SIM Fund - Team 2

Insider Investment Horizon

Arizona State University

SIM Fund Team 2

Maxwell Fields, Carson Stork, Antonio Nguyen, Ilya Illiashenko, Anushayana Pant, Tung-Lin Pai, Vlada Vaska

Team Introduction

ASU W. P. Carey School of Business
Arizona State University




Antonio Nguyen

Carson Stork

Maxwell Fields

Anushayana Pant



Vlada Vaska

(Fund Manager)

Tung-Lin Pai

Ilya Illiashenko

Insider Investment Horizon Strategy

Arizona State University

Insider Theory

Note: The graph depicts insider trading activity of an anonymous short horizon insider (Mr. A).

Source: Akbas, Ferhat, et al. "Insider Investment Horizon." *The Journal of Finance*, LXXV, no. 3, June 2020.

Insider Investment Horizon

Insider Horizon = Based on trade pattern consistency

Short-Horizon → frequent switchers → more likely informed

- *-0.3 < Net Order Flow < 0.3*

Long-Horizon → consistent buyers/sellers → often routine

- *Net Order Flow < -0.8 or Net Order Flow > 0.8*

Categorized using **Net Order Flow** over prior **12 months**:

$$\frac{P_{i,j,y} - S_{i,j,y}}{P_{i,j,y} + S_{i,j,y}}$$

Investment Horizon Findings

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- ★ Short Horizon insiders perform better than typical long horizon insiders.
  - ○ SH purchases returned **2.44%** in the following month (outperformed LH purchases by 0.81%)
- ★ Long Horizon insiders who execute unexpected trades perform better than short horizon insiders.
  - ○ LH unexpected purchases returned **4.10%** in the following month (outperformed SH purchases by 1.66%)

Source: Akbas, Ferhat, et al. "Insider Investment Horizon." *The Journal of Finance*, LXXV, no. 3, June 2020.

Trade Categorization

Routine Trades are classified as insider trades executed in the same month for the previous three years.

Opportunistic Trades are classified as insider trades that do not follow consistent calendar trading patterns (not traded in the same month for the previous three years).

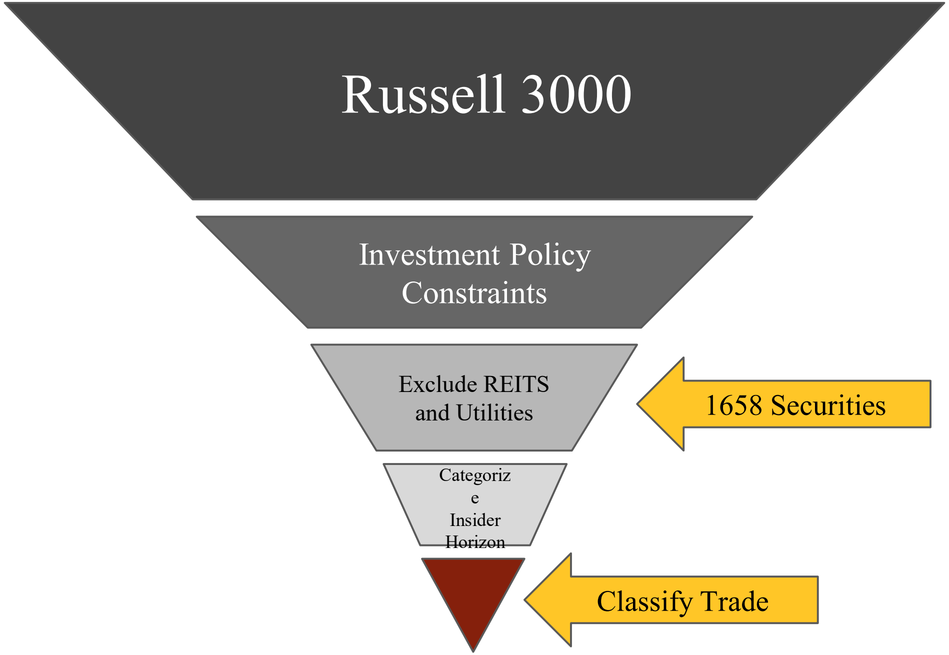
Source: COHEN, LAUREN, et al. "Decoding Inside Information." *The Journal of Finance*, LXVII, no. 3, 2012.

Strategy Implementation

Strategy Plan

1. Filter investable universe.
2. Collect historical insider data.
3. Categorize SH and LH insiders.
4. Develop an automated SEC scraping program.
5. Distinguish routine vs. opportunistic trades.
6. Generate a daily .csv of insider trades.

Investment Universe



Insider Categorization

In [10]:
```
categorized = cate_strength(insider_names, clean_df)
categorized
```

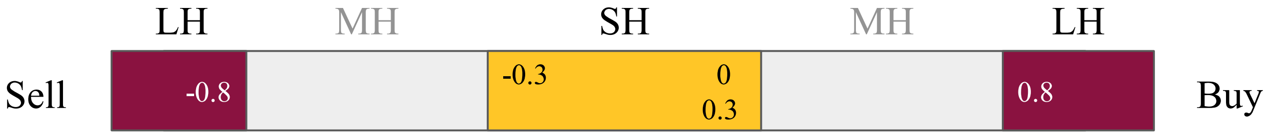
Out[10]:

	Insider name	cusip	symbol	trading strength	avg_ts	historical yrs	yrs_traded
0	SOTOK FREDERICK A	371901	GNTX	-1.000000	-1.000000	6.280630	6
1	COLTHARP DOUGLAS E	904311	UA	-1.000000	-1.000000	10.045175	5
2	CONROY KEVIN T	30063P	EXAS	-0.968663	-0.986522	10.327173	11
3	LIDGARD GRAHAM PETER	30063P	EXAS	-1.000000	-1.000000	7.186858	6
4	DOLBY DAGMAR	25659T	DLB	-1.000000	-1.000000	5.555099	6
...	...	...	...	...	...	...	...
5127	BROAD MATTHEW R	237194	DRI	-0.985399	-0.666667	5.152635	6
5128	SCHRADER ROBERT L	704326	PAYX	-1.000000	-1.000000	5.207392	5
5129	ARIAN MARK D.	500643	KFY	-0.990050	0.000000	5.768652	2
5130	GUERTIN TIMOTHY E	880770	TER	-1.000000	-1.000000	7.104723	2
5131	SCHMIDT JOHN W	129500	CAL	-0.949367	0.000000	5.125257	4

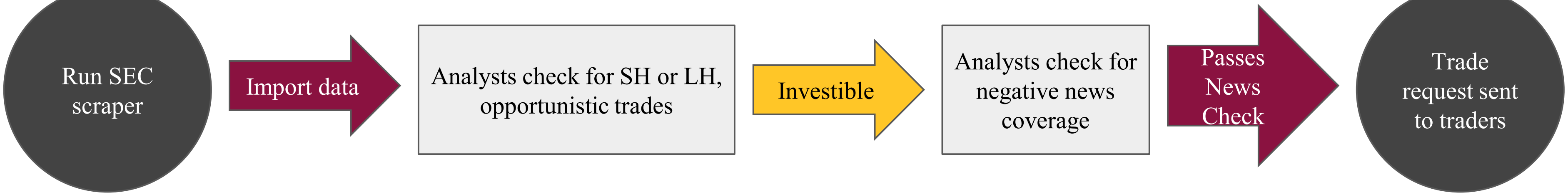
5132 rows × 7 columns

In [11]:
```
categorized.to_csv('categorized.csv', index=False)
```

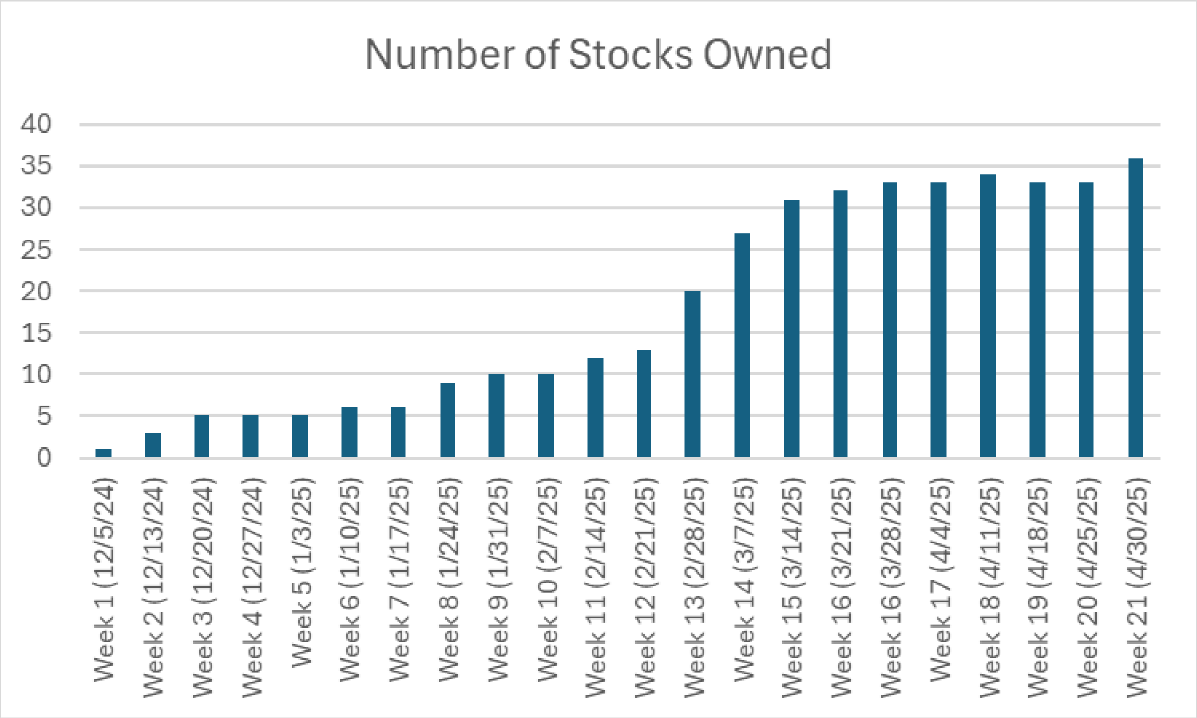
- ★ Short Horizon insiders have net order flows between -0.30 and 0.30.
- ★ Long Horizon insiders have net order flows less than -0.80 or greater than 0.80.



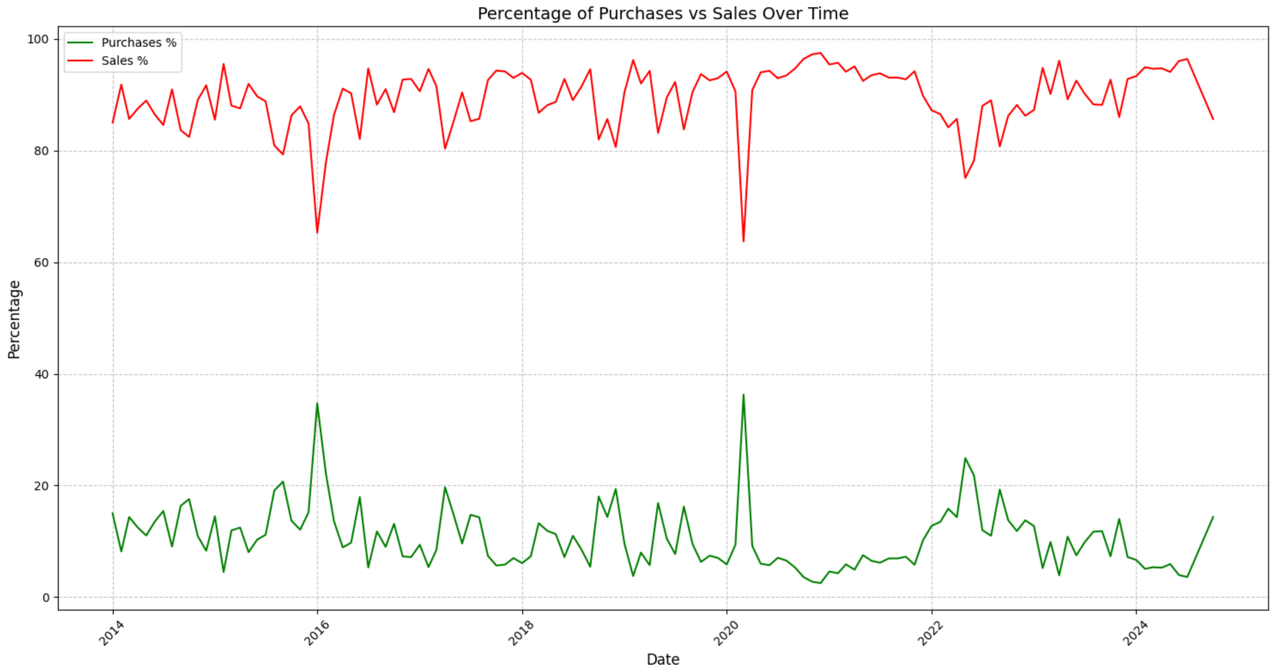
Daily Trading Process



Historic Growth in Our Portfolio



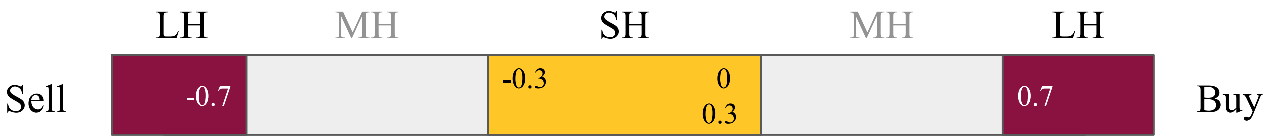
Insider Purchases vs Sales



Spring Semester Process Update

Updated:

- Long horizon: *Net Order Flow < -0.7 or Net Order Flow > 0.7*
- *Trading years from 5 to 3*



Performance + Attribution

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Performance vs Benchmark

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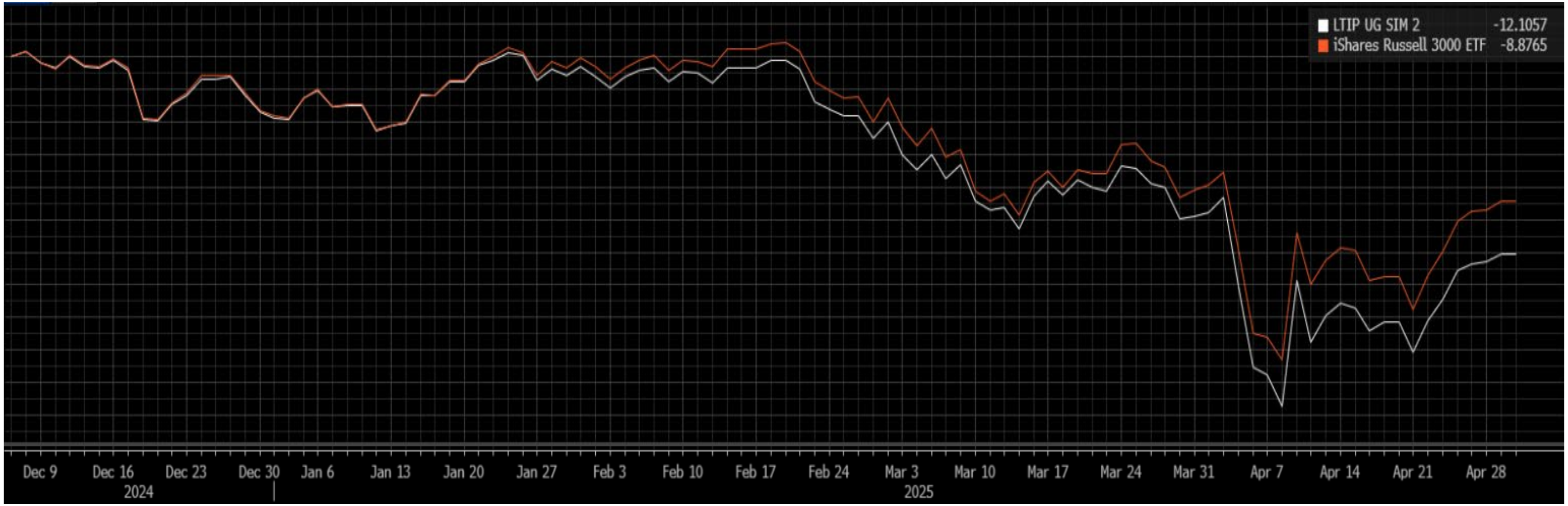


Attribution

Outperformance

-3.23 %

Port	-12.11
Bmrk	-8.88

Attribution Effects

Asset Allocation	0.26
Security Selection	-3.49

Bucket Name	Asset Allocation
Total	0.02
Equity	0.00
Communication Services	0.03
Consumer Discretionary	0.10
Consumer Staples	0.05
Energy	0.03
Financials	-0.12
Health Care	0.06
Industrials	0.01
Information Technology	0.16
Materials	0.00
Real Estate	-0.01
Utilities	-0.05

Top/Bottom Contributors by Security Selection

Neg Outper	Instrument Name	Outper	Pos Outper
	Top Contributors		
	FMC CORP	0.12	
	TEXAS PACIFIC LAND CORI	0.10	
	AKAMAI TECHNOLOGIES IN	0.07	
	MYR GROUP INC/DELAWAR	0.07	
	ARDELYX INC	0.03	
	CABLE ONE INC	0.03	
	DELTA AIR LINES INC	0.03	
	LKQ CORP	0.01	
	MAXIMUS INC	0.00	
	ISHARES RUSSELL 3000 EI	0.00	
	Bottom Contributors		
	INSPERITY INC	-0.16	
	U.S. PHYSICAL THERAPY II	-0.16	
	HUNTSMAN CORP	-0.18	
	HELMERICH & PAYNE	-0.18	
	BIOHAVEN LTD	-0.20	
	HILLENBRAND INC	-0.25	
	CHARLES RIVER LABORATO	-0.26	
	FRESHPET INC	-0.27	
	PBF ENERGY INC-CLASS A	-0.33	
	AMERESCO INC-CL A	-0.52	

Portfolio Style and Return Heatmap

Stock Style

	Value	Blend	Growth
Large	0	0	0
Mid	11	11	4
Small	43	18	14

Weight %
- 50+
- 25–49
- 10–24
- 0–9

	Value	Core	Growth
Large	–3.15	–7.03	–5.23
Mid	–4.51	–7.91	–9.15
Small	–10.82	–11.93	–10.84

3 Months

As of April 30th

Conclusion

What we learned:

- **Theoretic vs Live Portfolio Execution**
    - Backtested quantitative portfolio processes may not perform as expected in all market conditions.

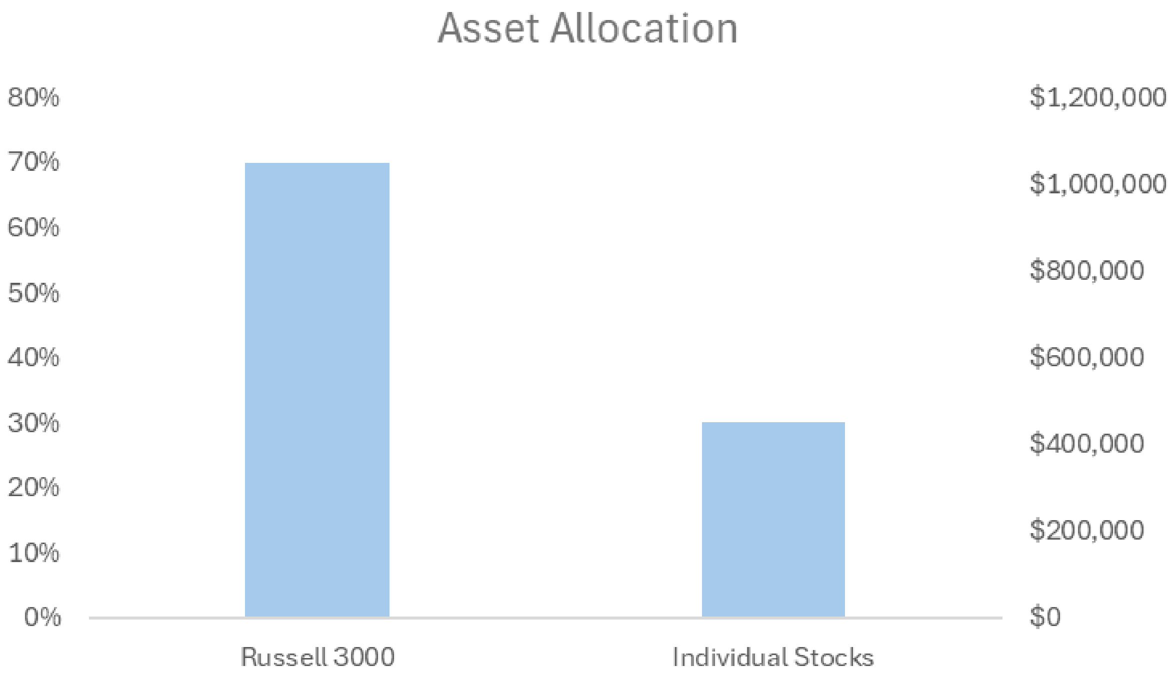
What we observed:

- Insiders purchases and sales volume may correlate with market performance.

Questions?

Appendix

Portfolio Asset Allocation



Initial Column Sorting

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```
clean_df = df[['PERSONID', 'CUSIP6','OWNER','TICKER','TRANDATE', 'TRANCODE','TPRICE', 'OWNERSHIP', 'SHARES', 'SHARESHELD', 'TPRIC
clean_df['TRANDATE'] = pd.to_datetime(clean_df['TRANDATE'])
clean_df = clean_df.loc[(clean_df['TRANCODE'] == 'P')| (clean_df['TRANCODE'] == 'S')]
clean_df
```

	PERSONID	CUSIP6	OWNER	TICKER	TRANDATE	TRANCODE	TPRICE	OWNERSHIP	SHARES	SHARESHELD	TPRICE_ADJ
2	13129904	371901	SOTOK FREDERICK A	GNTX	2014-07-28	S	29.02	D	6000.0	13500.0	14.5081
6	12220927	904311	COLTHARP DOUGLAS E	UA	2014-07-28	S	69.17	D	8400.0	NaN	69.1700
11	16138352	30063P	CONROY KEVIN T	EXAS	2014-07-25	S	15.99	D	11336.0	145563.0	15.9900
13	12063059	247361	HIRST RICHARD B	DAL	2014-07-28	S	38.32	D	132000.0	356030.0	38.3228
16	16116348	30063P	ARORA MANEESH K	EXAS	2014-07-25	S	15.99	D	9291.0	84893.0	15.9900
...	...	...	...	...	...	...	...	...	...	...	...
1341524	16290090	144200	WATSON JIMMY R.	CART	2015-07-28	P	5.50	I	270.0	21831.0	5.5000
1341526	16290125	144200	RHYNE JOHNATHAN L JR	CART	2015-10-26	P	5.67	D	200.0	130469.0	5.6700
1341527	16299206	144200	PASCHALL NANCY BORDERS	CART	2015-11-17	P	5.60	I	366.0	5617.0	5.6000
1341528	16157759	144200	OCHELTREE JERRY L	CART	2015-11-17	P	5.60	D	366.0	6490.0	5.6000
1341529	16299206	144200	PASCHALL NANCY BORDERS	CART	2015-05-06	P	5.29	D	744.0	NaN	5.2900

414223 rows × 11 columns

SEC Scraper

In [5]:
```python
def sec_scraper(cik, start=0, count=2):
    # Base URL for fetching insider transactions
    base_url = f"https://www.sec.gov/cgi-bin/browse-edgar?action=getcompany&CIK={cik}&type=4&owner=only&start={start}&count={cour

    # SEC headers (User-Agent is required)
    headers = {"User-Agent": "Antonio Nguyen antonio.nguyen203@gmail.com"}

    response = requests.get(base_url, headers=headers)
    if response.status_code != 200:
        raise Exception("Failed to fetch data from SEC EDGAR.")

    # Parse the XML response using BeautifulSoup
    soup = BeautifulSoup(response.content, "xml")
    entries = soup.find_all("entry")

    transactions = []

    # Loop through each entry to fetch transaction data
    for entry in entries[0:count]:
        base_link = 'https://www.sec.gov'
        # Fetch basic entry data
        filing_href = entry.find("link")['href']
        new_url = filing_href
        response_new = requests.get(new_url, headers=headers)
        new_soup = BeautifulSoup(response_new.content, "html.parser")
        outer_div = new_soup.find_all('div',id='formDiv')[1]
        xml_link = outer_div.find('a',href=True)['href']
        if xml_link not in lines:
            #clean xml_Link
            l = xml_link.split('/')
            cleanxml_link = f"/{l[1]}/{l[2]}/{l[3]}/{l[4]}/{l[5]}/{l[7]}"
            # Create xml transaction link
            new_link = f'https://www.sec.gov{cleanxml_link}'
            # Final response
            response_final = requests.get(new_link, headers=headers)
            final_soup = BeautifulSoup(response_final.content, "xml")
            owner_name = final_soup.find('rptOwnerName').text
            transaction_div = final_soup.find_all('nonDerivativeTransaction')
            for code in transaction_div:
                transaction_data = {}
                tc = code.find('transactionCode').text
                if (tc =='S') or (tc == 'P'):
                    transaction_data['insider'] = get_text_safe1(final_soup, 'rptOwnerName')
                    transaction_data['symbol'] = get_text_safe1(final_soup, 'issuerTradingSymbol')
                    transaction_data['company_name'] = get_text_safe1(final_soup, 'issuerName')
                    transaction_data['cik'] = get_text_safe1(final_soup, 'issuerCik')
                    transaction_data['date'] = get_text_safe2(code, 'transactionDate')
                    transaction_data['code'] = get_text_safe1(code, 'transactionCode')
```

```python
                tc = code.find('transactionCode').text
                if (tc =='S') or (tc == 'P'):
                    transaction_data['insider'] = get_text_safe1(final_soup, 'rptOwnerName')
                    transaction_data['symbol'] = get_text_safe1(final_soup, 'issuerTradingSymbol')
                    transaction_data['company_name'] = get_text_safe1(final_soup, 'issuerName')
                    transaction_data['cik'] = get_text_safe1(final_soup, 'issuerCik')
                    transaction_data['date'] = get_text_safe2(code, 'transactionDate')
                    transaction_data['code'] = get_text_safe1(code, 'transactionCode')
                    transaction_data['formtype'] = get_text_safe1(code, 'transactionFormType')
                    transaction_data['shares'] = get_text_safe2(code, 'transactionShares')
                    transaction_data['pricepershare'] = get_text_safe2(code, 'transactionPricePerShare')
                    transaction_data['sharesownedafter'] = get_text_safe2(code, 'sharesOwnedFollowingTransaction')
                    # there is also 'transactionAquiredDisposedCode' and 'directOrIndirectOwnership'
                    transactions.append(transaction_data)

            lines.append(xml_link)


    # Convert the transactions to a DataFrame
    df = pd.DataFrame(transactions)
    return df
```

In [6]:
```python
def freshinsiderdata(universe):
    insider_data = pd.DataFrame(columns=['insider', 'symbol', 'company_name', 'cik', 'date', 'code', 'formtype',
        'shares', 'pricepershare', 'sharesownedafter'])
    cik_list = stocklist_cik(universe)
    for x in cik_list:
        print(x)
        try:
            df = sec_scraper(x, start=0, count=3)
            insider_data = pd.concat([insider_data, df], ignore_index=True)
        except:
            print(f'Failed to fetch Data for: {x}')
            continue

    # Write updated list back to the file
    with open('cache.txt', 'w') as file:
        file.write('\n'.join(lines))  # Join list items with newline characters

    return insider_data
```

SEC Column Sorting

```python
hist = pd.read_csv('ptpuzdukcjydedar.csv', encoding='latin1')
clean_hist = hist[['PERSONID', 'CUSIP6','OWNER','TICKER','TRANDATE', 'TRANCODE','TPRICE', 'OWNERSHIP', 'SHARES', 'SHARESHELD', 'T
clean_hist['TRANDATE'] = pd.to_datetime(clean_hist['TRANDATE'])
clean_hist = clean_hist.loc[(clean_hist['TRANCODE'] == 'P')| (clean_hist['TRANCODE'] == 'S')]
clean_hist['month'] = clean_hist['TRANDATE'].dt.month
clean_hist['year'] = clean_hist['TRANDATE'].dt.year
clean_hist['first_name'] = [safe_process(x) for x in clean_hist['OWNER']]
clean_hist
```

	PERSONID	CUSIP6	OWNER	TICKER	TRANDATE	TRANCODE	TPRICE	OWNERSHIP	SHARES	SHARESHELD	TPRICE_ADJ	month	year	first_
2	13129904	371901	SOTOK FREDERICK A	GNTX	2014-07-28	S	29.02	D	6000.0	13500.0	14.5081	7	2014	
6	12220927	904311	COLTHARP DOUGLAS E	UA	2014-07-28	S	69.17	D	8400.0	NaN	69.1700	7	2014	c
11	16138352	30063P	CONROY KEVIN T	EXAS	2014-07-25	S	15.99	D	11336.0	145563.0	15.9900	7	2014	
13	12063059	247361	HIRST RICHARD B	DAL	2014-07-28	S	38.32	D	132000.0	356030.0	38.3228	7	2014	
16	16116348	30063P	ARORA MANEESH K	EXAS	2014-07-25	S	15.99	D	9291.0	84893.0	15.9900	7	2014	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1341524	16290090	144200	WATSON JIMMY R.	CART	2015-07-28	P	5.50	I	270.0	21831.0	5.5000	7	2015	
1341526	16290125	144200	RHYNE JOHNATHAN L JR	CART	2015-10-26	P	5.67	D	200.0	130469.0	5.6700	10	2015	
1341527	16299206	144200	PASCHALL NANCY BORDERS	CART	2015-11-17	P	5.60	I	366.0	5617.0	5.6000	11	2015	p
1341528	16157759	144200	OCHELTREE JERRY L	CART	2015-11-17	P	5.60	D	366.0	6490.0	5.6000	11	2015	oc
1341529	16299206	144200	PASCHALL NANCY BORDERS	CART	2015-05-06	P	5.29	D	744.0	NaN	5.2900	5	2015	p

414223 rows × 14 columns

Insider Horizon Categorization

Trading Strength = (Shares Bought - Shares sold)/Total trading volume of the stock

In [8]:
```python
def trading_str(insider_name):
    df = clean_df.loc[(clean_df['OWNER'] == insider_name)]
    shares_bought = df.loc[df['TRANCODE'] == 'P']['SHARES'].sum()
    shares_sold = df.loc[df['TRANCODE'] == 'S']['SHARES'].sum()
    total_trading = shares_bought + shares_sold
    trading_str = (shares_bought - shares_sold)/total_trading
    return trading_str

def avg_tradestrength(insider_name):
    df = clean_df.loc[(clean_df['OWNER'] == insider_name)]
    years = df['TRANDATE'].dt.year.unique().tolist()
    data = []
    for y in years:
        # Filter rows where the year in 'TRANDATE' matches the current year in the loop
        yearly_df = df[df['TRANDATE'].dt.year == y]
        shares_bought = yearly_df.loc[yearly_df['TRANCODE'] == 'P', 'SHARES'].sum()
        shares_sold = yearly_df.loc[yearly_df['TRANCODE'] == 'S', 'SHARES'].sum()
        total_trading = shares_bought + shares_sold
        trading_str = (shares_bought - shares_sold)/total_trading
        # Do something with shares_bought or append to data
        data.append(trading_str)

    avg = sum(data)/len(data)
    return avg
```

In [9]:
```python
def cate_strength(names, df):
    categorized_id = pd.DataFrame(columns=['Insider name','cusip','symbol','trading strength','avg_ts','historical yrs','yrs_trac
    for n in names:
        idf = df.loc[(df['OWNER'] == n)]
        idf['FDATE'] = pd.to_datetime(idf['TRANDATE'])
        insider = n
        hist_yrs = (idf['TRANDATE'].max() - idf['TRANDATE'].min()).days/365.25
        if hist_yrs >= 5:
            symbol = list(idf['TICKER'])[0]
            trading_strg = trading_str(n)
            cusip = list(idf['CUSIP6'])[0]
            avg_ts = avg_tradestrength(n)
            yrs_traded = len(idf['TRANDATE'].dt.year.unique().tolist())
            new_row = {'Insider name':insider,'cusip':cusip,'symbol': symbol, 'trading strength': trading_strg,'avg_ts':avg_ts,'h
            categorized_id.loc[len(categorized_id)] = new_row
        else:
            continue

    return categorized_id
```

Additional Functions/Tools

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In [4]:
```python
def stocklist_cik(stocks):
    new_list = []
    mapper = StockMapper()
    for ticker in stocks:
        cik = mapper.ticker_to_cik.get(ticker.upper())
        new_list.append(cik)

    return new_list

def get_text_safe1(tag, child_tag_name):
    try:
        # Attempt to find the child tag and return its text
        return tag.find(child_tag_name).text
    except (AttributeError, TypeError):
        # If tag or text not found, return "N/A"
        return "N/A"

def get_text_safe2(tag, child_tag_name):
    try:
        # Attempt to find the child tag and return its text
        return tag.find(child_tag_name).find('value').text
    except (AttributeError, TypeError):
        # If tag or text not found, return "N/A"
        return "N/A"
```

Tools Used: Jupyter Notebook, Python, Pandas df, Microsoft Excel, SEC EDGAR Database

PEAD.txt Investment Strategy – Final Presentation

Arizona State University

Prepared by the Undergraduate Student Investment Management Fund
Presented by Daniel Winkler and Nicholas Beeter

Under the designation of Dr. Sunil Wahal
| Friday May 2nd, 2025

Team Introduction

Mukul Anand

Nicholas Beeter

Vidhit Jitendra Jain

Aiden O'Connor

Kara Sierka

Evan Treger

Daniel Winkler

Brendan Weinberg - Portfolio Manager

Agenda

1. Investment Thesis Review

2. Portfolio Performance

3. Lessons Learned

Investment Thesis Review

Post-Earnings Announcement Drift (PEAD)

Earnings Announcement

Positive Earnings Surprise

Stock Price Increases

- Investors fail to price in earnings surprises immediately

PEAD.txt

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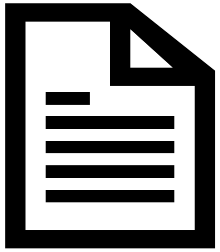
Earnings Announcement



Positive Textual Surprise

- Measures unexpected information from EC transcripts
- PEAD.txt is consistently larger than PEAD

Stock Price Increases

Academic Paper

Meursault, V., Liang, P. J., Routledge, B. R., & Scanlon, M. M. (2022). PEAD.txt: Post-earnings-announcement drift using text. *Journal of Financial and Quantitative Analysis*, *58*(6), 2299–2326. https://doi.org/10.1017/s0022109022001181

Earnings Call Transcript Processing

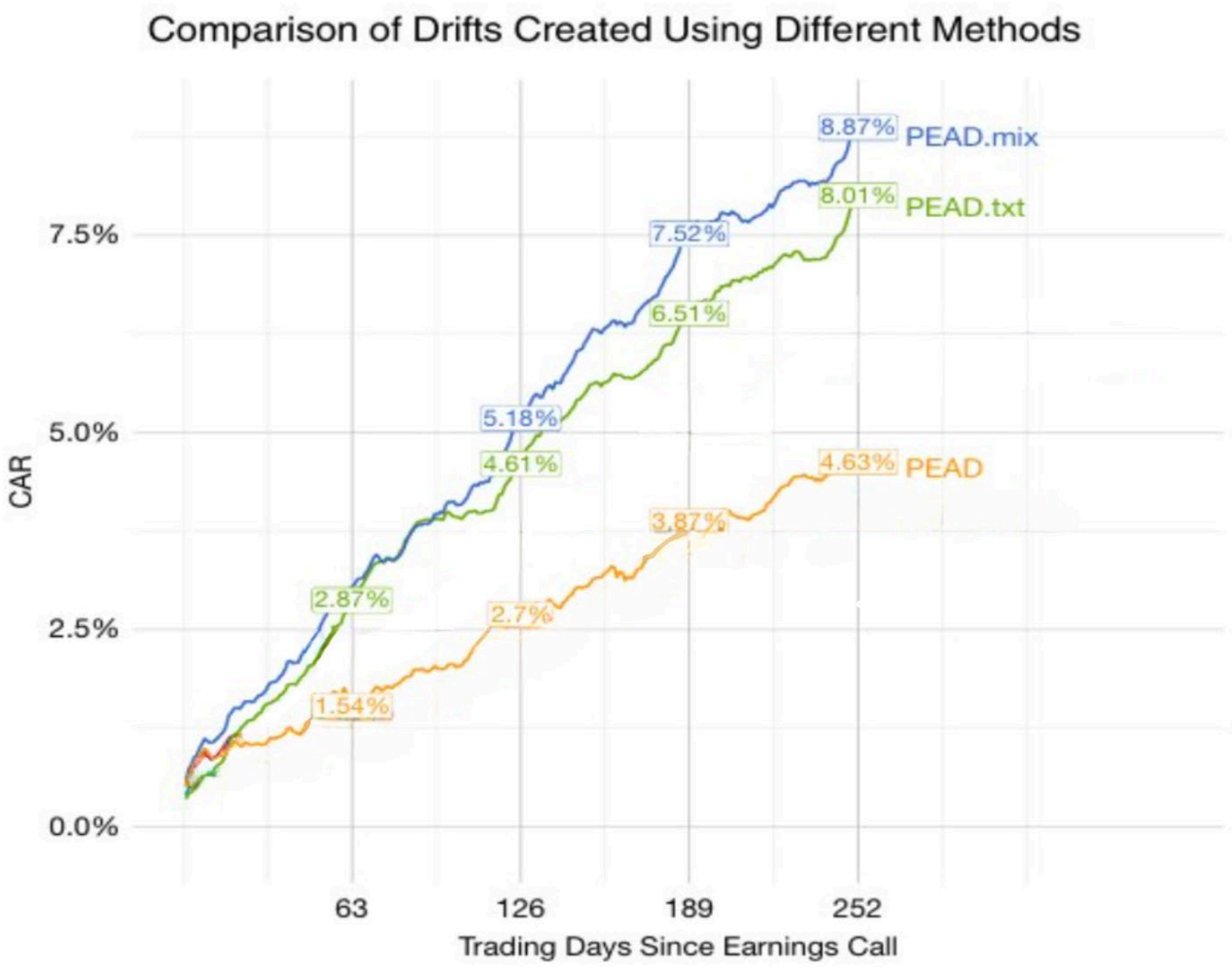
1. Input earnings call transcripts

2. Loads trained model and vectorizer

3. Analyzer performs sentiment analysis on key features

4. Model outputs PEAD.txt score and assigns a Quintile 1-5

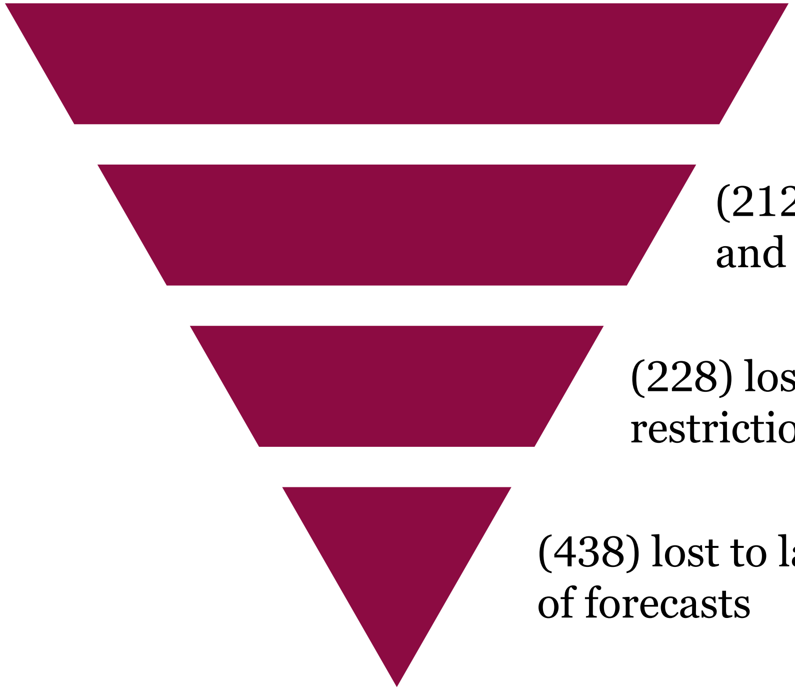
PEAD vs PEAD.txt vs PEAD.mix



Trading Process

Investable Universe

2977 active R3000 stocks at time of universe creation



(558) lost to Market Cap Restriction

(212) lost to Utilities and REITs restriction

(228) lost to Price restriction

(438) lost to lack of forecasts

1541 available R3000 securities + 56 ADRs

Gantt Chart – Seasonality of Earnings Reports

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Month	November	December	January	February	March	April	Total
Information Technology	21	27	44	161	34	93	**380**
Communication Services	4	3	9	46	1	26	**89**
Consumer Discretionary	11	6	35	121	38	92	**303**
Consumer Staples	6	3	10	48	17	35	**119**
Financials	24	19	197	111	6	261	**618**
Health Care	21	11	25	190	23	109	**379**
Energy	5	4	13	67	4	42	**135**
Industrials	12	15	77	170	20	170	**464**
Real Estate	0	2	1	8	0	6	**17**
Materials	4	7	21	41	4	49	**126**
Total Earnings Calls	**108**	**97**	**432**	**963**	**147**	**883**	**2630**

Model Output

Percent of Portfolio Value by Quintile

Q1	Q2	Q3	Q4	Q5
0%	0%	0%	1%	1.5%

Portfolio Performance and Attribution

The Impact of Tariffs

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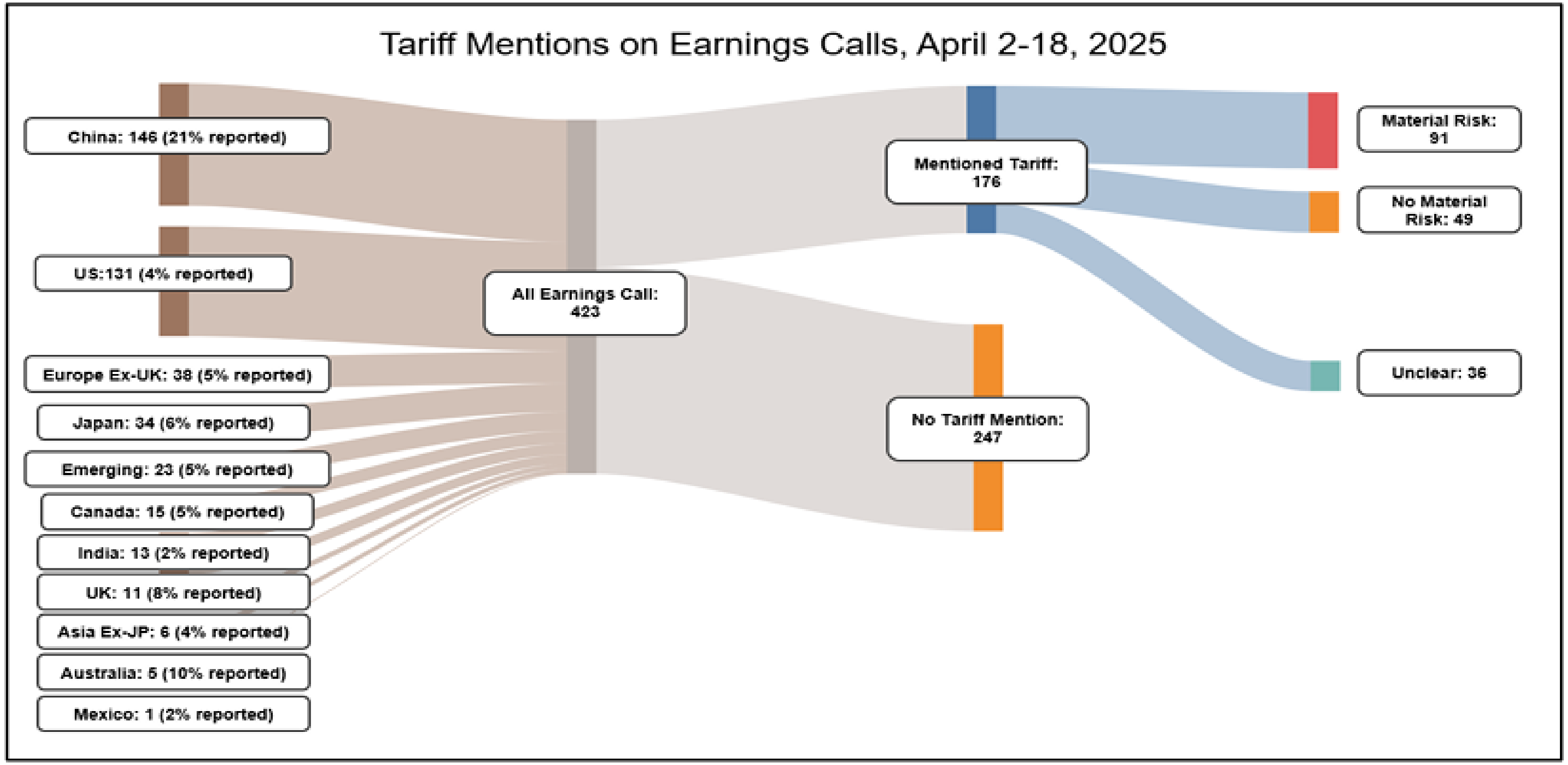
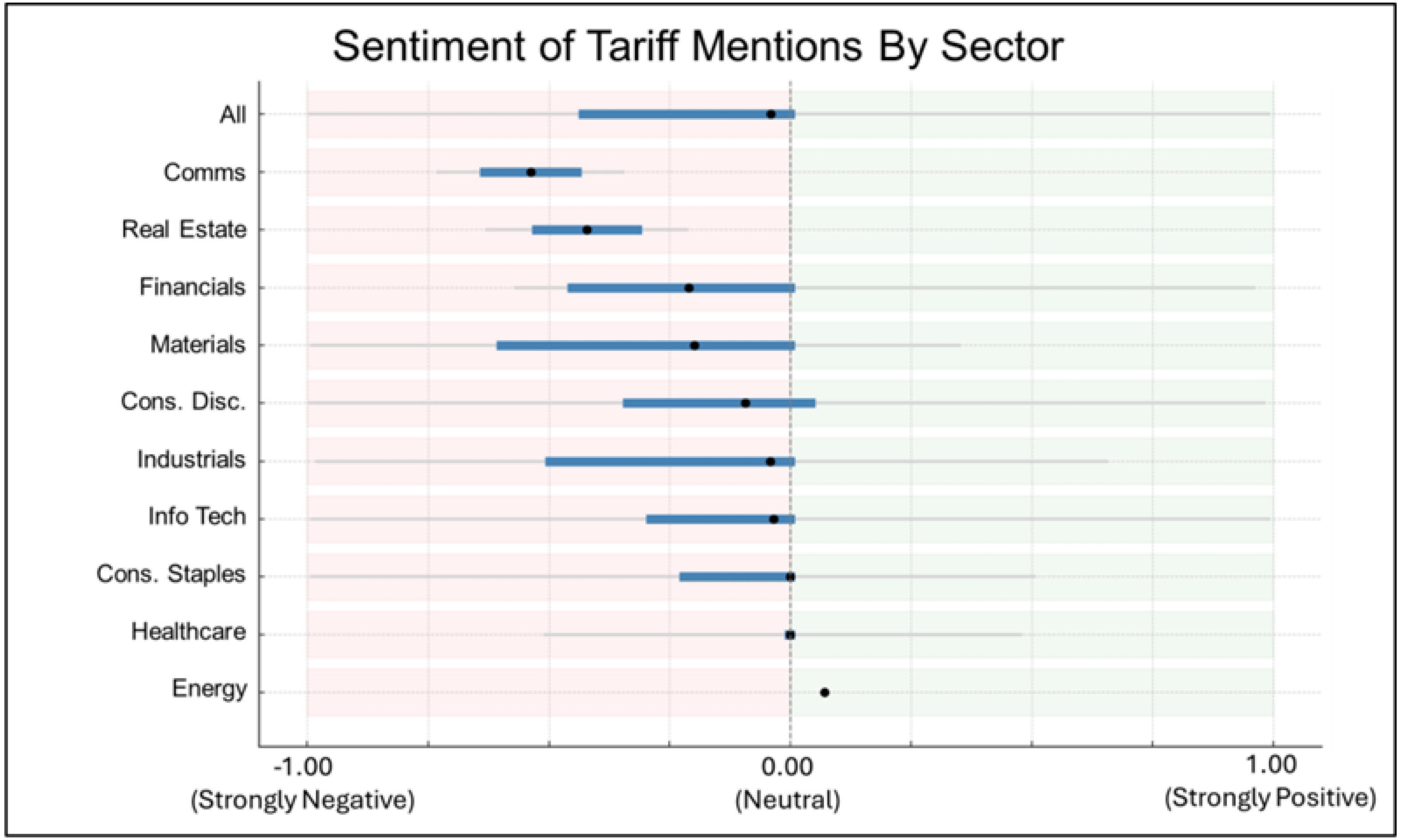


Source Figure 1: S&P Global Market Intelligence Quantitative Research & Solutions (QRS). Data as of 4/18/2025.

Contd.



Source Figure 3: S&P Global Market Intelligence Quantitative Research & Solutions (QRS). Data as of 4/18/2025.

Trading: Problems and Solutions

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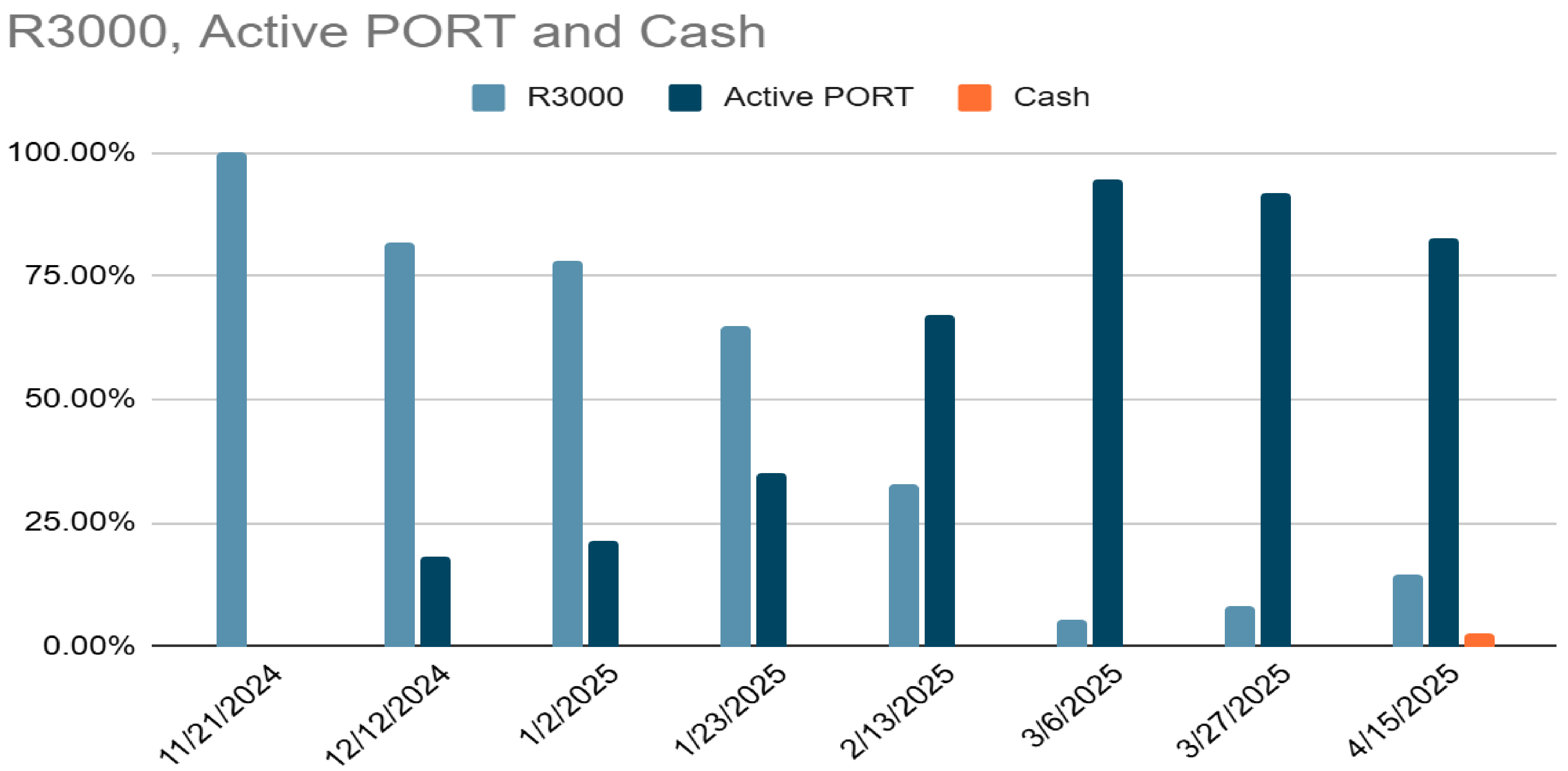
	Seasonality of Earnings Calls	Sector Constraints	Allocation Drift Towards Small-Cap Stocks
Problems:			
Solutions:	Manipulate holding lengths, sell directly into new securities	Withhold purchases in certain sector, purchase the Russell 3000 if needed	Assess valuation metrics for holdings and potential buys

Allocation


R3000, Active PORT and Cash
R3000
Active PORT
Cash
100.00%
75.00%
50.00%
25.00%
0.00%
11/21/2024
12/12/2024
1/2/2025
1/23/2025
2/13/2025
3/6/2025
3/27/2025
4/15/2025

Portfolio Valuation Styles

Arizona State University W. P. Carey School of Business

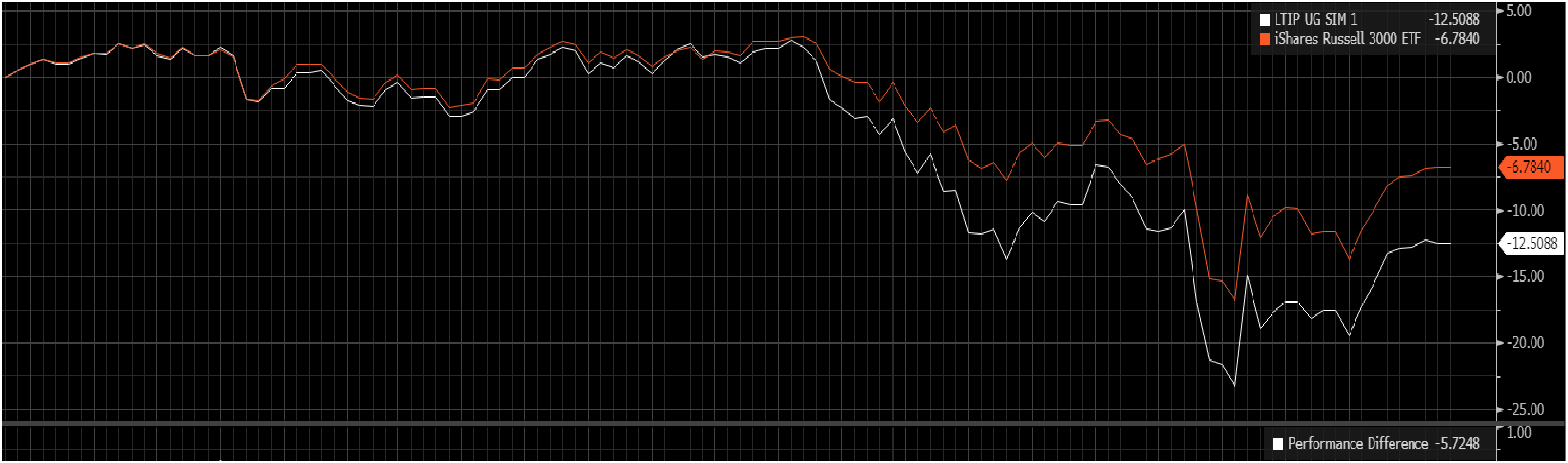
Portfolio Style Box 03/31/25

	Value	Core	Growth
Large	11%	1%	6%
Mid	4%	11%	8%
Small	17%	17%	25%

	Value	Core	Growth
Large	−2.98	−10.57	−12.10
Mid	−8.40	−11.68	−13.09
Small	−14.95	−15.60	−15.70

* Morningstar valuation style returns from the past 3 months, updated on 4/17.

Portfolio Performance



- Portfolio return compared to the benchmark (IWV) from initial seeding date on 11/21 to 5/1.

PEAD Strategy Last Year

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PEAD.txt Simulation for Last Year

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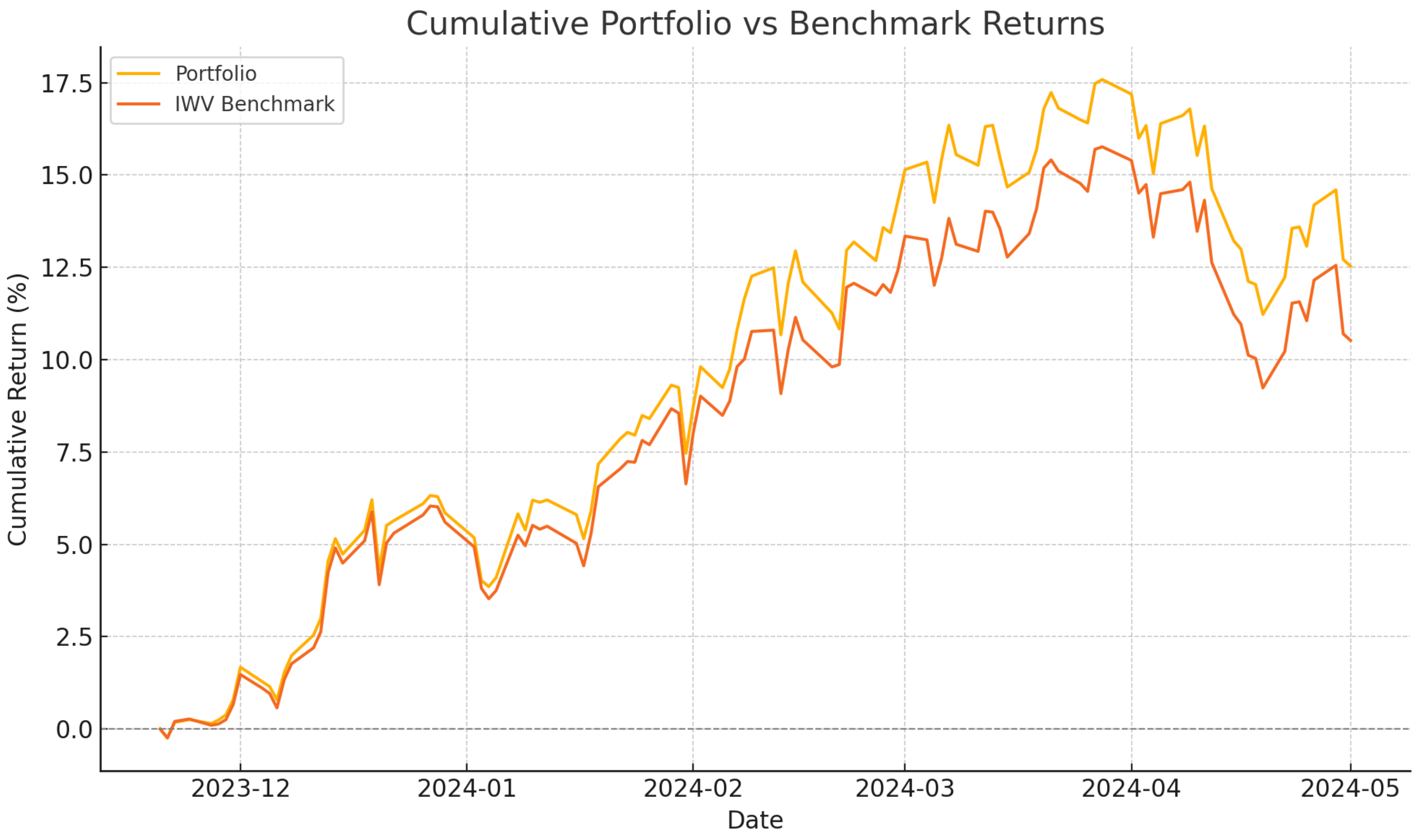
Arizona State University



Date Purchased	Ticker	Shares	Share Price	Total Value
2023-11-22	KEYS	111.00	134.56	14936.16
2023-11-22	ANF	303.00	74.03	22431.09
2023-11-27	ADSK	110.00	203.42	22376.20
2023-12-05	HQY	329.00	69.06	22720.74
2023-12-12	CASY	56.00	273.81	15333.36
2023-12-21	NKE	128.00	121.43	15543.04
2024-01-05	GBX	526.00	44.34	23322.84
2024-01-09	SNX	151.00	104.94	15845.94
2024-01-09	WDFC	66.00	237.83	15696.78
2024-01-16	GS	63.00	377.75	23798.25
2024-01-22	AGYS	194.00	82.84	16070.96
2024-01-23	PCAR	166.00	97.09	16116.94
2024-01-25	LUV	780.00	31.11	24265.80
2024-01-30	MANH	72.00	225.92	16266.24
2024-01-31	MOD	368.00	66.78	24575.04
2024-02-01	CLX	166.00	145.25	24111.50
2024-02-01	MKL	16.00	1497.43	23958.88
2024-02-05	CNA	380.00	43.32	16461.60
2024-02-06	MSGS	90.00	181.82	16363.80
2024-02-06	AZEK	621.00	39.55	24560.55
2024-02-06	F	2120.00	11.59	24570.80
2024-02-06	INSP	113.00	216.16	24426.08
2024-02-07	CNO	616.00	26.70	16447.20
2024-02-07	CFLT	1051.00	23.48	24677.48
2024-02-07	RPD	287.00	57.18	16410.66
2024-02-07	WYNN	246.00	100.06	24614.76
2024-02-08	EG	64.00	383.94	24572.16
2024-02-13	BL	416.00	60.84	25309.44
2024-02-13	MAR	101.00	248.84	25132.84
2024-02-20	JELD	1310.00	19.24	25204.40
2024-02-20	WK	268.00	93.80	25138.40
2024-02-21	CVI	484.00	34.47	16683.48
2024-02-21	DOCN	451.00	37.00	16687.00
2024-02-22	FND	228.00	109.29	24918.12
2024-02-26	TMDX	306.00	83.14	25440.84
2024-02-26	ZM	401.00	63.40	25423.40
2024-02-27	AIN	274.00	92.53	25353.22
2024-02-28	EME	92.00	277.47	25527.24
2024-02-28	NTNX	292.00	58.23	17003.16
2024-03-04	AVAV	201.00	128.73	25874.73

Portfolio Attribution

Bucket Name	Outperformance Asset Allocation	Outperformance Sec Selection	Weight (%) Port	Weight (%) Bmrk	Local Return Port	Local Return Bmrk
Total	-0.81	-4.91	100.00	100.00	-12.51	-6.79
Communication Services	-0.04	0.17	5.47	8.97	2.01	-1.36
Consumer Discretionary	-0.41	-0.16	16.07	10.95	-9.66	-9.59
Consumer Staples	-0.09	-0.16	5.31	5.47	-2.01	3.31
Energy	0.05	-0.26	2.10	3.47	-29.26	-16.17
Financials	0.27	-1.74	16.21	14.66	-11.53	-3.84
Health Care	-0.28	-0.61	9.15	10.77	-11.89	-2.82
Industrials	0.24	-0.96	11.61	9.59	-16.23	-8.65
Information Technology	0.29	-0.61	26.80	28.77	-14.57	-10.49
Materials	0.09	-0.61	2.96	2.38	-23.24	-10.36
Real Estate	-0.09	0.00	1.15	2.62	-5.83	-5.48
Utilities	-0.17	0.00	1.02	2.34	-2.18	-1.80
Not Classified	-0.66	0.02	2.15	0.02	1.83	0.00

Investment Outcomes and Events

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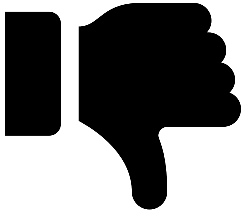
The Good

- **Cracker Barrel (CRBL) - Consumer Discretionary**
- Urban Outfitters (URBN) - Consumer Discretionary
- BJ's Wholesale (BJ) - Consumer Staples
- ANI Pharmaceuticals (ANIP) - Health Care

The Bad

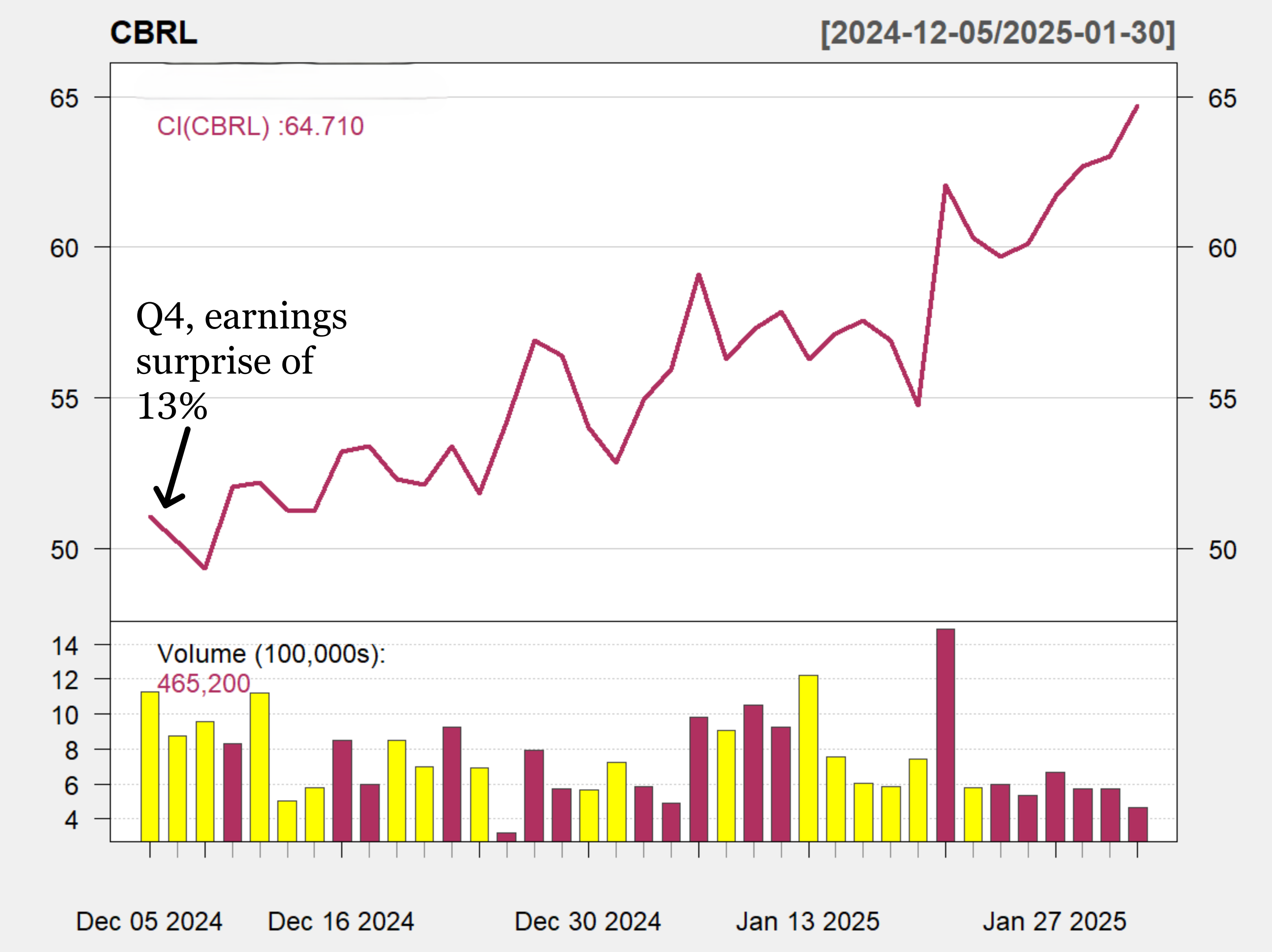


- Robinhood (HOOD) - Financials
- **V.F. Corporation (VFC) – Consumer Discretionary**
- C3 AI (AI) – Information Technology
- Atlassian Corp. (TEAM) – Information Technology

Idiosyncratic Events

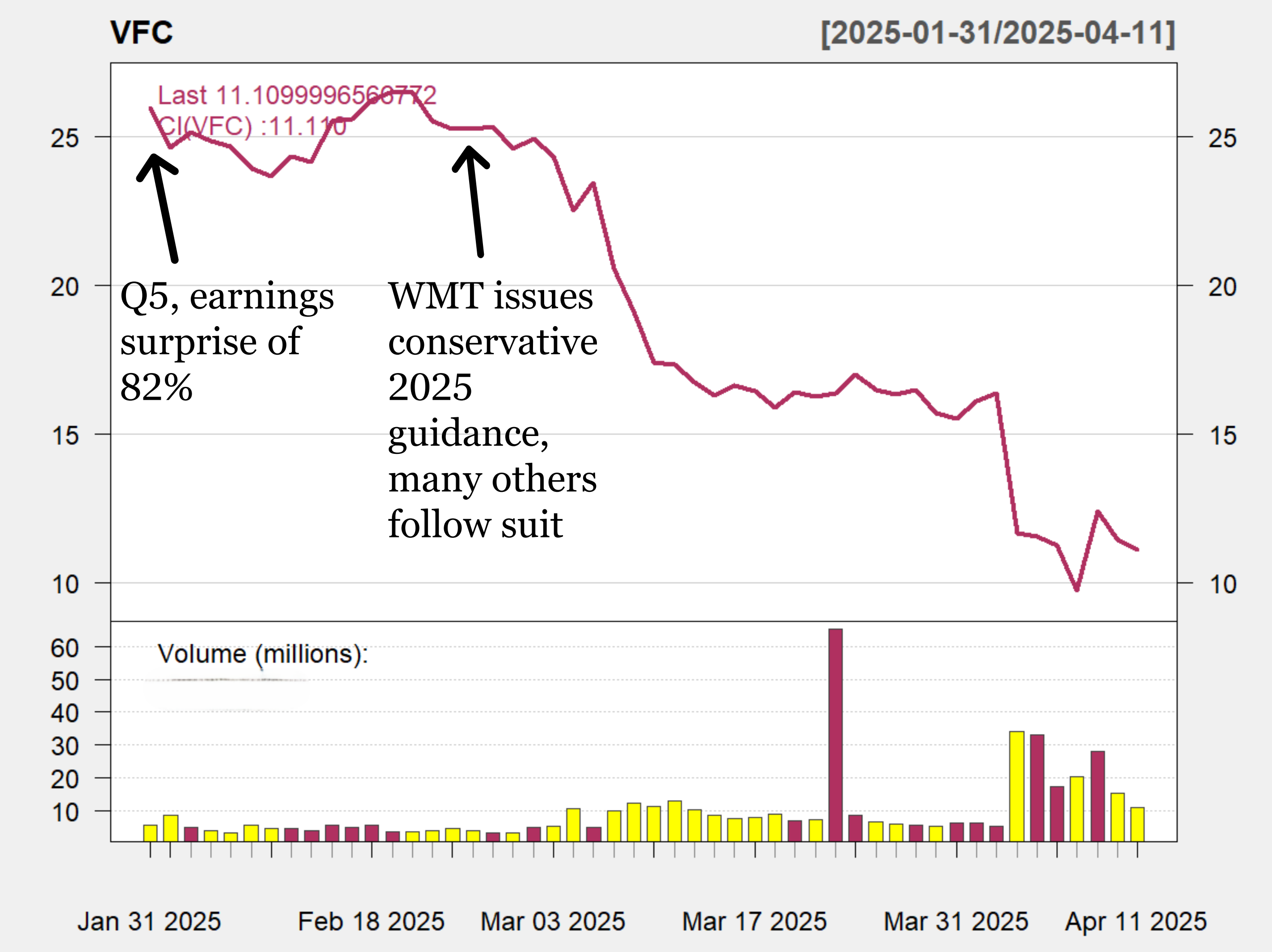
- **Carnival Corporation (CCL) - Consumer Discretionary: Negative Company News**
- The AZEK Company (AZEK) – Industrials : M&A Event

Cracker Barrel – PEAD.txt at its Finest



27% overall increase

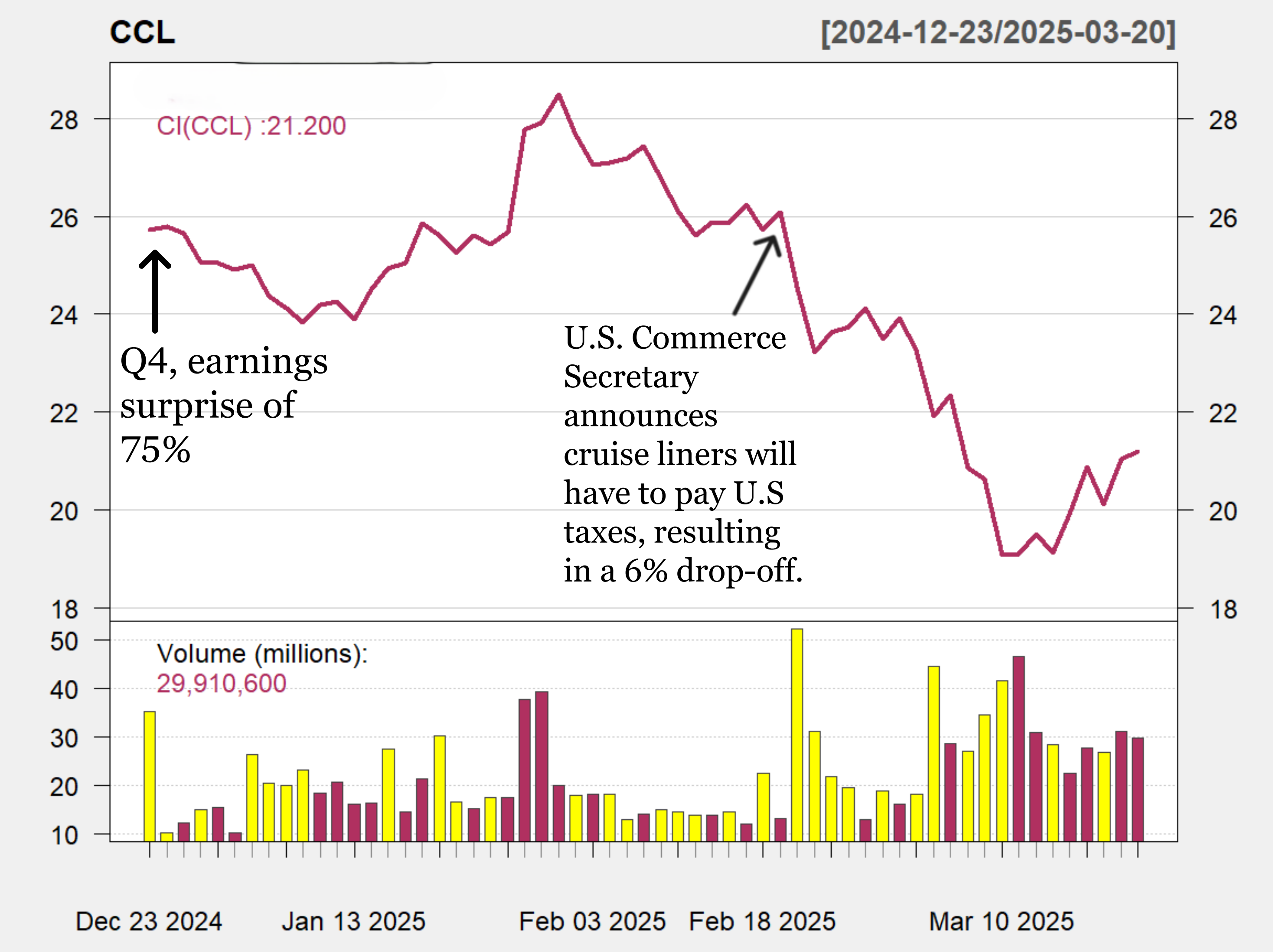
V.F. Corp (VFC) – Poor Retail Sentiment and Tariffs



58% overall decrease

Carnival Corp. (CCL) - Bad News Nullifies PEAD

In the case of firms with actively traded stock options, investors overreact to future announcements, leading to a subsequent reversal, or negative PEAD (Milian, 2015).



17% overall decrease

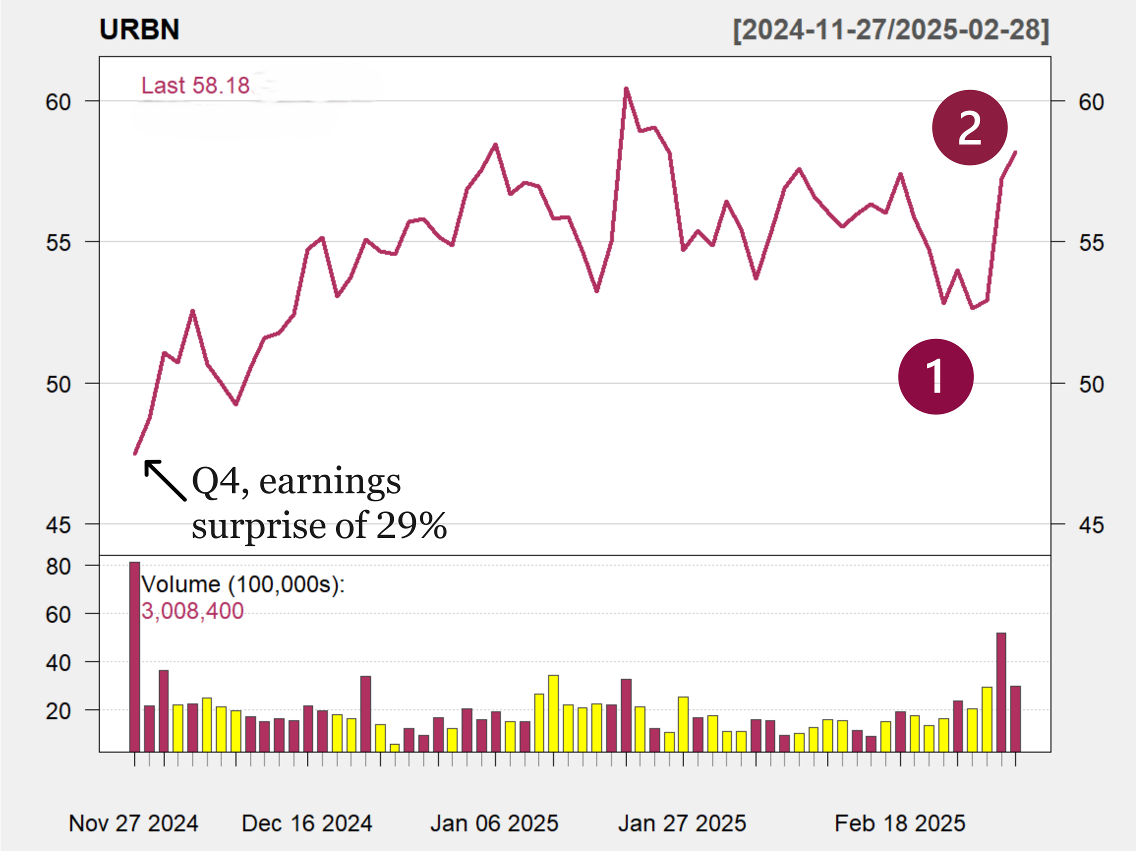
Lessons Learned

1. Sometimes investment strategies back you into a corner…

Portfolio Style Box 03/31/25

	Value	Core	Growth
Large	11% (+1)	1%	6% (+1)
Mid	4%	11% (+1)	8%
Small	17% (-2)	17%	25% (-1)

2. In portfolio management, constraints can help or hurt.



3. Understanding your limitations is crucial.

- 3/27/2025: Lululemon Athletica (LULU) announces an EPS surprise of 4.96%, and a positive revenue surprise.
- Model rates LULU's transcript a Q5, noting adjusted margin increases as well as a positive Q&A discussion regarding LULU's cost base flexibility.
- Shares tumble after-hours nearly 19% due to retail pessimism.

Takeaways For The Future

Questions?

Appendix

Model Dataset

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135 Total Stocks Included

8 Quarters of Historical Return Data and Earnings Calls

LARGE	MID	SMALL	ADR
COST	PLXS	SPFI	DAVA
JPM	ASB	NTGR	IMCR
AAPL	NMRK	MATW	TME
AMZN	PBH	CRSR	BABA

Example Output

```
2024-11-30 20:36:40,532 - INFO - Initialized analyzer with 3 classes
2024-11-30 20:36:40,552 - INFO - Number of pages in PDF: 15
2024-11-30 20:36:42,343 - INFO - Found content start marker: 'Presentation' at position 552
2024-11-30 20:36:42,346 - INFO - Found Q&A start marker: '
Q - Marie Thibault' at position 36607
2024-11-30 20:36:42,350 - INFO - Total valid paragraphs found: 7
2024-11-30 20:36:42,352 - INFO - Total valid paragraphs found: 15
2024-11-30 20:36:42,353 - INFO -
Final Statistics:
2024-11-30 20:36:42,353 - INFO - Presentation section length: 36055
2024-11-30 20:36:42,354 - INFO - Q&A section length: 17026
2024-11-30 20:36:42,354 - INFO - Number of presentation paragraphs: 7
2024-11-30 20:36:42,355 - INFO - Number of Q&A paragraphs: 15

Analysis Results:
SUE.txt Score: 2.117
Quintile: Q4
```

Output Cotd.

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Ex: Cracker Barrel (CBRL), 12/04/24

```
Analysis Results:
SUE.txt Score: 9.659
Quintile: Q5

Historical Performance for this Quintile:
Mean Abnormal Return: -0.78%
Standard Deviation: 2.14%
Sample Size: 292.0

Detailed Sentiment Analysis:

PRESENTATION Section:
Overall Sentiment Score: 0.17
Positive Phrases: 14
Negative Phrases: 2
Neutral Phrases: 46

Significant Positive Contexts:
- . Total cost of goods sold in the quarter was 30 (score: 1.00)
- . Restaurant cost of goods sold in the first quarter was 26 (score: 1.00)
- . First quarter retail cost of goods sold was 49 (score: 1.00)

Significant Negative Contexts:
- . Second, as noted earlier, we expect a headwind in Q2 related to the timing shift of gift card breakage as the $6 million EBITDA favorability we experienced in Q1 will largely be oset by unfavorability in Q2 (score: -1.00)
- . Second, as noted earlier, we expect a headwind in Q2 related to the timing shift of gift card breakage as the $6 million EBITDA favorability we experienced in Q1 will largely be oset by unfavorability in Q2 (score: -1.00)

QA Section:
Overall Sentiment Score: 0.06
Positive Phrases: 4
Negative Phrases: 2
Neutral Phrases: 27

Significant Positive Contexts:
- . We feel good about where we are right now (score: 1.00)
- . So we're feeling good about the holidays (score: 1.00)
- . And separate from that, the gross margins looked really good in the first quarter (score: 1.00)

Significant Negative Contexts:
- . So net-net, you kept your EBITDA guidance, but there's a $3 million headwind that you hadn't expected in the first quarter (score: -1.00)
- . So net-net, you kept your EBITDA guidance, but there's a $3 million headwind that you hadn't expected in the first quarter (score: -1.00)
```

Model: Problems and Solutions

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ISSUES

1 Pattern Recognition

- Features list included nonsensical words/patterns

2 Miscellaneous Errors

- Model complexity contributed to issues identifying coding errors

3 Model Runtime

- Initial versions were hardware and software intensive

SOLUTIONS

1 Implement Filters

- Filter out obstructive words and maintain pattern recognition

2 Log/Track Progress

- Model logs errors and track progress as it runs

3 Preprocessing

- Transcripts are processed and saved in a cache

Earnings Call Text Surprise and Cumulative Abnormal Returns Regression

- Note the size coefficient, which is negative.

	CAR(1,63)				
	1	2	3	4	5
SUE.txt	0.06***	0.06***	0.03**	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
SUE	0.02***	0.02***	0.01	0.01*	0.18
	(0.01)	(0.01)	(0.01)	(0.01)	(0.10)
SENT_DICT_NEG				−0.01	−0.01
				(0.01)	(0.01)
AR(0)				−0.01	−0.01
				(0.01)	(0.01)
CAR(−31,−1)				−0.05***	−0.05***
				(0.01)	(0.01)
SIZE				−0.70***	−0.70***
				(0.07)	(0.07)
TURNOVER				0.03*	0.03*
				(0.01)	(0.01)
IVOL				−0.06**	−0.06**
				(0.02)	(0.02)
COVERAGE				−0.00	−0.00
				(0.00)	(0.00)
SUE × SIZE					−0.12
					(0.09)
SUE × TURNOVER					0.01
					(0.01)
SUE × IVOL					−0.05**
					(0.02)
SUE × COVERAGE					−0.01
					(0.01)
No. of obs.	85,160	85,160	85,160	85,160	85,160
Fixed effects	None	Ind, YQ	Firm, YQ	Firm, YQ	Firm, YQ
Adj. R^2	0.00	0.02	0.05	0.08	0.08

In Table 4, we calculate earnings call text surprises (SUE.txt) using the output of a regularized logistic text regression that predicts 1-day return. We calculate CAR using the returns on the matched six size and book-to-market portfolios. The errors are clustered at the firm and year-quarter level. *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Sentiment Analysis

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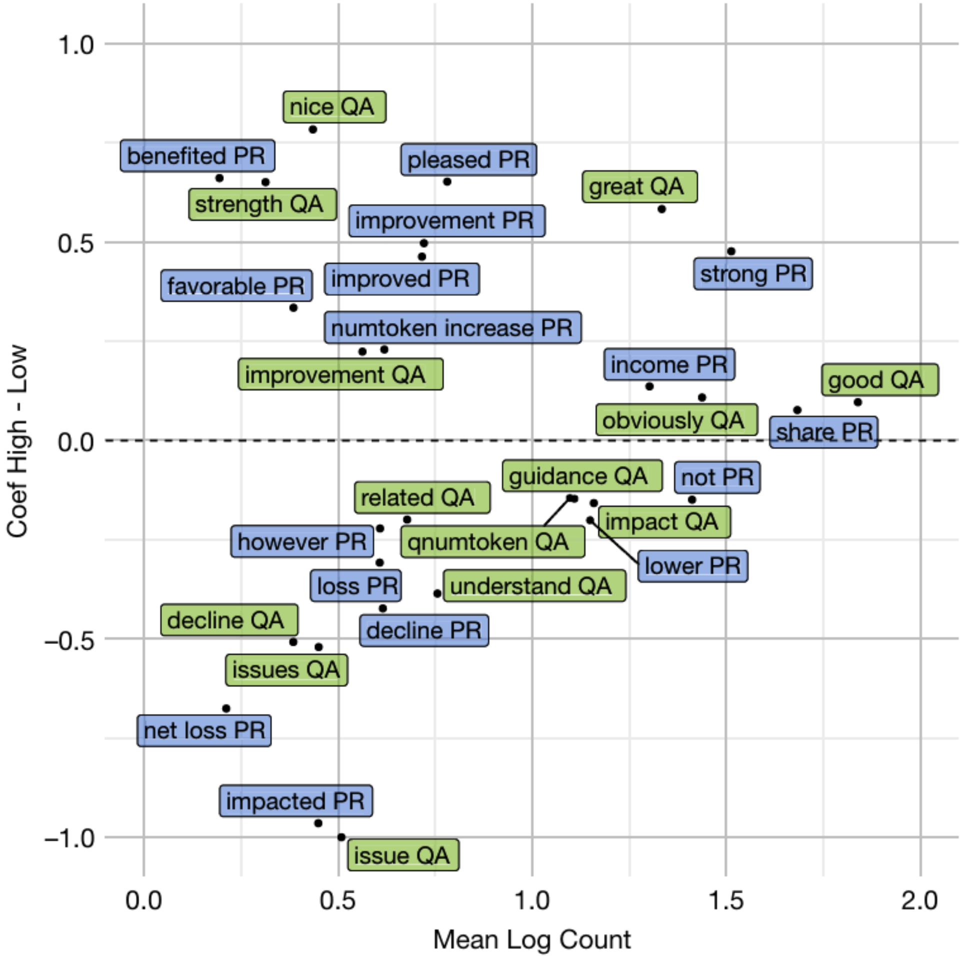
- Tokens above 0 are associated with high returns, and vice versa.



Multinomial Logistic Regression

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$$\text{for } r \in \{H, F, L\},$$

$$\text{log-odds}(r) = \log \frac{\Pr\left(R_{t=0} = r | X = x\right)}{\Pr\left(R_{t=0} \neq r | X = x\right)} = \beta_{0r} + \beta_r^T x,$$

Where:

$R_{t=0}$ is the earnings call day return split into categories
H (High): large positive abnormal returns
F (Flat): 33% of observations closest to zero
L (Low): Large negative abnormal returns

β_{0r} is the intercept

β_r^T is the vector of regression coefficients

40

Investable Universe

No Utilities

>500mm Market Cap

No REITs

# of EPS Forecasts >= 3

>$10 Share Price