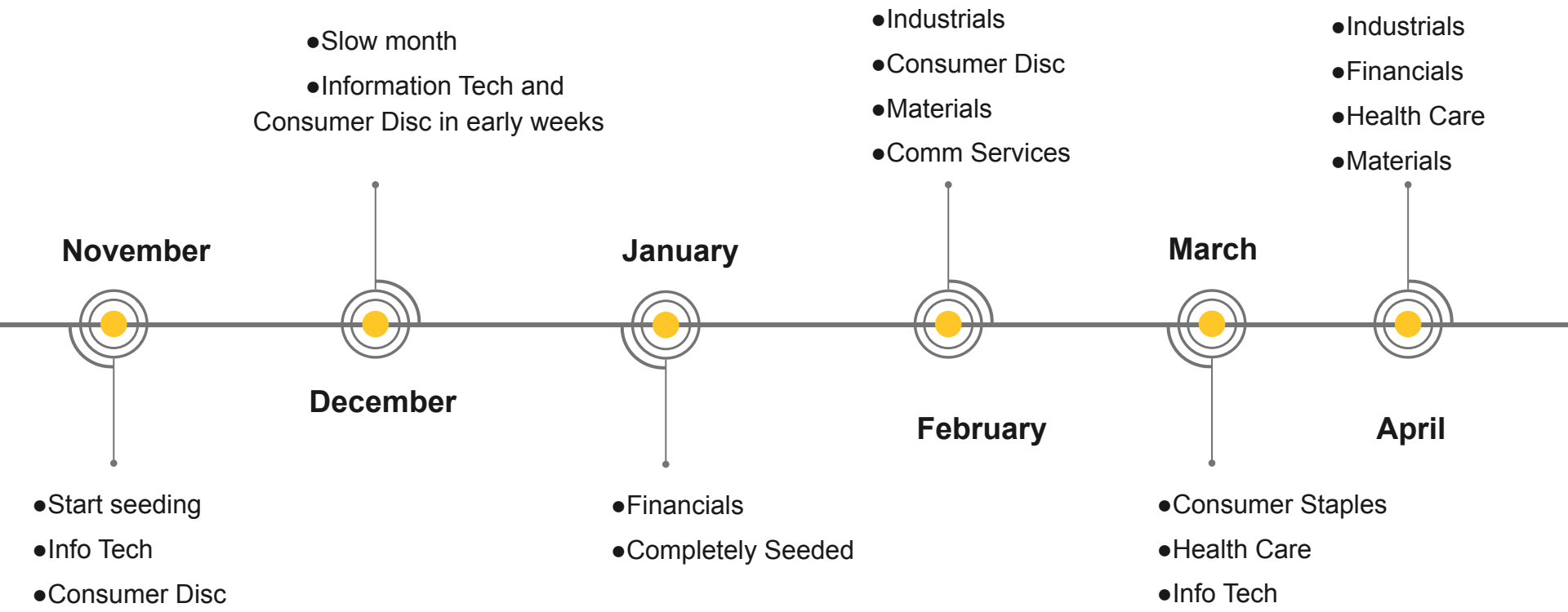
Solutions

		Week	47				
Company	**ER Date**	**Expected Return**	**Actual**	**Surprise**	**Relative Surprise**	**Benchmark**	**Beat**
American Eagle Outfitters Inc	11/21/23	0.478	0.49	0.012	2.4%	18.2%	No
Abercrombie & Fitch Co	11/21/23	1.145	1.83	0.685	37.4%	18.2%	Yes
Best Buy Co Inc	11/21/23	1.183	1.29	0.107	8.3%	18.2%	No
Burlington Stores Inc	11/21/23	0.969	0.98	0.011	1.1%	18.2%	No
Dick's Sporting Goods Inc	11/21/23	2.526	2.85	0.324	11.4%	18.2%	No
Guess? Inc	11/21/23	0.612	0.49	-0.122	-24.9%	18.2%	No
Jack in the Box Inc	11/21/23	1.145	1.09	-0.055	-5.0%	18.2%	No
Nordstrom Inc	11/21/23	0.12	0.25	0.13	52.0%	18.2%	Yes
Urban Outfitters Inc	11/21/23	0.821	0.88	0.059	6.7%	18.2%	No



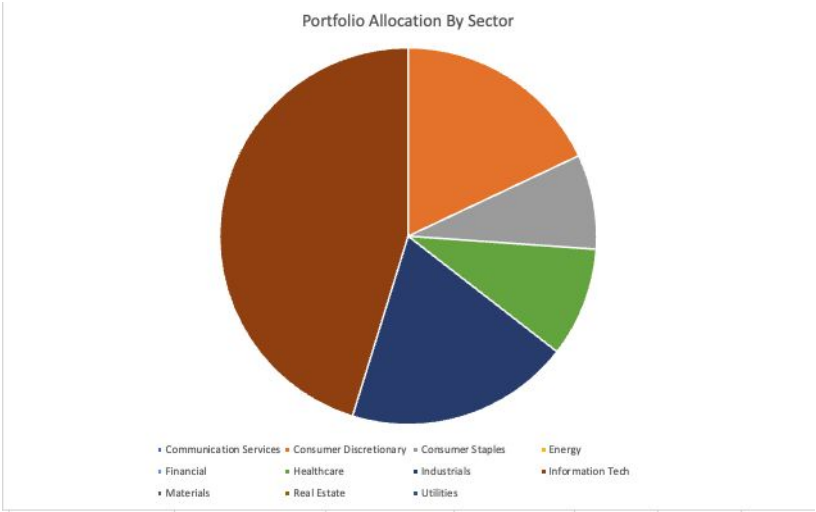
Implementation

Investment Timeline



Current Portfolio As Of 11/30/23

Sector	Percentage of Portfolio	Percentage of IWV	Number of Stocks
Communication Services	0.00%	6.27%	-
Consumer Discretionary	3.98%	8.32%	2.00
Consumer Staples	1.80%	4.48%	1.00
Energy	0.00%	3.25%	-
Financial	0.00%	10.38%	-
Healthcare	2.08%	9.64%	1.00
Industrials	4.27%	7.44%	2.00
Information Tech	10.02%	21.14%	5.00
Materials	0.00%	2.08%	-
Real Estate	0.00%	2.22%	-
Utilities	0.00%	1.80%	-
Cash	0.96%	0.00%	1.00
Total Live	23%	77%	11.00
Total Percentage	100%		



Date Bought	Company	Ticker	Sector	# of Shares	Share Price	Total	% of Portfolio
11/21/23	Agilent Technologies Inc.	AGILENT TECHNOLOGIES, INC. (XNYS:A)	Healthcare	200	$ 127.71	$ 25,569.92	2.08%
11/21/23	Keysight Technologies INC	KEYSIGHT TECHNOLOGIES, INC. (XNYS:KEYS)	Information Tech	176	$ 136.74	$ 24,116.44	1.96%
11/21/23	Zoom Video Communication	ZOOM VIDEO COMMUNICATIONS, INC. (XNAS:ZM)	Information Tech	365	$ 67.75	$ 24,762.17	2.02%
11/21/23	Central Garden and pet company	CENTRAL GARDEN & PET COMPANY (XNAS:CENT)	Consumer Staples	553	$ 39.97	$ 22,089.60	1.80%
11/22/23	Dycom Industries	DYCOM INDUSTRIES, INC. (XNYS:DY)	Industrials	240	$ 103.31	$ 24,793.20	2.02%
11/22/23	Abercrombie & Fitch Co	ABERCROMBIE & FITCH CO. (XNYS:ANF)	Consumer Discretionary	331	$ 75.45	$ 24,973.95	2.03%
11/22/23	Autodesk	AUTODESK, INC. (XNAS:ADSK)	Information Tech	116	$ 216.81	$ 25,149.96	2.05%
11/29/23	AZEK CO INC CL A CL A	THE AZEK COMPANY INC. (XNYS:AZEK)	Industrials	804	$ 34.28	$ 27,557.10	2.25%
11/29/23	Splunk Inc	SPLUNK INC. (XNAS:SPLK)	Information Tech	162	$ 150.75	$ 24,421.50	1.99%
11/29/23	Intuit Inc	INTUIT INC. (XNAS:INTU)	Information Tech	43	$ 569.82	$ 24,502.05	2.00%
11/30/23	Foot Locker Inc	FOOT LOCKER, INC. (XNYS:FL)	Consumer Discretionary	876	$ 27.28	$ 23,908.55	1.95%

Questions?

Appendix - A

- Submit trades to traders for the following day by 8 PM.
- Holding Period - Trailing 4-week period, can decrease when ER volume increases
- Limit the number of stocks we can buy in 1 week based on the 4-week weight.
- Sell the oldest stocks in the sector to fund new ER in the sector
- Communicate with team when nearing benchmark cap
- Understand difference between Firm and Sector specific earnings effects
- Ensure the magnitude of the surprise has beat the median benchmark
- Pick the stocks with the highest magnitude - on condition that sufficient market research has been conducted

Appendix - B

Week	46	47	48	49	50	51	52	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	Total
Total Events per week	58	26	40	40	11	19	1	13	15	48	191	232	253	216	296	242	53	35	21	28	14	8	105	394	83	2442
Communication Services	0	0	0	2	1	0	0	0	0	1	4	5	15	10	12	8	3	0	1	0	0	0	4	8	3	77
Consumer Disc	16	9	7	12	3	4	0	1	1	0	7	30	30	28	42	46	9	10	8	5	0	1	8	46	9	332
Consumer Staples	8	4	3	5	0	1	1	5	3	0	4	14	16	7	6	15	8	1	1	3	5	2	1	9	3	125
Energy	3	1	1	0	0	1	0	0	0	2	8	6	6	11	33	15	4	2	1	1	1	0	3	23	4	126
Financial	0	1	0	0	0	1	0	0	6	37	92	39	45	16	20	17	1	1	1	1	0	2	62	98	17	457
Healthcare	8	1	3	2	0	0	0	1	0	0	7	28	26	27	57	63	7	5	2	3	1	0	3	40	11	295
Information Tech	8	4	21	13	3	1	0	0	1	1	24	34	47	39	23	32	11	9	0	8	0	0	5	38	8	330
Industrials	9	6	4	5	4	10	0	4	3	4	29	50	51	38	61	30	9	5	5	6	4	3	14	89	16	459
Materials	3	0	1	1	0	1	0	2	1	3	13	18	13	19	14	4	1	1	2	1	3	0	4	27	6	138
Real Estate	0	0	0	0	0	0	0	0	0	0	1	0	0	3	7	4	0	0	0	0	0	0	1	3	0	19