Active Investment Strategy

Strategy Overview, Process

ACTIVE INVESTMENT STRATEGY

OVERVIEW AND MOTIVATION - SENTIMENT PROPAGATION STRATEGY

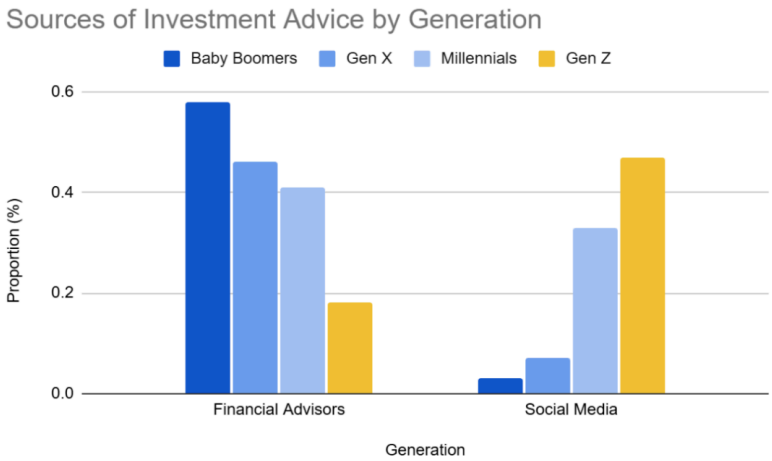
At ACE Capital, our active investment strategy integrates a rigorous framework for assessing investor sentiment derived from social media posts linked to specific assets. This approach is grounded in the belief that preliminary sentiment signals can be identified before they fully propagate across social networks. These signals, which can have non-negligible effects on asset pricing, enable us to acquire assets with early positive sentiment, positioning our active portfolio for returns that outperform benchmarks.

GROWING IMPACT OF SOCIAL MEDIA ON IRRATIONAL HERDING BEHAVIOUR

Research highlights that social media sentiment relative to an asset contributes to irrational herding behaviour in stock markets, subsequently driving asset price movements. (Li et al, 2023). Key insights include:

- Social media sentiment encourages herding behaviour among investors, often diminishing their rational decision-making.
- Sentiment disseminated through unofficial or informal accounts exerts a greater influence on market herding behaviour than sentiment emanating from official accounts, since the latter often exaggerate information to garner attention.

Additional information also suggests that social media plays an increasingly large influence in the decision making process of retail investors. A 2023 study concluded that around 47% of Gen Z investors used social media for investment advice, alongside 31% of Millennials. In contrast, just 7% of Gen X and 3% of Baby Boomers reported doing the same (Rose, 2023).



Based on these findings, ACE Capital recognizes the substantial influence of social media sentiment on trading behaviour, particularly among the growing population of retail investors. We also believe that accurately capturing sentiment from informal social media sources offers a reliable indicator of how sentiment fluctuations correlate with asset price movements.

DELAYED SENTIMENT PROPAGATION IN LESS PROMINENT POSTS

A fundamental premise of our strategy is the ability to detect sentiment in posts that have not yet been fully propagated across social media networks, leveraging the lag in propagation to anticipate future price movements.

Studies indicate that the diffusion of information across social media is not always uniform. By accurately identifying slower-diffusing posts, we aim to extract sentiment levels that have not yet been fully propagated through the network. The Gradual Information Flow (GIF) model demonstrates that the speed of information diffusion through the investing public influences how quickly stock prices change in response to new information (Hong & Stein, 2007). Studies relying on this model have drawn various conclusions about its impact within social media. For instance, research has demonstrated that finance-related tweets from users with follower counts below the median exhibited an important impact on future returns within a span of 10 to 20 days. In contrast, insights from posts made by more prominent figures diffuse rapidly, leaving fewer exploitable opportunities (Sul et al., 2016).

It is important to recognize, however, that follower count is not the sole determinant of slow-diffusing posts. Factors such as the underlying algorithms of the social media platform, which influence how and when content is shown to users across the network, often plays an even more significant role in shaping the rate of diffusion.

By identifying particular characteristics that define low-popularity social media posts, we can identify sentiment signals that remain unpriced in the market. These insights form a cornerstone of our investment strategy and will be elaborated upon in the next section.

REDDIT AS THE IDEAL PLATFORM FOR SENTIMENT ANALYSIS

Given the outlined characteristics of slower-diffusing posts, we have identified Reddit as the optimal platform for executing our sentiment analysis.

Reddit's unique structure, centered around "Subreddits", fosters community-driven discussions on specific topics, enabling us to isolate posts directly relevant to financial sentiment. For instance, filtering content from "r/Investments" ensures targeted analysis compared to broader data extraction from generic social media feeds.

Additionally, Reddit's algorithm emphasizes user engagement, measured by upvotes, downvotes, and comments, rather than amplifying content from large organizations. This organic dissemination prioritizes individual user posts, which are less prone to the influence of official entities. The platform's decentralized nature also results in slower information dissipation, creating opportunities to capitalize on delayed sentiment propagation.

Furthermore, Reddit's accessible API facilitates efficient data extraction and analysis, making it a powerful tool for assessing retail investor sentiment. These platform attributes align seamlessly with our strategy to derive alpha from early sentiment signals.

Active Investment Strategy Implementation

IMPLEMENTATION BREAKDOWN

Our active strategy consists of a systematic process executed at the start of each seven-day holding period, encompassing four key steps: data collection, sentiment analysis, stock selection, and stock trading. In the data collection phase, we scrape text-based posts from popular retail investor subreddits that mention keywords linked to S&P 500 stocks and other ETFs. Next, during sentiment analysis, we calculate compound sentiment scores (CSS) for each mentioned stock using the VADER machine learning model to measure the intensity and polarity of sentiment. The stock selection step involves ranking S&P 500 stocks based on metrics like CSS, comment activity, and upvotes, followed by a manual review to refine the list. Finally, in the stock trading process, we take long positions in the top five positively ranked stocks for the next seven days, provided they meet minimum sentiment thresholds. This structured approach allows us to leverage social media sentiment as a core component of our investment strategy.

DATA COLLECTION PROCESS

At the beginning of each seven-day holding period, we systematically collect data from posts within specific subreddits and related to a defined set of tickers. This data includes the main post content, as well as all comments made on relevant posts pertaining to the given tickers.

Subreddits	Tickers					
r/Wallstreetbets r/Investing r/Trading r/Stocks r/Stockmarket	AMD NVDA **AMC** SPY TSLA BA	SMCI AAPL PYPL DTE JPM **RDDT**	SBUX **MSTR** **GME** MSFT LLY **CAVA**	QQQ META SNAP INTC MCD	GOOGL GOOG **TSM** VOO NFLX	**PLTR** KO RTX LMT IBM

Subreddits were chosen based on a curated list of the most active communities related to stock trading, as identified by sources such as (Investopedia, 2021) and (QuantifiedTrading, 2020). We intentionally excluded channels that focused on asset classes outside of our scope, such as r/forex, as well as those dedicated to specific services or niche assets, such as r/robinhood and r/GME. This selection process ensured that the posts we analysed were relevant to the broader stock market and aligned with our trading objectives.

Tickers were selected through a preliminary analysis process, in which we assessed the frequency of mentions for each stock in the SPY and popular ETFs across the selected subreddits. From this analysis, we identified the top 5% of securities based on mention volume, resulting in a pool of 26 individual stocks. Additionally, to capture a broader spectrum of market sentiment, we included seven smaller stocks, which comprised of both “meme” stocks and international tickers, that are more prone to heightened retail investor attention. These stocks, highlighted in bold in the table above, were excluded from the trading process but were included in the analysis for the purpose of analysing sentiment trends outside of our primary investment universe. One of these stocks, TSM, was later integrated into our tradeable universe following further analysis.

For each ticker, posts were collected using regular expressions (regex) that identified instances of the ticker symbol (e.g. “AAPL”) within the title or body of the post, regardless of case. This ensured a comprehensive capture of all relevant mentions.

Given that Reddit does not have a concept of "followers" or predetermined post visibility, we did not implement any filtering based on the perceived "impact" of individual users. Each post began with equal standing, and its visibility was entirely dependent on user interaction and engagement, allowing sentiment to evolve organically without bias toward any particular user or account.

SENTIMENT ANALYSIS PROCESS

Once the relevant post and comment data is gathered during each holding period, sentiment scores are computed for each stock ticker under analysis.

VADER MODEL - FUNCTIONALITY AND RATIONALE

To assess sentiment in the collected data, we employed advanced machine learning models that allow for the efficient analysis of large datasets with minimal manual intervention. Specifically, we utilized VADER (Valence Aware Dictionary and sEntiment Reasoner), a rule-based sentiment analysis tool designed to detect sentiment in various forms of text, particularly social media posts, reviews, and informal communications. VADER relies on a pre-established lexicon of words linked to positive, negative, or neutral sentiments, along with modifiers such as intensifiers (e.g., "very", "extremely") and negations (e.g., "not"). The model also factors in the context of words by considering punctuation, capitalization, degree modifiers, and negations, thereby refining the sentiment analysis process (Medium, 2019).
For each post, the following key metrics were calculated:

Relevant Metric	Calculation	Significance
Post_sentiment (pi)	Aggregate sentiment scores from the post’s title and content, using the VADER model.	Represents the overall sentiment reflected in the post (or comment) related to a specific ticker, ranging from -1.0 (negative) to 1.0 (positive), with 0.0 being neutral.
comment_sentiment (ci)	Average sentiment score across all comments on the post, calculated using the VADER model.	Reflects the collective sentiment of user comments related to the post, offering a broader perspective on the sentiment surrounding the ticker.
delta (δi)	The difference (in days) between the creation date of a post, and the median date of its comments.	Used as a measure of propagation speed for each individual post, scored as a real number above or equal to 0. Since we only retrieved posts from a window of 24 hours prior to the holding period date, these values were all between 0 and 1. If a delta value is higher, more comments were written further in the future relative to a post’s creation date, indicating a more spread out “diffusion” of the post’s information.

SENTIMENT SCORE COMPUTATION

To compute the average compound sentiment score for each ticker, we developed a formula based on the metrics derived by our program. This formula was designed to capture key insights from our prior research on the dynamics of social media posts. The formula for calculating the sentiment score of each ticker is as follows:

$$x_T = \frac{1}{n_T \cdot \bar{\delta}} \cdot \left(\sum_{i=1}^{n_T} ((1+\delta_i) \cdot (0.8 \cdot s(p_i) + 0.2 \cdot s(c_i))) \right)$$

In this formula, x_T represents the compound sentiment score for ticker T during a given holding period, while n_T denotes the total number of posts related to that ticker. The remaining variables correspond to the definitions provided in the table above for each individual post associated with ticker T. The cumulative score for each ticker is intended to yield a global sentiment indicator for the future, where posts with slower diffusion—indicated by a higher delta—are given greater weight. This approach reflects the assumption that posts with slower diffusion have a greater potential to influence sentiment over time. Moreover, because the sentiment expressed in the post's content is considered the primary indicator of the poster's stance on the ticker, it is weighted more heavily than the sentiment of the comments associated with the post.

STOCK SELECTION

After calculating sentiment scores, we assess whether any of the compound sentiment scores for each ticker exceed our predefined threshold of 0.6. Only those securities—excluding the "meme" stocks analyzed in our program with sentiment scores above this threshold—are selected for purchase during the current week.

SENTIMENT THRESHOLD DETERMINATION

Before implementing the active strategy, extensive backtesting was conducted to identify the compound sentiment score at which we observed a measurable correlation with future positive performance. Essentially, the compound sentiment score for each ticker reflects future sentiment, amplified by posts that have not yet fully propagated through the network. This score serves as a predictive indicator of future sentiment trends.

The backtesting process involved calculating compound sentiment scores based on historical data for our selected tickers, followed by an analysis of future performance relative to these precomputed scores. Based on this analysis, we determined that a score of 0.6 or higher was a reliable threshold for indicating a strong likelihood of positive sentiment propagation, which we believed would contribute to future returns. This threshold also allowed us to predict that, on average, 1-2 securities from our investment universe would meet the criteria for selection in each holding period, a number that partially informed our decisions regarding the size of our purchases.

STOCK TRADING

At the beginning of each holding period, we took 7-day long positions in tickers that had compound sentiment scores exceeding our threshold of 0.6. Some securities were held for more than one consecutive period if their sentiment score remained above the threshold in the subsequent holding period.

The decision to use a 7-day holding period was based on several factors. Primarily, this duration was derived from backtesting, as detailed earlier in the strategy, where we tested trade durations of 3, 7, 10, and 20 days. The 7-day period was determined to be optimal for maximizing returns. This timeline was also supported by prior research, which indicated that Twitter posts made by users with low followers typically fully propagated within 10 to 20 days through the network. We aimed to strike a balance between capturing the effects of sentiment propagation on a security and avoiding excessively long holding periods. A 7-day duration allowed us to capture the relevant sentiment while mitigating potential transaction fees from more frequent trades.

Trade sizes were initially set in the range of $10,000 to $15,000 per valid ticker each trading period. This range was chosen to accommodate multiple trades, such as in instances where 4 or 5 tickers were identified with high sentiment in a given period. However, as the strategy was executed, we found that typically only 1 or 2 tickers met the high sentiment criteria, leading us to increase the trade size for each individual ticker.

Active Holdings

Securities Held, Holdings Rationale

ACTIVE HOLDINGS AND PERFORMANCE

Securities that met the sentiment thresholds described earlier were purchased and held for one-week intervals. Throughout our trading period, which spanned from mid-May to mid-October 2024, we executed trades in a total of seven distinct assets, completing ten separate transactions. A portion of the portfolio was consistently allocated to the benchmark ETF, BUZZ, while the remaining balance was divided between cash reserves and actively traded securities.

OVERALL ALLOCATION PROPERTIES AND JUSTIFICATION

Approximately two-thirds of our portfolio was held in cash (USD) to ensure sufficient liquidity for executing trades, even in scenarios where four or five tickers exceeded the sentiment threshold in a given week. The remaining balance, roughly $50,000 USD, was allocated to BUZZ, our benchmark ETF. This allocation was initially intended as a stable benchmark investment but was gradually reduced in favor of increased liquidity as we scaled up the amounts allocated to active trades over the investment period.

ACTIVE HOLDINGS

The table below summarizes the trades we executed over the course of our trading period.

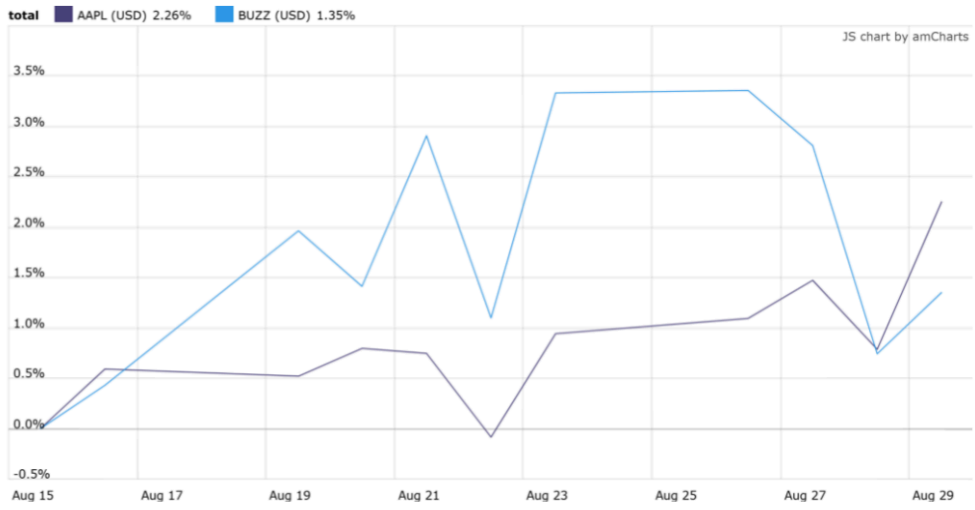
DATE	TICKER	BUY/SELL	BUY/SELL PRICE	GAIN/LOSS*	FEES	SENTIMENT SCORE
2024-05-14	BUZZ	B	-$50 340.51	$0.00	-$74.25	-
2024-05-23	TSM	B	-$10 847.72	$0.00	-$50.00	0.72265
2024-05-30	SMCI	B	-$ 12 685.54	$0.00	-$50.00	-
2024-05-30	TSM	S	$10 487.72	-$360.06	-$50.30	-
2024-06-14	SMCI	S	$12 653.59	-$31.95	-$50.36	-
2024-07-18	MSFT	B	-$15 593.50	$0.00	-$50.00	0.8375
2024-07-18	TSLA	B	-$12 604.50	$0.00	-$50.00	0.61
2024-07-29	MSFT	S	$14 945.33	-$648.17	-$50.42	-
2024-07-29	TSLA	S	$11 261.68	-$1342.82	-$50.32	-
2024-08-15	AAPL	B	-$12 428.30	$0.00	-$50.00	0.78955

2024-08-30	MSFT	B	-$16 654.40	$0.00	-$50.00	0.6696
2024-08-30	AAPL	S	$12 555.09	$126.79	-$50.36	-
2024-09-13	MCD	B	-$14 830.00	$0.00	-$50.00	0.7313
2024-09-13	MSFT	S	$17 153.12	$498.72	-$50.48	-
2024-09-23	MCD	S	$14 899.58	$69.58	-$50.42	-
2024-10-07	META	B	-$14 824.75	$0.00	-$50.00	0.71145
2024-10-07	MSFT	B	-$16 740.24	$0.00	-$50.00	0.76775
2024-10-17	META	S	$14 368.59	-$456.16	-$50.41	-
2024-10-17	MSFT	S	$16 593.93	-$146.31	-$50.47	-

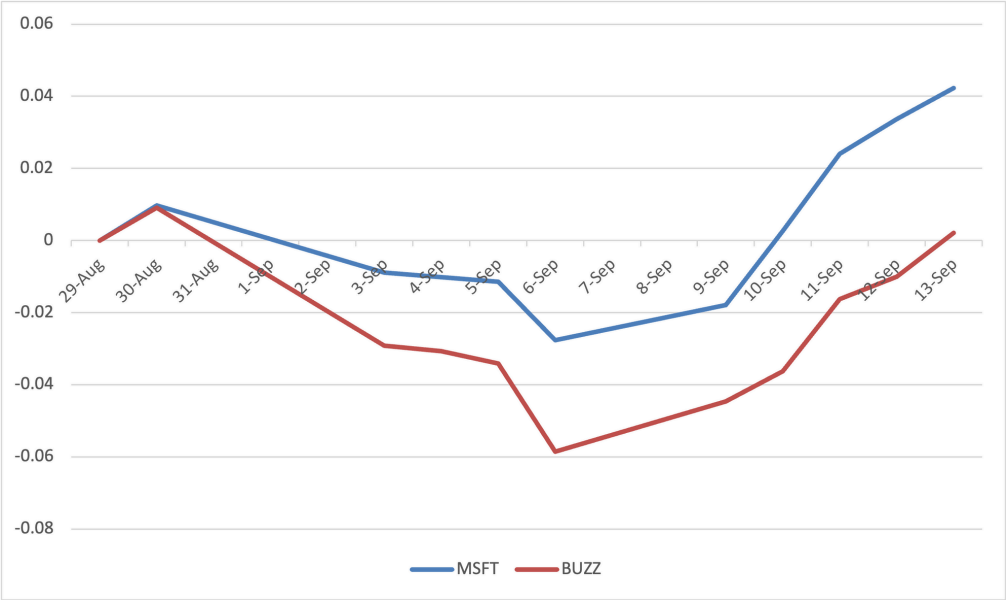
INDIVIDUAL PERFORMANCE - BEST PERFORMERS

The graphs below plot the performance of the underlying benchmark against the asset for the period in which it was held. This demonstrates the efficiency of our algorithm in identifying preliminary sentiment as opposed to other approaches.

AAPL - 08/15/24 - 08/30/24



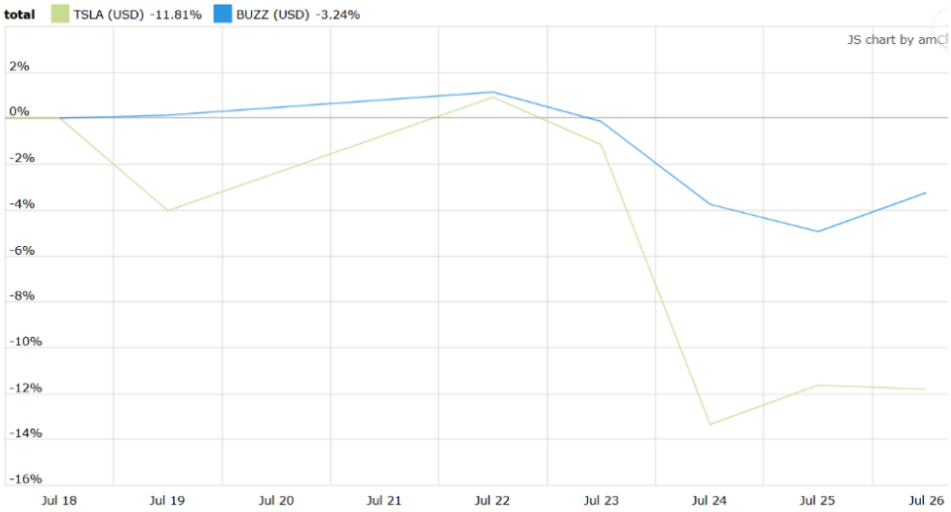
MSFT - 08/29/24 - 09/13/24



INDIVIDUAL PERFORMANCE - WORST PERFORMER

Below, we illustrate the performance comparison of our worst trade against the benchmark for its holding period.

TSLA - 07/18/24 - 07/27/24



Appendix

Additional Materials & Analysis

PASSIVE STRATEGY WORKS CITED

Statcan 1: https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410006001&pickMembers%5B0%5D=4.2&cubeTimeFrame.startYear=2013&cubeTimeFrame.endYear=2023&referencePeriods=20130101%2C20230101

Statcan 2:
https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410006001&pickMembers%5B0%5D=4.3&cubeTimeFrame.startYear=2013&cubeTimeFrame.endYear=2023&referencePeriods=20130101%2C20230101

Forbes 1:
https://www.forbes.com/advisor/investing/investing-time-horizon/

Canada 1:
https://www.canada.ca/en/financial-consumer-agency/services/mortgages/mortgage-terms-amortization.html

Numbeo 1:
https://www.numbeo.com/cost-of-living/in/Montreal#:~:text=Summary%20of%20cost%20of%20living,1%2C360.2C%24

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https://www03.cmhc-schl.gc.ca/hmip-pimh/en/TableMapChart/TableMatchingCriteria?GeographyType=MetropolitanMajorArea&GeographyId=1060&CategoryLevel1=Population%2C%20Households%20and%20Housing%20Stock&CategoryLevel2=Household%20Income&ColumnField=HouseholdIncomeRange&RowField=Neighbourhood&SearchTags%5B0%5D.Key=Households&SearchTags%5B0%5D.Value=Number&SearchTags%5B1%5D.Key=Statistics&SearchTags%5B1%5D.Value=AverageAndMedian

ITools 1:
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Retraite Quebec 1:
https://www.retraitequebec.gouv.qc.ca/fr/salle_presse/2023/Pages/20231121.aspx

CIC news 1:
https://www.cicnews.com/2023/12/comparing-international-and-domestic-student-fees-in-canada-1240494.html#gs.5ivsor

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https://www.studycanada.ca/english/accommodation.htm#:~:text=Residence%2FDormitory&text=In%20some%20cases%2C%20there%20are,7%2C500%20CDN%20per%20school%20year.

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Taxtips 1:
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Invesco 1:
https://www.invesco.com/qqq-etf/en/performance.html#:~:text=Invesco%20QQQ%20Market%20Price%3A%20YTD,%25%3B%20Since%20Inception%3A%209.44%25.

Fraser 1:
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Ecolesprivees 1:
https://ecolespriveesquebec.ca/en/private-school/faq/

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BlackRock XST:
https://www.blackrock.com/ca/investors/en/products/239838/ishares-sptsx-capped-consumer-staples-index-etf

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https://www.bmogam.com/ca-en/products/exchange-traded-fund/bmo-clean-energy-index-etf-zcln/

BlackRock ICLN:
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Growth of Renewable Energy Sector:
https://www.mckinsey.com/industries/oil-and-gas/our-insights/global-energy-perspective-2023-energy-value-pools-outlook

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2025 OUTLOOK WORKS CITED

Vanguard U.S. Consumer Staples ETF (VDC):
https://investor.vanguard.com/investment-products/etfs/profile/vdc

BlackRock's iShares ESG ETF 1 (XSCR):
https://www.blackrock.com/ca/investors/en/products/313580/ishares-esg-advanced-msci-canada-index-etf

BlackRock's iShares ESG ETF 2 (XUSR):
https://www.blackrock.com/ca/investors/en/products/313743/ishares-esg-advanced-msci-usa-index-etf

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BERT Model:
Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. (Devlin et al, 2019) arXiv preprint arXiv:1810.04805 [cs.CL]. https://arxiv.org/ abs/1810.04805.

SPDR S&P 500 ETF (SPY):
https://www.ssga.com/us/en/intermediary/etfs/spdr-sp-500-etf-trust-spy

PASSIVE STRATEGY PORTFOLIO

APPENDIX A - KEY METRICS DERIVED FROM HISTORICAL DATA

	AVERAGE RET		VOLATILITY	
	Mon.	Ann.	Mon.	Ann
XWD	0.78%	9.81%	4.40%	15.25%
ZCLN-F	-0.18%	-2.10%	6.98%	24.20%
XST	0.85%	10.67%	3.27%	11.31%

APPENDIX B - KEY METRICS DERIVED FROM THE CAPM

CAPM INPUTS (Yahoo Finance)				
	Beta	CAPM mu	Sigma (Ann.)	Weight
XWD	1.05	11.02%	16.25%	0.40
ZCLN	1.02	10.79%	15.60%	0.70
XST	0.57	7.31%	17.31%	0.40
rf	2.91%			
MKT - rf	7.72%			

APPENDIX C - OPTIMAL PORTFOLIO KEY METRICS

Asset	XST (Consumer Staples)	XWD (World Market)	ZCLN (Clean Energy)	Risk-Free Assets	Optimal Portfolio
Expected Return	9.33%	10.29%	6.92%	2.91%	8.27%
Volatility	13.71%	15.65%	19.90%	~0%	10.5%
ESG ranking (MSCI)	7.25	6.97	7.10	-	7.12
Weighting	40.39%	32.15%	9.89%	17.57%	100%

APPENDIX D - SIMULATION VARIABLES

Variable	Value
Retirement Age (Christophe, Coralie)	69 yrs, 65 yrs
TruckAI (E(R), Stdev)	18.0%, 40.0%
Death Age (Christophe, Coralie)	85 yrs, 90 yrs
Num. of Sick Leave Periods (Coralie)	2
Living Expenses (With Children, Without Children, Retirement)	$120K, $100K, $200K
Child Postsec. Education Duration	3 yrs
Inflation Rate	3.0%
Children's Education Costs (High School, University)	$3 500, $18 100
Average Mortgage Rate	6.0%
Portfolio (E(R), Stdev)	8.27%, 10.5%

APPENDIX E - SIMULATION RESULTS

Significant Variable	Best-Case	Worst-Case
Retirement Age (CH, CO)	69 yrs, 65 yrs	65 yrs, 63 yrs
TruckAI (E(R), Stdev)	20.0%, 35.0%	12.0%, 50.0%
Death Age (CH, CO)	83 yrs, 87 yrs	87 yrs, 92 yrs
Num. of Sick Leave Periods (CO)	1	5
Living Expenses (With Children, Without Children, Retirement)	$100K, $80K, $180K	$140K, $120K, $225K
Child Postsec. Education Duration	3	5
Inflation Rate	2.8%	3.3%
Final Endowment Amount (PV)	$20M	$2.5M
Mean IRR	5.56%	5.98%
Median IRR	6.25%	6.81%
IRR Standard Deviation	3.46%	1.91%

DCM EXTERNAL ALLOCATION STRATEGY

APPENDIX F - FAMA-FRENCH 5-FACTOR MODEL REGRESSION OUTPUTS:

GE:

```
Call:
lm(formula = log_returns ~ Mkt.RF + SMB + HML + RMW + CMA, data = data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.38670 -0.00582  0.00094  0.00713  0.03826 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.0006671  0.0006630  -1.006  0.31467    
Mkt.RF       0.6231636  0.0309908  20.108  < 2e-16 ***
SMB          0.1245732  0.0555050   2.244  0.02511 *  
HML          0.2986067  0.0522395   5.716 1.58e-08 ***
RMW          0.0155946  0.0724941   0.215  0.82974    
CMA         -0.3600168  0.0935777  -3.847  0.00013 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01789 on 737 degrees of freedom
Multiple R-squared:  0.4515,	Adjusted R-squared:  0.4478 
F-statistic: 121.3 on 5 and 737 DF,  p-value: < 2.2e-16
```

FI

```
Call:
lm(formula = log_returns ~ Mkt.RF + SMB + HML + RMW + CMA, data = data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.032189 -0.003652 -0.000045  0.003733  0.036450 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.0003199  0.0002524   1.268 0.205314    
Mkt.RF      -0.0563244  0.0116254  -4.845 1.55e-06 ***
SMB          0.0196005  0.0210678   0.930 0.352496    
HML         -0.1225013  0.0196382  -6.238 7.49e-10 ***
RMW          0.0963801  0.0274730   3.508 0.000479 ***
CMA         -0.0168856  0.0352494  -0.479 0.632058    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.006787 on 733 degrees of freedom
Multiple R-squared:  0.134,	Adjusted R-squared:  0.1281 
F-statistic: 22.69 on 5 and 733 DF,  p-value: < 2.2e-16
```

A2:

```
Call:
lm(formula = log_returns ~ Mkt.RF + SMB + HML + RMW + CMA, data = data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.034647 -0.005903 -0.000097  0.006292  0.035672 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.0010037  0.0005596  -1.794  0.07367 .  
Mkt.RF       0.6691487  0.0235098  28.463  < 2e-16 ***
SMB          0.1301647  0.0431374   3.017  0.00272 ** 
HML         -0.0087603  0.0380240  -0.230  0.81792    
RMW         -0.1521153  0.0526560  -2.889  0.00409 ** 
CMA         -0.0419877  0.0656650  -0.639  0.52294    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01076 on 373 degrees of freedom
Multiple R-squared:  0.7399,	Adjusted R-squared:  0.7364 
F-statistic: 212.2 on 5 and 373 DF,  p-value: < 2.2e-16
```

SRI:

```
Call:
lm(formula = log_returns ~ Mkt.RF + SMB + HML + RMW + CMA, data = data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.029988 -0.006765  0.000140  0.006618  0.032426 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.001119   0.000614  -1.822 0.069462 .  
Mkt.RF       0.750308   0.024105  31.126  < 2e-16 ***
SMB          0.133395   0.045820   2.911 0.003871 ** 
HML         -0.154250   0.039425  -3.913 0.000113 ***
RMW         -0.053900   0.054699  -0.985 0.325237    
CMA         -0.141755   0.069165  -2.050 0.041285 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01059 on 298 degrees of freedom
Multiple R-squared:  0.8165,	Adjusted R-squared:  0.8135 
F-statistic: 265.3 on 5 and 298 DF,  p-value: < 2.2e-16
```

APPENDIX G - ALPHA AND INFORMATION RATIOS BASED ON BENCHMARKS

The information ratios were derived by comparing each fund's performance YTD with data gathered from the Yahoo Finance API regarding each fund's respective benchmark (tickers below):

- Global Equities Fund: ^GSPTSE and ^GSPC
- Fixed Income Fund: BMOAX, XBB and IGOV
- Alpha Squared Fund: ^GSPTSE and ^GSPC
- SRI Fund: SPYX and TXFFN:TOR

```
GE DATA:
Weekly alpha: -0.0009
Weekly IR: -0.1440
Annualized Alpha (YTD): -0.0491
Information Ratio (YTD): -1.0385
```

```
FI DATA:
Weekly alpha: 0.0001
Weekly IR: 0.0168
Annualized Alpha (YTD): 0.0012
Information Ratio (YTD): 0.1209
```

```
A2 DATA:
Weekly alpha: -0.0027
Weekly IR: -0.3233
Annualized Alpha (YTD): -0.1310
Information Ratio (YTD): -2.3314
```

```
SRI DATA:
Weekly alpha: -0.0020
Weekly IR: -0.2082
Annualized Alpha (YTD): -0.1016
Information Ratio (YTD): -1.5010
```

ACTIVE STRATEGY - TRADE LOG

DATE	TICKER	BUY/SELL	BUY/SELL PRICE	GAIN/LOSS*	FEES	SENTIMENT SCORE
2024-05-14	BUZZ	B	-$50 340.51	$0.00	-$74.25	-
2024-05-23	TSM	B	-$10 847.72	$0.00	-$50.00	0.72265
2024-05-30	SMCI	B	-$ 12 685.54	$0.00	-$50.00	-
2024-05-30	TSM	S	$10 487.72	-$360.06	-$50.30	-
2024-06-14	SMCI	S	$12 653.59	-$31.95	-$50.36	-
2024-07-18	MSFT	B	-$15 593.50	$0.00	-$50.00	0.8375
2024-07-18	TSLA	B	-$12 604.50	$0.00	-$50.00	0.61
2024-07-29	MSFT	S	$14 945.33	-$648.17	-$50.42	-
2024-07-29	TSLA	S	$11 261.68	-$1342.82	-$50.32	-
2024-08-15	AAPL	B	-$12 428.30	$0.00	-$50.00	0.78955
2024-08-30	MSFT	B	-$16 654.40	$0.00	-$50.00	0.6696
2024-08-30	AAPL	S	$12 555.09	$126.79	-$50.36	-
2024-09-13	MCD	B	-$14 830.00	$0.00	-$50.00	0.7313
2024-09-13	MSFT	S	$17 153.12	$498.72	-$50.48	-
2024-09-23	MCD	S	$14 899.58	$69.58	-$50.42	-
2024-10-07	META	B	-$14 824.75	$0.00	-$50.00	0.71145
2024-10-07	MSFT	B	-$16 740.24	$0.00	-$50.00	0.76775
2024-10-17	META	S	$14 368.59	-$456.16	-$50.41	-
2024-10-17	MSFT	S	$16 593.93	-$146.31	-$50.47	-
2024-09-13	MSFT	S	$17 153.12	$498.72	-$50.48	-
2024-09-23	MCD	S	$14 899.58	$69.58	-$50.42	-
2024-10-07	META	B	-$14 824.75	$0.00	-$50.00	0.71145
2024-10-07	MSFT	B	-$16 740.24	$0.00	-$50.00	0.76775
2024-10-17	META	S	$14 368.59	-$456.16	-$50.41	-
2024-10-17	MSFT	S	$16 593.93	-$146.31	-$50.47	-