Stock Return Prediction Using Television Advertising Data

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ABSTRACT
This study proposes the TV Index, a novel alternative data source constructed from 6.6 million television commercial records spanning 965 Tokyo Stock Exchange-listed firms, and demonstrates its utility for systematic equity investment in the Japanese market. By applying Golden Cross strategies (traditionally applied to price series) to this attention-based signal, this study shows that television advertising intensity contains predictive information about future stock returns that is not captured by conventional risk factors. The best-performing strategy achieves a Sharpe ratio of 1.030 and a cumulative return exceeding the TOPIX benchmark by approximately 65 percentage points over the 2019–2024 sample period. Multiple performance evaluations, including risk-adjusted analysis and sub-period decomposition, consistently confirm the robustness of these findings. These results demonstrate that television advertising data constitute a viable and practically implementable alternative data source, bridging behavioral finance theory with quantitative and econometric implementation.

KEYWORDS
Stock Return Prediction; Television Advertising; TV Index; Alternative Data; Investor Attention; Golden Cross Strategy; Japanese Equity Market; Fama–French Model

INTRODUCTION

Traditional finance posits that markets allocate resources efficiently because security prices “fully reflect all available information.”[1] Behavioral finance, however, emphasizes that investor attention is a limited cognitive resource: when faced with thousands of securities, investors cannot process all information and tend to overreact to salient cues rather than fundamental information. Consequently, stocks that attract more investor attention often experience increased buying pressure and systematic attention-driven price patterns.[2] Among media channels, television advertising is particularly effective at drawing investor attention, influencing market outcomes independently of informational content.[3, 4]

Prior research has documented several mechanisms through which advertising affects markets, primarily operating through two complementary channels: liquidity enhancement and attention-driven mispricing. On the liquidity side, Grullon *et al.* show that advertising increases investor awareness and broadens the shareholder base, enhancing liquidity in line with Merton’s investor-recognition hypothesis.[5, 6] On the mispricing side, higher advertising expenditures are associated with elevated returns during the year of increased advertising, followed by subsequent return reversal as attention effects fade, suggesting temporary price pressure from attention-constrained investors.[7]

The development of alternative data has enabled more direct and timely measurement of these attention effects. Search-based measures such as Google’s Search Volume Index (SVI) provide high-frequency, observable proxies for retail investor attention that precede trading activity and return pressure.[8] Television commercials similarly induce temporary spikes in both search activity and trading volume, establishing a clear link between media exposure and measurable investor behavior.[9]

While prior research has documented the impact of advertising on investor attention and market outcomes, it remains unclear whether these attention signals can be systematically incorporated into profitable trading strategies. One potential approach is to apply technical analysis methods to attention-based indicators rather than to price data alone. The Golden Cross—a pattern in which a short-term moving average crosses above a long-term moving average—is a widely-used trend-detection method in technical analysis. Empirical evidence suggests that moving-average crossover strategies can generate excess returns and outperform standard time-series momentum approaches, particularly for small- and mid-cap stocks.[10, 11] Miwa and Ueda demonstrate that moving-average crossover patterns serve as effective trend-detection signals in the Japanese market.[12] However, existing applications of these technical methods focus exclusively on price data, leaving unexplored the potential to apply such rules to alternative attention-based signals derived from advertising exposure.

This study proposes a novel extension by constructing a television commercial intensity index (TV Index) to measure firm-level advertising activity and applying the Golden Cross rule to this attention-based index. The approach is motivated by two mechanisms. First, rising advertising exposure attracts investor attention, which triggers gradual price adjustments. Applying trend-following rules to such attention signals is expected to capture temporary mispricings arising from the slow diffusion of information.[13] Supporting this view, momentum effects—where stocks with high recent returns continue to outperform over three- to twelve-month horizons—indicate that attention-induced trading activity can generate tradable trend-like patterns in prices.[14] Second, aggregating attention signals at the industry level filters out idiosyncratic firm-specific noise while preserving common attention shocks that affect entire sectors. This aggregation improves the signal-to-noise ratio by smoothing out random fluctuations in individual firm advertising while retaining systematic patterns that predict stock performance.

To test this framework, this study uses approximately 6.6 million television commercial records for Tokyo Stock Exchange firms spanning 2019–2024 to construct a weekly normalized TV Index. Thirty-six portfolio implementations are evaluated: 30 Golden Cross configurations varying the aggregation method (industry-level versus firm-level), coverage thresholds (controlling the share of the universe included), and concentration levels (the percentage of high-signal stocks selected for investment), plus an equal-weighted benchmark for each of the six data configurations. Fama–French regressions are then employed to determine whether the observed returns constitute excess performance beyond conventional risk factors,[15] testing whether TV Index signals contain unique predictive information.

METHODS AND PROCEDURES

Data Sources

The analysis combines eight datasets covering the period from April 5, 2019 to December 6, 2024, corresponding to 297 weekly observations.

Television Commercial Data: The dataset comprises 6,645,474 television commercial records from 965 Tokyo Stock Exchange-listed firms, each identified by a unique four-digit ticker. **Table 1** summarizes the broadcast and product attributes included in each record. Commercials are attributed to the parent company's Tokyo Stock Exchange ticker; subsidiaries and affiliates are aggregated under the parent.

Viewership Rate Data: Time-slot-specific viewership rates, measured at half-hour intervals throughout the day, are obtained from the 2017 National Individual Ratings Survey.[16] These rates are combined with commercial duration to compute viewer-weighted exposure for each firm.

Stock Price Data: Weekly stock returns for all 965 firms are constructed from daily adjusted closing prices obtained via the yfinance API.[17] Daily prices are adjusted for stock splits, dividends, and rights issues. Weekly returns are calculated

Variable	Type	Description
BROADCAST_START_TIME	Timestamp	Time when the commercial aired
CM_LENGTH	Numeric	Duration in seconds
TICKER_CODE	Categorical	Four-digit stock ticker of the firm
CATEGORY_LARGE	Categorical	Broad product category (*e.g.*, Food & Beverage)
CATEGORY_MEDIUM	Categorical	Intermediate product category (*e.g.*, Alcoholic Drinks)
CATEGORY_SMALL	Categorical	Specific product category (*e.g.*, Beer)
BROADCASTER	Categorical	Television network (*e.g.*, TBS, Fuji TV)
AREA	Categorical	Geographic coverage of the broadcast

Table 1. Variables included in the television commercial dataset.

using Friday closing prices to align with standard market practice and ensure consistency across all securities:

$$R_{i,w} = \frac{P_{i,w} - P_{i,w-1}}{P_{i,w-1}} \quad \textbf{Equation 1.}$$

where $P_{i,w}$ is the adjusted closing price of firm i at the end of week w (Friday). Weekly aggregation aligns with the TV Index measurement frequency.

To ensure a consistent return series without gaps, the analysis is restricted to firms continuously listed on the Tokyo Stock Exchange throughout the entire sample period. Firms that were delisted or newly listed during this period are excluded, resulting in a fixed panel of continuously observed stocks.

Firm Metadata: Firm-level characteristics—including sector classification, industry classification, and market capitalization—are obtained via the yfinance API.[17] **Table 2** summarizes these variables.

Variable	Type	Description
TICKER_CODE	Categorical	Four-digit stock ticker
COMPANY_NAME	String	Official company name
SECTOR	Categorical	Broad sector classification
INDUSTRY	Categorical	Industry classification within sector
MARKET_CAP	Numeric	Market capitalization in Japanese yen

Table 2. Variables included in the firm metadata dataset.

TOPIX Benchmark Data: Weekly TOPIX index returns are constructed from daily closing values obtained from Investing.com,[18] aggregated using Friday closing prices following **Equation** 1.

Exchange Rate Data: Daily USD/JPY exchange rates are obtained from the Bank of Japan to convert US-dollar-denominate Fama–French factor returns into Japanese yen.[19]

Fama–French Three-Factor Data: This study employs the Fama–French three-factor model using Japanese market factors obtained from Kenneth French's data library.[20] The three-factor model has been shown to perform well in explaining Japanese stock returns, with the value factor demonstrating particularly strong explanatory power in this market context.[21] Since the factors are reported in US dollars, these factors are converted to Japanese yen using the daily USD/JPY exchange rates described above to reflect the experience of yen-based investors. Weekly factor returns are then calculated by compounding daily yen-denominated returns over each week. Portfolio excess returns are computed as:

$$R_{p,t}^{\text{excess}} = R_{p,t} - RF_t \quad \textbf{Equation 2.}$$

where RF_t is the weekly risk-free rate. The three-factor regression specification is:

$$R_{p,t}^{\text{excess}} = \alpha + \beta_{\text{Mkt}}\,\text{Mkt-RF}_t + \beta_{\text{SMB}}\,\text{SMB}_t + \beta_{\text{HML}}\,\text{HML}_t + \epsilon_t \quad \textbf{Equation 3.}$$

where α represents excess performance beyond conventional risk factors and the β coefficients capture factor exposures.[15]

Risk-Free Rate Data: The Japanese 3-month government bond yield (obtained from Bloomberg) serves as the short-term risk-free rate.[22] The 3-month maturity is chosen to align with standard asset pricing practice. **Table 3** summarizes the variables used.

Variable	Type	Description
`DATE`	Date	Observation date
`PX_LAST`	Numeric	Last observed price
`YLD_YTM_MID`	Numeric	Mid-point annualized yield to maturity, used as RF_t
`YLD_YTM_BID`	Numeric	Bid yield to maturity

Table 3. Variables included in the Japanese government bond dataset.

Sample Selection and Investable Universe

While the dataset includes 965 Tokyo Stock Exchange-listed firms, not all firms maintain consistent television advertising activity throughout the sample period. To construct a reliable TV Index, the analysis must identify firms with sufficient advertising exposure. The firm-level advertising fill rate is defined as the proportion of weeks in which a firm broadcasts at least one television commercial. **Figure 1** shows that this distribution is highly right-skewed: most firms advertise sporadically or not at all, while a smaller subset maintains consistent advertising campaigns.

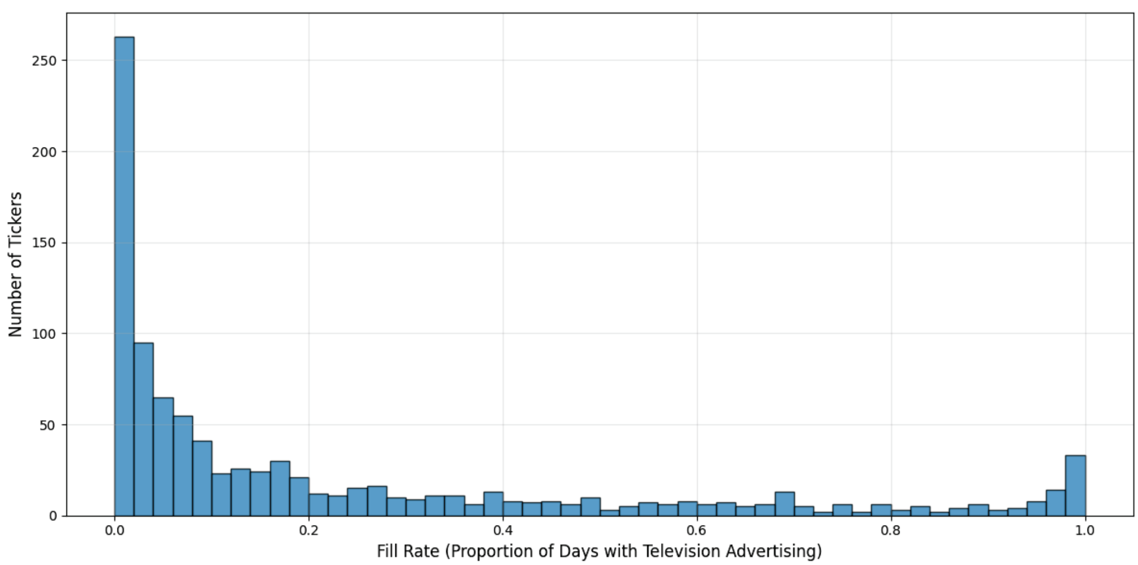

Figure 1. Distribution of television advertising fill rate by firm.

However, the fill rate alone—which measures only the proportion of weeks with advertising activity—does not capture the volume or strategic significance of that activity. A firm may advertise sporadically across many weeks with minimal total exposure, yielding a moderate fill rate but limited investor attention. Conversely, a firm may concentrate substantial advertising resources in fewer weeks, resulting in a lower fill rate but significant market impact. To address this limitation, this study employs two distinct filtering approaches that go beyond simple frequency measures, each capturing different dimensions of advertising intensity and economic relevance:

- **Industry-level filtering:** This approach aggregates the total volume of advertising records (measured by cumulative commercial counts) at the industry level, rather than relying on fill rates. It selects industries based on their aggregate exposure, emphasizing statistical reliability by ensuring sufficient data coverage across broader industry categories and reducing the impact of firm-specific noise.
- **Firm-level strategic scoring:** This approach evaluates individual firms based on both the volume of their advertising and the strategic importance of the product categories each firm targets. Rather than frequency alone, it assigns higher weight to firms advertising in high-visibility, economically prominent categories, thereby emphasizing campaign quality and market relevance.

Both approaches are applied independently, generating separate sets of portfolio strategies. This parallel implementation allows for direct comparison of their effectiveness in capturing attention-driven return patterns and identifies which filtering dimension—aggregate industry exposure versus firm-level strategic focus—produces stronger predictive signals.

Industry-Level Filtering

At the industry level, firms are filtered based on the total volume of commercial records aggregated by sector-industry classification. Industries with substantial aggregate advertising activity are expected to provide more robust signals for portfolio construction, as aggregation across multiple firms within an industry reduces idiosyncratic noise while preserving systematic attention patterns.

To determine coverage thresholds, commercial records are ranked by sector-industry combinations (**Figure 2**). The sharply concave distribution confirms that a small subset of industries dominates advertising activity: the top 41% of combinations account for 90% of all commercial records.

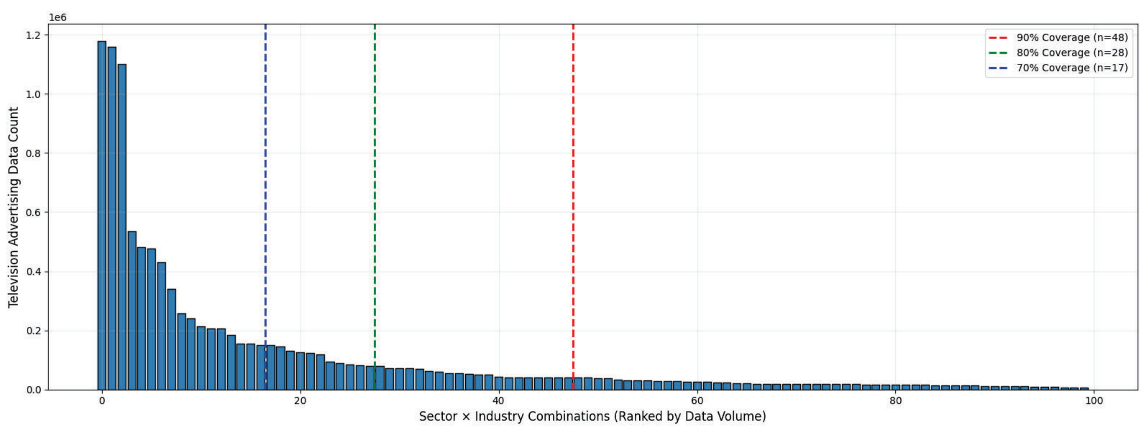

Figure 2. Sector-industry commercial data distribution with coverage thresholds.

Three coverage thresholds are defined based on the cumulative share of commercial records:

- **90% Coverage:** Top 48 industry combinations (41.0% of all combinations), covering 90.0% of commercial records, corresponding to 604 firms
- **80% Coverage:** Top 28 industry combinations (23.9% of all combinations), covering 80.0% of commercial records, corresponding to 475 firms
- **70% Coverage:** Top 17 industry combinations (14.5% of all combinations), covering 68.7% of commercial records, corresponding to 330 firms

Table 4 lists the top 10 sector-industry combinations by total commercial records.

Sector × Industry	Commercial Records	Cumulative Coverage (%)
Technology × Information Technology Services	1,177,538	10.84
Communication Services × Internet Content & Information	1,158,024	21.49
Consumer Cyclical × Internet Retail	1,101,070	31.62
Consumer Defensive × Household & Personal Products	534,328	36.54
Consumer Defensive × Beverages – Non-Alcoholic	481,263	40.97
Consumer Defensive × Packaged Foods	477,198	45.36
Consumer Cyclical × Auto Manufacturers	431,709	49.33
Communication Services × Telecom Services	341,428	52.47
Real Estate × Real Estate – Development	257,645	54.84
Consumer Cyclical × Restaurants	239,456	57.05

Table 4. Top 10 sector-industry combinations by total commercial records.

Firm-Level Strategic Scoring

At the firm level, the investable universe is defined through a strategic evaluation of individual companies' advertising activities. Rather than relying solely on total advertising volume, this approach emphasizes the alignment of advertising efforts with economically prominent product categories. The underlying premise is that advertising in high-visibility, widely consumed categories is more likely to attract broad investor attention and generate tradable signals.

Each firm i is assigned a strategic score based on how its advertising portfolio aligns with market-wide category prominence:

$$\text{StrategicScore}_i = \sum_c (E_{i,c} \times G_c) \qquad \textbf{Equation 4.}$$

where $E_{i,c}$ represents the proportion of firm i's total advertising exposure allocated to product category c, and G_c represents the market-wide share of category c across all firms. This formulation rewards firms that concentrate their advertising in categories with high overall market presence, under the assumption that such categories command greater investor attention.

- **90% Coverage:** Top 764 firms, contributing 90% of cumulative strategic score
- **80% Coverage:** Top 678 firms, contributing 80% of cumulative strategic score
- **70% Coverage:** Top 587 firms, contributing 70% of cumulative strategic score

This approach differs from industry-level filtering in two key ways. First, it operates at the individual firm level rather than aggregating across industries, allowing for finer-grained selection. Second, it incorporates the strategic composition of each firm's advertising portfolio—not just the total volume—by weighting exposure according to category prominence. As a result, firm-level strategic scoring captures a broader set of firms (*e.g.*, 764 firms at 90% coverage versus 604 for industry-level filtering) while emphasizing those whose advertising patterns align with high-attention market segments.

Table 5 presents the top 10 product categories by global exposure share, illustrating the market segments that carry the highest weight in the scoring framework.

Category Combination	Global Share (%)
Computer/AV + Other + Website	12.68
Alcohol A + Beer + Domestic Beer	4.28
Communication + Domestic Communication + Mobile Phone	3.78
Vehicle + Passenger car/Domestic + RV	2.17
Real Estate + Real Estate + Real Estate	2.12
Finance/Insurance + Insurance + Life Insurance	2.06
Real Estate + Housing + Housing	1.90
Distribution + Restaurant + Fast Food	1.77
Food + Health Food + (Other)	1.56
Other + Business + (Other)	1.53

Table 5. Top 10 product categories by global exposure share.

TV Index Construction

After defining the investable universe through either industry-level or firm-level filtering, the TV Index is constructed to quantify each firm's television advertising exposure. For firm i on day t, daily advertising exposure is computed as:

$$\text{Exposure}_{i,t} = \text{Duration}_{i,t} \times \text{ViewershipRate}_t \qquad \textbf{Equation 5.}$$

where $\text{Duration}_{i,t}$ is the total length (in seconds) of all commercials aired by firm i on day t, and ViewershipRate_t represents the time-slot-specific audience rating corresponding to the broadcast time.

Viewership rates provide time-slot-specific audience shares at half-hour intervals throughout the day. While this data predates the sample period (2019–2024), the structure of intraday viewing patterns—when audiences are typically watching television—is relatively stable over time, even as absolute viewership levels may decline. This approach prioritizes capturing the relative attention value of different broadcast times rather than absolute audience size.

Daily exposures are aggregated to weekly totals to align with the weekly frequency of stock return data. The weekly TV Index is then normalized relative to the cross-sectional mean exposure of the selected universe G (either industry-filtered or firm-filtered):

$$\text{TVIndex}_{i,w} = \frac{\text{Exposure}_{i,w}}{\overline{\text{Exposure}_{G,w}}} \qquad \textbf{Equation 6.}$$

where $\overline{\text{Exposure}_{G,w}}$ denotes the mean weekly exposure across all firms in universe G during week w. This normalization ensures that the TV Index is interpretable as a relative measure: a value of $\text{TVIndex}_{i,w} = 2.5$ indicates that firm i received 2.5 times the average advertising exposure of its peers. Weekly stock price data are aligned with this weekly TV Index for portfolio construction.

Portfolio Formation and Trading Strategy

The Golden Cross strategy adapts classic moving average crossover rules to TV Index signals. The strategy operates on a weekly signal generation cycle with monthly portfolio rebalancing. This monthly rebalancing frequency represents a practical compromise between capturing multi-week attention dynamics and controlling transaction costs, consistent with documented best practices for diversified portfolio management.[23]

Moving Average Signals

The strategy employs two moving averages of the TV Index for firm i in week w: a short-term 4-week signal capturing recent advertising intensity (MA4) and a long-term 12-week baseline of sustained activity (MA12):

$$\text{MA4}_{i,w} = \frac{1}{4}\sum_{k=0}^{3} \text{TVIndex}_{i,w-k} \qquad \textbf{Equation 7.}$$

$$\text{MA12}_{i,w} = \frac{1}{12}\sum_{k=0}^{11} \text{TVIndex}_{i,w-k} \qquad \textbf{Equation 8.}$$

Golden Cross Signal

A Golden Cross occurs when short-term attention exceeds the long-term baseline, indicating accelerating advertising exposure:

$$\text{GoldenCross}_{i,w} = \mathbb{1}(\text{MA4}_{i,w} > \text{MA12}_{i,w}) \qquad \textbf{Equation 9.}$$

Portfolio Selection and Weighting

At each monthly rebalancing date, the portfolio is constructed by selecting the top $q\%$ of firms exhibiting an active Golden Cross signal, ranked by their current TV Index level. Five concentration levels are evaluated: $q \in \{5, 10, 15, 20, 25\}$.

$$\text{Portfolio}_w^{(q)} = \text{Top-}q\%\{i : \text{GoldenCross}_{i,w} = 1\},\ \text{ranked by TVIndex}_{i,w} \qquad \textbf{Equation 10.}$$

Selected stocks are assigned equal weights, isolating the information content of the attention-based selection rule from mechanical size effects.

Rebalancing and Return Calculation

Portfolios rebalance monthly. The 297-week sample spans 71 rebalancing events following an initial 12-week period required to compute the 12-week moving average. Returns incorporate a one-week implementation lag to reflect realistic execution:

$$\text{StrategyReturn}_{w+1} = \sum_{i=1}^{N} w_{i,w} \times \text{StockReturn}_{i,w+1} \qquad \textbf{Equation 11.}$$

Strategy Variants and Benchmark

The analysis evaluates 36 portfolio implementations: 5 concentration levels $\times$ 2 filtering methods (industry vs. firm) $\times$ three coverage thresholds (90%, 80%, 70%), plus an equal-weighted benchmark for each of the 6 data configurations. The equal-weighted benchmark holds all stocks in the investable universe with equal weights, rebalanced monthly to match the Golden Cross rebalancing frequency. This benchmark isolates the incremental value of the Golden Cross selection rule by controlling for rebalancing effects, ensuring that performance differences reflect the quality of TV Index-based stock selection rather than mechanical rebalancing benefits.

JPY-Based Fama–French Factor Construction

To conduct factor analysis for Japanese equity portfolios, the USD-denominated Fama–French three-factor data[20] are converted to Japanese yen using daily exchange rate returns and the Japanese 3-month government bond yield as the risk-free rate. The full construction procedure and resulting monthly factor values are provided in **Appendix A**. **Figure 3** supports the validity of the currency adjustment by comparing JPY-based market returns with TOPIX monthly returns; the correlation of 0.983 confirms the consistency of the conversion.

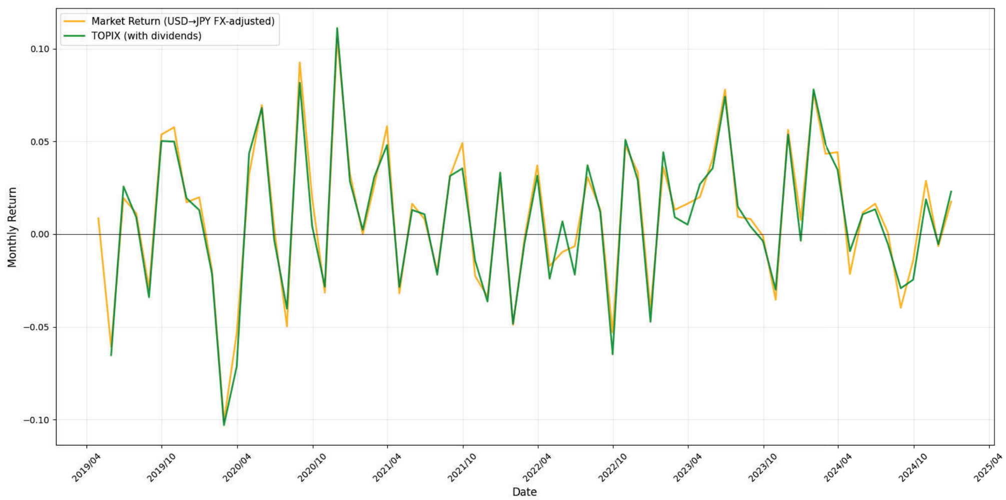

Figure 3. Validation of JPY currency conversion: Fama–French market factor versus TOPIX monthly returns.

Performance Evaluation and Statistical Inference

Portfolio performance is assessed using both standard return-based metrics and risk-adjusted factor analysis, with statistical significance evaluated through multiple hypothesis tests. For detailed analyses, the configuration with the highest Sharpe ratio across all 30 Golden Cross configurations is used consistently.

Return-Based Performance Metrics

Four primary metrics are calculated from weekly returns:

Total Return: Cumulative compound return over the full 297-week sample period (April 2019 to December 2024).

Sharpe Ratio: Risk-adjusted performance, annualized from weekly returns:

$$\text{Sharpe Ratio} = \frac{\bar{r}_p - \bar{r}_f}{\sigma_p} \times \sqrt{52} \qquad \textbf{Equation 12.}$$

where $\bar{r}_p$ is the mean weekly portfolio return, $\bar{r}_f$ is the mean weekly risk-free rate, and σ_p is the standard deviation of weekly excess returns.

Maximum Drawdown: The largest peak-to-trough decline in portfolio value:

$$\text{Max DD} = \min_t \left(\frac{V_t - \max_{s \le t} V_s}{\max_{s \le t} V_s} \right) \qquad \textbf{Equation 13.}$$

where V_t represents the cumulative portfolio value at time t.

TOPIX Excess Return: The difference between portfolio cumulative return and TOPIX cumulative return over the same period.

Factor-Based Performance Analysis

To assess whether portfolio returns reflect compensation for systematic risk factors or represent genuine excess performance beyond systematic risk factors, Fama–French three-factor regressions Equation 3. are applied to monthly-aggregated portfolio returns, following standard practice in factor model estimation. A positive and statistically significant alpha indicates that the Golden Cross strategy generates performance beyond what can be explained by systematic factor exposures, suggesting that TV Index signals contain unique predictive information.

Statistical Hypothesis Tests

Statistical significance of performance differences is evaluated using standard t-tests. Three categories of hypothesis tests are conducted:

1. **Filtering Method Comparison (Two-Sample t-tests):** Industry-level versus firm-level filtering methods are compared across all performance metrics. This analysis pools results across all five concentration levels and three coverage thresholds, yielding 15 observations per method. Two-sample t-tests assess whether the two filtering approaches produce systematically different risk-adjusted returns, maximum drawdowns, and excess returns relative to TOPIX.
2. **Strategy vs. Benchmark Comparison (Paired t-tests):** For each of the six data configurations (2 methods $\times$ 3 thresholds), the best Golden Cross strategy (selected by Sharpe ratio) is compared against the equal-weighted benchmark using paired t-tests across the six patterns. This tests whether the Golden Cross selection rule adds value beyond passive equal-weighted exposure.
3. **Alpha Significance (Rolling Fama–French Regressions):** Rolling 12-month window regressions are estimated to analyze time-varying factor exposures and alpha patterns. For each data configuration, monthly aggregated portfolio returns are regressed on the three JPY-based factors using a rolling window approach. This provides visual assessment of whether positive alpha persists throughout the sample period after controlling for market, size, and value factors.

Transaction Cost Sensitivity

To assess the economic viability of the strategy under realistic trading frictions, net returns are computed for four one-way cost scenarios: 0, 5, 15, and 40 basis points (bps), calibrated to bid-ask spread estimates for Japanese equities reported by Wakamatsu.[24] The 5 bps scenario reflects the retail investor environment following the elimination of brokerage commissions by major Japanese online brokers in 2023, leaving the bid-ask spread as the primary remaining cost. The 15 bps scenario represents standard institutional execution costs, and the 40 bps scenario serves as a conservative stress test. Monthly portfolio turnover is measured empirically from actual portfolio composition changes at each rebalance: comparing the set of holdings before and after each monthly rebalance reveals a mean turnover of 66% across 71 rebalancing events (range: 51%–79%). The monthly net return is then:

$$r_{p,m}^{\text{net}} = r_{p,m}^{\text{gross}} - \tau \times 2 \times c \qquad \text{Equation 14.}$$

where $\tau = 0.66$ is the empirically measured mean monthly turnover rate, c is the one-way cost in decimal form, and the factor of 2 accounts for both the entry and exit legs of each trade. Monthly costs are distributed evenly across the weeks within each rebalancing period. Net cumulative returns and TOPIX excess returns are computed from the resulting weekly net return series.

COVID-19 Sub-Period Analysis

Since the 2019–2024 sample period encompasses the entire COVID-19 pandemic, it is necessary to verify whether the reported results reflect a persistent behavioral mechanism rather than pandemic-specific dynamics. The full sample is divided into three sub-periods based on key COVID-19 milestones in Japan to assess whether strategy performance holds across distinct market regimes:

1. **Pre-COVID** (April 2019–February 2020): from strategy inception to the month preceding the World Health Organization (WHO) pandemic declaration.
2. **During-COVID** (March 2020–December 2021): from the WHO declaration through the period of widespread restrictions and vaccine rollout.
3. **Post-COVID** (January 2022–December 2024): following the progressive lifting of *Manen Bōshi* (epidemic prevention) measures and the resumption of normal social activity in Japan.

For each sub-period, cumulative return, annualized return, and TOPIX excess return are computed using the same methodology as the full-sample analysis. Fama–French three-factor regressions are additionally estimated for each subperiod to obtain period-specific monthly alpha and its t-statistic, providing a risk-adjusted assessment of whether outperformance persists across distinct market regimes after controlling for systematic risk factors.

RESULTS

Performance Comparison Across Patterns

Table 6 summarizes the performance of Golden Cross (GC) strategies across six data patterns. For each pattern, the best-performing strategy is selected from five concentration thresholds (Top 5%, 10%, 15%, 20%, 25%) based on the highest Sharpe ratio, which balances risk and return. Detailed performance metrics for all 36 configurations are provided in **Appendix B**. Cumulative return trajectories and performance comparisons across all strategies are visualized in **Appendix C** and **Appendix D**.

The Industry Level 90% Coverage pattern with Top 10% concentration achieves the highest Sharpe ratio (1.030) with a cumulative return of 133.33% with an average of 58 stocks. Across all six patterns, the best-performing strategies deliver average returns of 130.27% (Industry) and 126.62% (Firm), substantially exceeding TOPIX's 68.68%. Maximum drawdowns range from -24.84% to -28.72%, comparable to TOPIX's -29.18%. Industry-level patterns exhibit significantly lower average drawdowns (-26.16%) than Firm-level strategies (-28.51%), a difference confirmed by two-sample t-test ($t(28) = 5.57$, $p < 0.001$, where $df = 30 - 2 = 28$ for two groups of 15 strategies each). Statistical comparisons across all 30 Golden Cross strategies confirm this pattern (**Table 7**):

Industry-level filtering provides statistically significant improvements in risk-adjusted returns (Sharpe ratio difference +0.060, $p = 0.017$) and maximum drawdown (+1.69 percentage points (pp) lower, $p < 0.001$). While the difference in absolute returns (+6.33 percentage points) is not statistically significant at conventional levels ($p = 0.220$), the consistent superiority in risk metrics supports the preference for industry-level aggregation in constructing TV Index portfolios. This finding validates the hypothesis that sector-level smoothing enhances signal quality by filtering out firm-specific noise while preserving systematic attention effects.

Method: Threshold	Coverage	Best Strategy	Return (%)	Sharpe	Max DD (%)	TOPIX Excess (%)
Industry Level	90% Coverage	GC Top 10% (58 stocks)	133.33	1.030	-26.81	+64.65
	80% Coverage	GC Top 5% (22 stocks)	129.99	0.993	-26.84	+61.32
	70% Coverage	GC Top 5% (15 stocks)	127.50	0.995	-24.84	+58.83
Firm Level	90% Coverage	GC Top 5% (36 stocks)	129.02	0.967	-28.37	+60.35
	80% Coverage	GC Top 5% (32 stocks)	120.84	0.925	-28.42	+52.17
	70% Coverage	GC Top 5% (28 stocks)	130.01	0.955	-28.72	+61.33
Avg Industry			**130.27**	**1.006**	**-26.16**	**+61.60**
Avg Firm			**126.62**	**0.949**	**-28.51**	**+57.95**
Difference			**+3.65**	**+0.057**	**+2.35**	**+3.65**

Table 6. Golden Cross strategy performance summary (297 weeks, 2019-04-05 to 2024-12-06). TOPIX return over the same period = 68.68%, Sharpe ratio = 0.589. Stock numbers indicate average portfolio size.

Metric	Industry Level	Firm Level	Difference	p-value
Avg Return (%)	114.18	107.85	+6.33	0.220
Avg Sharpe Ratio	0.927	0.866	+0.060	0.017
Avg Max DD (%)	-27.41	-29.09	+1.69	<0.001
Avg TOPIX Excess (%)	+45.51	+39.17	+6.33	0.220

Table 7. Industry versus firm level filtering: average performance across all Golden Cross strategies.

Cross-Configuration Performance

All 30 Golden Cross configurations outperform TOPIX over the full sample (cumulative returns 88.75%–140.98% vs. TOPIX 68.68%; **Appendix B**), confirming that the TV Index signal provides broad predictive value across diverse parameter choices.

Figure 4 presents the Sharpe ratio heatmap for all 30 Golden Cross configurations (six patterns × five concentration levels). Industry 90% Coverage achieves the highest Sharpe ratio among the six patterns in three of the five concentration levels (Top 5%, Top 10%, Top 20%), and ranks second in the remaining two (Top 15%, Top 25%).

Portfolio Concentration Analysis

Table 8 examines how portfolio concentration affects performance within the Industry Level 90% Coverage pattern. Modern portfolio theory predicts a trade-off between concentration and diversification: concentrated portfolios capture stronger signals but bear higher idiosyncratic risk, while diversified portfolios reduce variance at the cost of diluting signal strength.[25]

The Top 5% portfolio achieves the highest absolute return (140.98%) but with slightly higher drawdown risk (-27.81%). The Top 10% portfolio achieves nearly identical risk-adjusted performance (Sharpe ratio 1.030 vs. 1.026) with marginally lower drawdown (-26.81%). Performance deteriorates monotonically as concentration decreases beyond 10%, with the Top 25% portfolio delivering only 98.97% return and a Sharpe ratio of 0.850. These results suggest an optimal concentration around 5–10%, where signal strength remains high while idiosyncratic risk stays manageable.

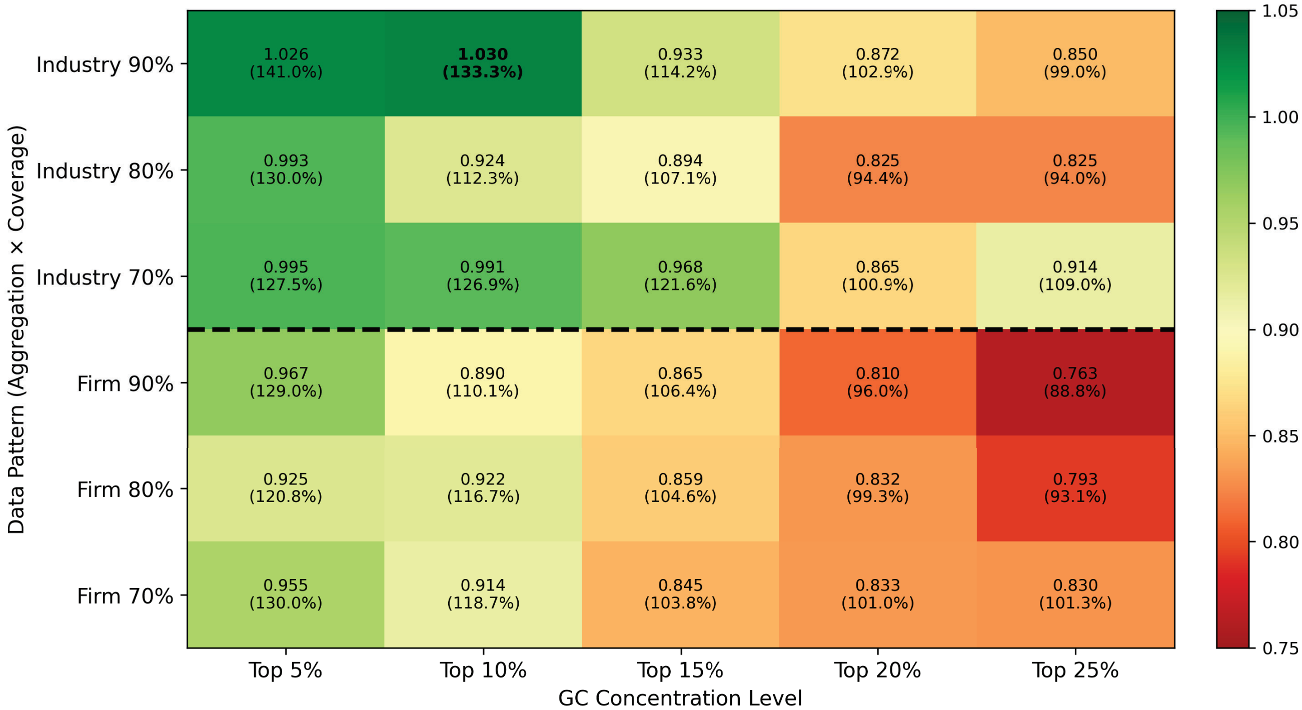

Figure 4. Sharpe ratio heatmap for all 30 Golden Cross configurations (six data patterns × five concentration levels). Cell values show Sharpe ratio (cumulative return).

Method: Threshold	Coverage	Strategy	Return (%)	Sharpe	Max DD (%)	TOPIX Excess (%)
Industry Level	90% Coverage	GC Top 5%	**140.98**	1.026	-27.81	+72.30
		GC Top 10%	133.33	**1.030**	**-26.81**	+64.65
		GC Top 15%	114.16	0.933	-27.10	+45.48
		GC Top 20%	102.90	0.872	-27.53	+34.22
		GC Top 25%	98.97	0.850	-28.52	+30.29

Table 8. Portfolio concentration effects: Industry Level 90% Coverage pattern.

Fama–French Three-Factor Analysis

Rolling 12-month Fama–French three-factor regressions assess whether TV Index-based returns reflect systematic risk exposures or genuine alpha. Monthly portfolio returns are regressed on the three JPY-based factors using a 12-month rolling window, generating 57 rolling estimates over the 69-month sample period (March 2020 to December 2024). **Figure 5** shows the time-varying factor loadings for the best-performing portfolio (Industry 90% Coverage, GC Top 10%). Time-varying factor loadings for all six data patterns are provided in **Appendix E**.

Table 9 summarizes the distribution of factor loadings across the 57 rolling windows.

Alpha: The rolling alpha remains persistently positive throughout most of the sample period, averaging 0.79% monthly, which translates to 9.90% annualized (computed as $1.0079^{12} - 1$). Alpha exhibits substantial temporal variation, ranging from -0.16% to 1.46% monthly, yet remains positive across most of the sample period despite shifting market conditions. The regression R^2 of 66.2% indicates that approximately two-thirds of return variation is explained by the three systematic factors while the remaining one-third reflects portfolio-specific sources including TV Index signals.

Figure 5. Rolling 12-month Fama–French three-factor regression: alpha, market beta (Mkt-RF), size (SMB), and value (HML) factor loadings.

Factor	Mean	Min	Max	Range
Alpha (monthly %)	0.79	-0.16	1.46	1.62
Market Beta (Mkt-RF)	0.657	0.311	1.137	0.826
Size Beta (SMB)	0.270	-0.305	0.770	1.075
Value Beta (HML)	-0.092	-0.447	0.176	0.623

Table 9. Summary statistics of rolling 12-month Fama–French factor loadings (Industry 90% Coverage, GC Top 10%). Based on 57 rolling windows covering March 2020 to December 2024.

Market Beta: The mean market beta of 0.657 indicates moderate systematic risk exposure, ranging from 0.311 (December 2024) to 1.137 (December 2021). Beta exhibits an inverted-U pattern over time: rising from 0.78 in early 2020 to above 1.0 during late 2021, then declining steadily to 0.31–0.38 in late 2024. This declining trend suggests that the portfolio's systematic market exposure moderated progressively over the sample period.

Size and Value Factor Exposure: The positive SMB beta (mean 0.270, range -0.305 to 0.770) indicates a small-cap tilt that varies over time. SMB exposure peaks during 2020–2021 (0.43–0.77), then declines toward zero or negative values in 2023–2024. The negative HML loading (mean -0.092, range -0.447 to 0.176) suggests that advertising-intensive firms are predominantly growth-oriented. HML exposure is most negative during 2020–2022 (-0.44 to -0.26), before moderating toward neutral in 2023–2024. This pattern aligns with the broader Japanese equity market context, where a pronounced value premium has been documented: the negative HML loading indicates that firms with high recent advertising exposure tend to occupy the growth end of Japan's book-to-market cross-section.[21]

Comparison to Equal-Weighted Benchmark

Table 10 compares the best Golden Cross strategies to equal-weighted benchmark portfolios that hold all stocks in each universe with monthly rebalancing.

Method: Threshold	Coverage	Strategy	Return (%)	Sharpe	TOPIX Excess (%)
Industry Level	90% Coverage	Best GC (Top 10%)	133.33	1.030	+64.65
		EW Benchmark	68.27	0.656	-0.41
	80% Coverage	Best GC (Top 5%)	129.99	0.993	+61.32
		EW Benchmark	64.59	0.633	-4.09
	70% Coverage	Best GC (Top 5%)	127.50	0.995	+58.83
		EW Benchmark	68.84	0.673	+0.16
Firm Level	90% Coverage	Best GC (Top 5%)	129.02	0.967	+60.35
		EW Benchmark	84.35	0.721	+15.68
	80% Coverage	Best GC (Top 5%)	120.84	0.925	+52.17
		EW Benchmark	85.18	0.725	+16.50
	70% Coverage	Best GC (Top 5%)	130.01	0.955	+61.33
		EW Benchmark	86.92	0.728	+18.25
Avg (All GC)		**Golden Cross**	**128.45**	**0.977**	**+59.77**
Avg (All EW)		**EW Benchmark**	**76.36**	**0.690**	**+7.68**
GC – EW		**Difference**	**+52.09**	**+0.287**	**+52.09**

Table 10. Golden Cross strategies versus equal-weighted (EW) benchmark portfolios.

Paired t-tests across the six patterns confirm highly significant outperformance by Golden Cross strategies: returns ($t = 10.12$, $p < 0.001$) and Sharpe ratios ($t = 9.57$, $p < 0.001$). On average, Golden Cross strategies deliver 52.09 percentage points higher returns and 0.287 higher Sharpe ratios compared to equal-weighted benchmarks. These results demonstrate that TV Index-based stock selection combined with Golden Cross timing rules substantially improves both absolute and risk-adjusted performance relative to passive equal-weighted exposure, providing evidence that television advertising signals contain predictive information for stock returns.

Transaction Cost Sensitivity

The baseline analysis excludes transaction costs to isolate the predictive power of TV Index signals. **Table 11** reports net cumulative returns and net Sharpe ratios under four cost scenarios using the empirically measured mean monthly portfolio turnover of 66%.

Scenario	Cost (bps)	Net Return (%)	Net Sharpe	vs. TOPIX (pp)
Zero Cost (Baseline)	0	133.33	1.030	+64.65
Low Cost (5 bps)	5	125.44	0.991	+56.76
Standard (15 bps)	15	110.44	0.914	+41.77
Stress Test (40 bps)	40	77.17	0.721	+8.49
TOPIX Benchmark	—	68.68	0.589	—

Table 11. Transaction cost sensitivity analysis (Industry 90% Coverage, GC Top 10%; empirical monthly turnover: 66%).

Figure 6 illustrates the cumulative return trajectories for each scenario alongside TOPIX. Under the 5 bps scenario, the strategy achieves a net cumulative return of 125.4% with a net Sharpe ratio of 0.991. Under the 15 bps scenario, the net cumulative return is 110.4% with a net Sharpe ratio of 0.914, outperforming TOPIX by 42 percentage points. Even under the 40 bps stress-test scenario, the net cumulative return of 77.2% (Sharpe 0.721) remains above TOPIX, confirming that outperformance is robust under elevated trading frictions. Institutional investors with access to lower-cost execution (5–15 bps one-way) would retain 85–94% of gross alpha, indicating strong economic viability across realistic implementation environments.

Figure 6. Cumulative return trajectories under four transaction cost scenarios and TOPIX benchmark (Industry 90% Coverage, GC Top 10%; empirical monthly turnover: 66%).

Sub-Period Performance and COVID-19 Effect

To address concerns that results may be driven by pandemic-specific dynamics, **Table 12** decomposes strategy performance across three sub-periods defined by the COVID-19 timeline: Pre-COVID (April 2019–February 2020), During-COVID (March 2020–December 2021), and Post-COVID (January 2022–December 2024).

Period	Mo.	Cum. (%)	Ann. (%)	vs. TOPIX (pp)	α (%/mo) [t]
Pre-COVID (Apr 2019–Feb 2020)	10	16.27	19.83	+12.2	2.961 [3.75]
During-COVID (Mar 2020–Dec 2021)	23	29.26	14.33	+11.0	0.575 [1.35]
Post-COVID (Jan 2022–Dec 2024)	36	55.25	15.79	+17.6	1.257 [3.16]
Full Sample (Apr 2019–Dec 2024)	69	133.33	15.88	+64.65	0.905 [3.31]

Table 12. Sub-period performance: Industry 90% Coverage, GC Top 10%. COVID-19 periods defined by WHO pandemic declaration (March 2020) and resumption of normal social activity in Japan (January 2022).

The Pre-COVID period (10 months, 44 weeks) produces an apparent monthly alpha of 2.96% ($t = 3.75$); however, this sub-period is too short for reliable statistical inference. With only 10 monthly observations, the Fama–French regression has six degrees of freedom—well below the minimum of 24–36 months required for stable factor-loading estimates—and the apparent significance is inflated by the use of normal-distribution critical values at this sample size. These figures are therefore reported for completeness only and should not be interpreted as robust evidence of predictability.

The two sub-periods of sufficient length are During-COVID (23 months) and Post-COVID (36 months). The During-COVID period yields statistically insignificant alpha ($t = 1.35$). The Post-COVID period (January 2022–December 2024) delivers the strongest results: monthly alpha of 1.257% ($t = 3.16$, $p < 0.01$).

DISCUSSION

Interpretation and Mechanisms

Three complementary mechanisms likely explain why television advertising signals predict equity returns in the Japanese market.

Investor Attention: Limited attention theory suggests that investors focus on salient cues when faced with numerous investment opportunities.[2] Television advertising serves as such a cue, particularly for consumer-facing firms. The Golden Cross filter—where a 4-week moving average exceeds a 12-week baseline—isolates periods of accelerating attention, capturing transitions from baseline visibility to heightened investor focus. This temporal filtering is central to the strategy's predictive power: it is not advertising exposure per se, but the acceleration of exposure relative to a recent baseline, that triggers the attention-driven price response.

Soft Information Signaling: As an alternative data source, advertising acts as a non-financial signal that complements formal disclosures. For firms with infrequent earnings announcements or limited analyst coverage—characteristics common among small-cap Japanese equities—advertising intensity may signal business momentum that precedes measurable changes in fundamentals.[26] Japan's strict self-regulatory advertising standards and industry-specific broadcasting restrictions create heterogeneous signaling environments across sectors. Pharmaceuticals and financial services face tighter constraints, while consumer goods enjoy greater flexibility. The superior performance of industry-level aggregation may partly reflect this regulatory structure: sector-level pooling captures systematic attention shifts while filtering firm-specific noise or regulatory idiosyncrasies that dilute signals at the firm level.

Liquidity and Ownership Effects: Advertising broadens shareholder bases and reduces liquidity constraints.[5, 6] Elevated advertising exposure attracts incremental demand, with monthly rebalancing capturing attention-driven price adjustments before markets fully equilibrate. The moderate market beta (mean 0.657) combined with significant positive alpha suggests that returns partly arise from gradual investor accumulation rather than pure factor exposure.

Practical Interpretation

For investors with existing Japanese equity exposure, the TV Index is most naturally applied as a portfolio tilt rather than a standalone strategy. At the stock level, the signal identifies which holdings to overweight: firms whose 4-week moving average of advertising activity has crossed above its 12-week baseline are candidates for increased allocation, with positions reversed when activity reverts—exploiting the predictive relationship between TV Index signals and subsequent returns documented in this study. At the sector level, the same logic applies in aggregate: since industry-level filtering is shown to outperform firm-level filtering, when the share of firms in a sector triggering the Golden Cross signal reaches a meaningful threshold, the sector itself becomes a candidate for overweighting relative to benchmark. This sector-level application requires no individual stock selection and is implementable with ETFs or index instruments, making it accessible to investors who prefer top-down allocation.

Limitations

In-Sample Optimization and Selection Bias: Performance evaluation is conducted using the single configuration (Industry Level 90% Coverage, GC Top 10%) that recorded the highest Sharpe ratio among all 30 candidates, which raises concern about the precision of the reported performance figures. This concern bears on the figures for the selected configuration—which is used consistently for all detailed analyses including Fama–French regressions, sub-period decomposition, and transaction cost sensitivity—not on the paper's central claim that the TV Index predicts equity returns: all 30 Golden Cross configurations outperform TOPIX (cumulative returns 88.75%–140.98%), confirming that the signal is broadly effective regardless of parameter choice. The cross-configuration Sharpe ratio heatmap (**Figure 4**) reveals a systematic pattern: Industry-level configurations consistently outperform Firm-level counterparts, and higher-concentration strategies (Top 5% and Top 10%) tend to deliver superior risk-adjusted returns across aggregation types. The selected configuration—combining industry-level aggregation, high concentration, and broad coverage—sits within the high-performance region of this parameter space, suggesting that its superiority reflects a convergence of structural advantages rather than arbitrary selection among equally plausible options. Reported performance figures should therefore be interpreted as in-sample benchmarks subject to potential overfitting, not as unconditional forecasts.

Viewership Data Constraints: The analysis uses 2017 NHK hourly viewership data as a fixed proxy for time-of-day audience distribution throughout 2019–2024. While intraday viewing patterns (*e.g.*, evening peaks) are generally stable, overall viewership levels fluctuated substantially during the sample period, particularly during COVID-19 when daytime at-home viewing increased. This assumption treats relative time-slot strength as constant, potentially misestimating absolute exposure during periods of unusual viewing behavior. Furthermore, the dataset reflects NHK, Japan's sole public broadcaster. While NHK's national reach makes it appropriate for measuring broad attention, commercial broadcasters exhibit different audience demographics and time-slot compositions. The absence of broadcaster-specific or year-specific viewership data limits the precision of exposure measurement and may introduce systematic error if viewing patterns shifted meaningfully over the five-year period.

Transaction Costs and Scalability: Table 11 demonstrates that the strategy's outperformance is robust across all four cost scenarios, including a conservative 40 bps stress test. The moderate positive SMB loading (mean 0.270) indicates some small-cap tilt, which implies that transaction costs for a subset of holdings may be non-trivial and warrants attention in live implementation. The strategy's capacity—the asset size at which returns degrade due to price impact at scale—remains unquantified. Practitioner guidelines suggest that rebalancing frequency should balance risk management against execution costs;[23] the monthly frequency employed here may be suboptimal under realistic cost structures for certain investor types.

Parameter Selection and Day-of-Week Effects: The Golden Cross parameters (MA4 and MA12) follow common technical analysis practice but were not optimized in-sample. While this avoids data snooping, the robustness of findings to parameter variation remains untested. Additionally, weekly returns use Friday closing prices, following standard practice to align with institutional reporting cycles. However, day-of-week effects—where Friday returns systematically differ from other weekdays due to weekend sentiment or trading patterns—could influence results. The sensitivity of findings to weekday selection has not been examined.

Sample Period and Regime Dependence: As reported in the sub-period analysis (**Table 12**), the During-COVID period yields paradoxically weak results: although limited attention theory[2] would predict that increased at-home viewership during lockdowns amplifies the TV Index signal by heightening advertising salience, elevated market-wide volatility inflated estimation noise, the alpha does not reach statistical significance ($\alpha = 0.575\%/\text{month}$, $t = 1.35$). This pattern mitigates concerns that overall results are inflated by pandemic-specific dynamics. Nonetheless, the 36-month post-pandemic window, while encouraging, represents a single market regime.

Future Research Directions

Out-of-Sample Validation and Parameter Robustness: True out-of-sample testing with data beyond December 2024 would address selection bias concerns and validate the strategy's predictive power. Systematic evaluation of Golden Cross parameters through grid search over plausible window ranges (*e.g.*, 3–8 weeks short-term, 8–26 weeks long-term), ideally using pre-registered specifications, would clarify whether results depend critically on specific parameter values or represent robust phenomena.

Refined Exposure Measurement: Incorporating year-specific or broadcaster-adjusted viewership data would improve exposure estimates and test sensitivity to viewing pattern shifts. Demographic-segmented viewership (*e.g.*, age-specific audiences) could refine attention measurement by linking advertising reach to investor demographics, potentially improving signal quality by weighting exposure toward audiences more likely to translate viewing into trading activity. Additional dimensions such as regional broadcast variation, spot positioning within programs, and creative intensity measures (*e.g.*, repetition frequency) would provide more nuanced representations of advertising exposure.

Implementation Design and Capacity Constraints: While **Table 11** demonstrates robustness across representative cost scenarios, future work should model position-size-dependent market impact functions to estimate net returns at meaningful asset scale.[27] Characterizing the asset threshold beyond which price impact erodes alpha—and identifying optimal rebalancing frequencies that balance signal capture against execution costs—would make strategy capacity constraints operationally precise for institutional deployment.

Cross-Country Comparative Studies: Japan's uniquely structured media environment may amplify attention effects. Media consumption habits, advertising regulations, and investor behavior differ substantially across countries. Markets with lower television viewership, stricter advertising restrictions, or institutional investor dominance may exhibit weaker or absent attention effects. Extending the analysis to diverse international settings would clarify whether television advertising universally signals investor attention or whether results are context-dependent. Such comparative work would also illuminate which institutional features—media concentration, retail investor participation, information asymmetry—amplify or dampen advertising-driven returns.

CONCLUSIONS

This study demonstrates that television advertising exposure contains predictive information for stock returns in Japan when filtered through a Golden Cross momentum rule applied to the TV Index. Using over 6.6 million commercials from 965 TSE-listed firms between April 2019 and December 2024, the analysis evaluates 36 portfolio implementations: 30 Golden Cross configurations varying aggregation methodology (Industry versus Firm level), coverage thresholds (90%, 80%, 70%), and concentration levels (Top 5–25%), plus an equal-weighted benchmark for each of the six data configurations. The best-performing configuration by Sharpe ratio—Industry-level filtering at 90% coverage with Top 10% concentration—achieves a cumulative return of 133.33%, a Sharpe ratio of 1.030, and maximum drawdown of -26.81%, outperforming TOPIX by 64.65 percentage points. Fama–French three-factor analysis reveals persistent positive alpha: the full-sample regression yields 0.905% monthly (11.42% annualized), with rolling 12-month windows averaging 0.79% monthly, confirming that alpha remains positive throughout most of the sample period. Industry-level aggregation demonstrates statistically significant superiority over firm-level approaches in risk-adjusted performance (Sharpe ratio difference +0.060, $p = 0.017$) and downside risk (maximum drawdown improvement +1.69 percentage points, $p < 0.001$), highlighting the value of sector-level smoothing in filtering idiosyncratic noise while preserving systematic attention effects.

These findings address a fundamental question in behavioral finance: whether investor attention, measured through media exposure, can generate predictive signals for equity returns. The results provide an affirmative answer in the Japanese context, where limited attention theory predicts that salient cues—such as television commercials—influence trading behavior when investors face information overload. The results are consistent with three complementary mechanisms identified in the Discussion: attention effects, soft information signaling, and liquidity broadening. The R^2 of 66.2% further confirms that roughly one-third of return variation remains unexplained by standard risk factors, pointing to TV Index signals as an independent return source. The superior performance of industry-level versus firm-level aggregation reveals that signal extraction benefits from sector-level smoothing, capturing systematic attention shifts across industries while filtering firm-specific advertising idiosyncrasies.

For practitioners, these findings suggest television advertising data may complement traditional signals in quantitative strategies. Transaction cost sensitivity analysis confirms economic viability across retail and institutional cost scenarios, even under a conservative 40 bps stress test with mean monthly turnover of 66%. The Post-COVID period (January 2022–December 2024) delivers the strongest risk-adjusted performance ($\alpha = 1.26\%$, $p < 0.01$), demonstrating that the signal reflects a persistent behavioral mechanism. However, implementation considerations include the strategy's unquantified capacity constraints, untested parameter robustness, and the in-sample nature of the reported performance figures.

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PRESS SUMMARY

Television commercials are a constant presence in the Japanese media landscape—yet the commercial data behind these broadcasts have remained largely underexplored as a source of investment information. This study constructed the TV Index, a weekly measure of television advertising intensity for 965 companies listed on the Tokyo Stock Exchange, using over six million commercial broadcast records. An investment strategy that buys stocks when their advertising momentum is accelerating consistently outpaced Japan's broad market benchmark (TOPIX) over the five-year period from 2019 to 2024. Crucially, this outperformance cannot be attributed to conventional market forces such as company size or value characteristics, pointing to a genuine and distinct source of investment information. The underlying mechanism appears to lie in investor attention. When companies intensify their advertising, they become more salient to everyday investors, who subsequently buy shares—driving prices upward before the broader market fully adjusts.

By identifying this pattern systematically, the strategy captures a premium that standard financial models miss. Television commercial data have seen little systematic use in investment to date. This study suggests they may offer a distinct edge—one rooted not in price history or financial statements, but in the everyday media environment that shapes how millions of people perceive companies.