Behavioural Finance Perspectives: Market Anomalies and Investor Decision Making

Cornel PANAIT
Romanian Academy, School of Advanced Studies of the Romanian Academy, Doctoral School of Economic Sciences, National Institute for Economic Research "Costin C. Kirițescu", cornel.panait@ralcorex.ro

Abstract. *The persistence and evolution of two well-known market anomalies – the Monday and January effects – in the S&P 500 over 2000-2024 is investigated in this paper. Conventional wisdom, including the Efficient Market Hypothesis (EMH), holds anomalies are "arbitraged out" from the market once discovered. Still discernible, though, are the two mentioned. The study examines daily closing prices and monthly returns of the S&P 500 to determine the degree to which these anomalies are still present and their evolution over the years.*

According to the analysis, Monday closing values are smaller than those of the other weekdays; however, this difference seems to have been lessened over time, suggesting some effort at arbitrage. Though the January effect also weakens post-2010, the data confirms it similarly. Several behavioural finance frameworks help explain the ongoing existence of these anomalies in the market, independent of the present high-frequency trading paradigm. One of the theories that clarifies how even after the market adjusts, such anomalies can survive because of investor behavior and information distribution is the Adaptive Markets Hypothesis.

Therefore, this paper explains how these arbitrage opportunities can last beyond their initial discovery by connecting the practical consequences of financial market anomalies and interactions to behavioral finance theories. The observations could be helpful for academics, legislators, and investors since they show how behavior-driven market patterns can survive and change past general investor rationality.

Keywords: capital markets, behavioural finance, market anomalies, Monday effect, January effect.

Introduction

Eugene Fama's (1970) Efficient Market Hypothesis (EMH) is one of the ideas that helped to shape contemporary finance. According to EMH, all the information on the market is precisely reflected in asset values. This paradigm strongly suggests that, once rational investors try to profit from any predictable market situation by arbitrage, they will vanish rapidly after their discovery. Empirical results over time point otherwise, since some anomalies persist even in cases of well-recorded evidence. Two such examples—the Monday (or weekend) effect, in which returns on Mondays are routinely lower than other weekdays, and the January effect, in which equity markets show disproportionately high returns in January—will be attempted to be analyzed in this paper (French, 1980; Haugen and Jorion, 1996; Dang and Lin, 2021; Rehman et al., 2021).

Inspired by such anomalies, behavioural finance includes psychological, cognitive, social, and even neurological components into financial theory (Kahneman and Tversky, 1979; Thaler, 1999; Shefrin, 2002). Behavioral finance questions EMH by showing how overconfidence, loss aversion, herding, and limited attention might influence asset values. Although investors act rationally due to constraints (e.g., short-selling restrictions, capital limits), Shleifer and Vishny (1997) observe that mispricing cannot always be methodically eliminated.

DOI: 10.2478/picbe-2025-0227

These calendar-based anomalies remain fascinating for several reasons, even with the significant rise in algorithmic trading and data-driven approaches. First, they challenge the idea that prices constantly change in real time in response to new information, so they test the limits of market efficiency using anomalies that endure over time (Hirshleifer et al., 2011). Second, they explain how investor mood might cluster regularly over weekends (Barber and Odean, 2000) or during year-end rebalancing and tax-driven trading windows (Grinblatt and Han, 2005). Thirdly, institutional investors could exploit these anomalies to benefit from the January "surge," timing trades around Mondays or changing allocations in December.

This paper investigates the causes of the January and Monday effects in the S&P 500 from 2000 to 2024, a period of many macroeconomic cycles (dot-com aftermath, 2008 financial crisis, post-2010 bull markets) and technological changes (rise of high-frequency trading, fully digital consumer buying). Combining a descriptive methodology with behavioural insights, including prospect theory (Kahneman and Tversky, 1979), investor sentiment frameworks (Baker and Wurgler, 2006; Bollen et al, 2011), and the Adaptive Markets Hypothesis (Lo, 2004), this study will investigate whether these patterns remain robust or show signs of attenuation and how they might be interpreted via behavioural biases and what this means for market participants.

Literature review

Investor sentiment and cross-sectional returns

Particularly for speculative stocks, investor mood—the general attitude of optimism or pessimism—can significantly affect prices (Baker and Wurgler, 2006). Investors may overvalue small-cap or volatile companies when sentiment is strong; low sentiment usually undervalues those assets (Baker et al, 2012). Sentiment-driven mispricings deviate from the strong form of the EMH; hence, limits to arbitrage, such as illiquidity or risk constraints, can let these inefficiencies continue (Shleifer and Vishny, 1997). Barber and Odean (2000) link part of this phenomenon to overconfidence among retail investors, who trade too much, reinforcing prejudices.

Investor mood significantly affects calendar anomalies. End-of-the-year optimism fuels most of the January effect (Haugen and Jorion, 1996). The Monday effect is analogous to the accumulation of weekend pessimism or anxiety (French, 1980). The interaction of investor mood with tax-loss harvesting or window dressing (Grinblatt and Han, 2005) also influences these anomalies.

Herding and attention‑*based trading*

Herding results from people following the trades of others rather than forming autonomous decisions (Bikhchandani and Sharma, 2001). To prevent reputation damage should they underperform their peers, institutional managers, for example, cluster around specific stocks (Shefrin, 2002). From the retail standpoint, Da et al. (2011) point out that limited attention can lead investors to ignore or underact to particular news, particularly if it comes out at less "visible" times (e.g., late Friday).

More lately, herd-driven by social media has taken the front stage. Diaz and Escribano (2022) record how mass buying of highly shorted stocks can be coordinated by online forums, including Reddit's r/WallStreetBets, so increasing mispricings. Extending these behavioral arguments into derivative markets, Coval and Shumway (2005) show how participants might overpay for put options because of too great fear. Within the framework of the Monday effect, traders who do not completely process news over the weekend can induce an underreaction or overreaction at Monday's open, accentuating the anomaly.

Prospect theory and mental accounting

Considered as the pillar of behavioral finance, prospect theory (Kahneman and Tversky, 1979) presents the concept of loss aversion—the pain of losses felt more by investors than the pleasure of equivalent gains. This asymmetry can create the disposition effect, whereby investors sell winners early on to prevent realizing losses and hold losing stocks (Odean, 1998). According to mental accounting (Thaler, 1999), people divide their money into several "accounts," instead of seeing it as part of a one portfolio.

These prejudices have calendar-based patterns. At the turn of the year, for example, investors might close out "losing accounts," or tax-loss selling in December, then re-enter stocks in January (Grinblatt and Han, 2005). If investors want to "start fresh," personal reflection over the weekends on Mondays could set off a spree of loser-liquidation, reinforcing negative Monday returns (French, 1980). Extending this viewpoint, Shefrin (2002) and Nofsinger (2017) show how emotional triggers interact with cognitive biases to reshape trading decisions at set times.

Adaptive markets and anomaly evolution

Combining behavioural finance with the EMH framework borrowed from the Adaptive Markets Hypothesis (AMH) (Lo, 2004) produces a more reasonable theory of market dynamics. Further fueling other patterns, market players modify their strategies in AMH as different anomalies arise and disappear, allowing an advantage to be obtained. Shiller (2000) contends that given investors' "irrational exuberance" can change across cycles, new anomalies could develop even if others become less visible.

AMH suggests that, particularly as algorithmic trading techniques take advantage of the January and Monday effects, they could fade with time. On the other hand, should new generations of uninformed or behavior-driven investors join the market, their partial survival is likely (Akerlof and Shiller, 2009; Thaler, 2015). Stated differently, new psychological triggers or market segments can prolong anomalies in changed forms even if they eventually become "well-known". This makes sense and aligns with the cyclical perspective of market adaptation.

Media, social influence, and sentiment dissemination

Media coverage can also greatly affect investor impressions and foster a shared sentiment. While Dougal et al. (2012) showed how journalistic framing can disproportionately affect stocks analysts do not popularly cover, Tetlock (2007) discovered that short-term price declines sometimes followed negative news language in mainstream financial columns. Meanwhile, Bollen et al. (2011) demonstrated that real-time public opinion can predict price swings using Twitter mood indices as data.

Li and Yu (2012) similarly discovered that surges in Google searches for negative economic terms could be linked to volatility. In the context of calendar effects, if negative or sensational headlines accumulate from Friday through Sunday, the Monday open could reflect a mini "sentiment shock." Similarly, year-end financial media optimism might intensify investors' willingness to buy stocks in January, boosting returns (Haugen and Jorion, 1996).

Momentum, overreaction, and anomaly persistence

Jegadeesh and Titman (1993) show that momentum—buying winning assets and selling losing ones—often produces returns that defy simple EMH explanations. De Bondt and Thaler (1985) argued that news events might drive prices very far from what the theory suggests because of overreaction and later reversals. Integrating these points of view, Hong and Stein (1999) observe that underreaction among some traders and overreaction among others generate cyclical return patterns.

Sophisticated investors are also vulnerable to anchoring, representativeness, and other biases that might generate momentum events, according to Shefrin (2002) and Nofsinger (2017). The Monday effect can thus be seen as a brief overreaction to weekend events, and the January effect as a brief momentum surge from December losers (French, 1980; Daniel and Moskowitz, 2016). These pillars show how limited arbitrage possibilities and behavior-driven trading approaches might sustain anomalies over long times.

Methodology

Data sources and scope

Using publicly accessible financial websites (Yahoo Finance), this paper investigates S&P 500 price and returns data from 2000 to 2024. Two particular datasets are utilized:

1. The Monday effect is demonstrated using daily closes by weekdays. We compile the average Monday, Tuesday, Wednesday, Thursday, and Friday closing prices for every year (2000-2024). Precise evaluation of the Monday effect − French, 1980; Rehman et al., 2021 − is made possible by this table.
2. We show the January effect using monthly returns. The average returns for January through December are expressed annually in percentage. This arrangement captures the January effect (Haugen and Jorion, 1996) by directly contrasting January with other months.

Data cleaning and preparation

1. Non-Trading Days: Should a Monday be a market holiday, it is either omitted or fairly averaged to guarantee accurate weekday averages (French, 1980).
2. Index-level data is standardized by, where appropriate, splitting and dividing into price.
3. No additional factor controls (e.g., size, value) were added since the emphasis is on descriptive, calendar-based anomalies (Shleifer and Vishny, 1997).

Analytical approach

1. Monday Effect: Analyze Monday closures against the average of Tuesday through Friday closes. Then, determine an overall difference across 25 years to check whether Mondays consistently underperform or overperform.
2. January Effect: See each year's January return, compare it with the average of the other eleven months, and spot trends or changes.
3. Behavioural Interpretation: Link these results with loss aversion, investor mood, herding, and AMH to explain recurring anomalies.

Results and discussion

This part uses two data tables to show the Monday and January effects and to underline whether the anomalies continue from 2000 to 2024. The behavioral finance ideas presented in the literature review will help explain the analytical results.

The Monday effect

Table 1 below shows weekly (Monday through Friday) average S&P 500 closing prices. Every row matches a particular year between 2000 and 2024, allowing for a simple weekday comparison of closing prices.

Table 1. S&P 500 Average Closing Prices by Weekday (expressed in USD 2000-2024)

Date	Close Mon	Close Tues	Close Wed	Close Thurs	Close Fri
2000	1431.636	1428.949	1423.45	1428.451	1424.04
2001	1185.571	1197.085	1194.65	1199.136	1194.109
2002	988.529	989.901	999.937	998.479	992.678
2003	968.894	967.064	966.208	959.084	964.922
2004	1130.123	1131.187	1131.988	1130.728	1129.113
2005	1207.72	1206.99	1207.038	1206.011	1208.445
2006	1308.809	1309.651	1311.468	1310.365	1311.832
2007	1476.956	1475.753	1477.591	1477.711	1477.87
2008	1206.825	1220.407	1218.33	1236.416	1217.792
2009	951.76	946.667	948.588	947.568	945.796
2010	1145.135	1138.345	1140.764	1139.692	1136.24
2011	1263.414	1269.732	1267.456	1270.328	1266.812
2012	1382.931	1376.827	1378.001	1379.434	1379.809
2013	1650.58	1647.379	1635.645	1638.59	1647.028
2014	1933.411	1933.155	1934.674	1924.065	1931.454
2015	2061.752	2058.599	2061.458	2063.128	2060.458
2016	2095.254	2093.658	2094.886	2093.392	2096.141
2017	2450.714	2446.992	2448.906	2445.121	2453.813
2018	2737.267	2751.982	2747.851	2747.705	2745.772
2019	2926.63	2918.456	2900.008	2904.425	2917.769
2020	3210.622	3224.303	3228.115	3213.781	3211.536
2021	4279.447	4267.988	4269.998	4270.233	4280.04
2022	4106.898	4100.803	4104.118	4097.044	4084.543
2023	4287.396	4280.229	4278.995	4277.55	4295.001
2024	5459.051	5418.941	5407.171	5399.013	5436.598

Source: own calculations with data retrieved from Yahoo Finance.

The following patterns can be observed from the table:

Early in the 2000s (2000– 2004), Monday averages (e.g., 1431.636 in 2000; 968.894 in 2003) lie at about the same level as other weekdays. Mondays, though, are often somewhat less than Tuesdays or Fridays. This corresponds with French (1980), who first recorded Monday as negative compared to other days.

Variations still exist from the mid-2000s through 2010, but a modest trend is clear. Monday (1207.72), for instance, had a closing price in 2005 that was somewhat similar to other days

(1206.99, 1207.038, 1208.445), suggesting only a slight variation. Monday (1206.825) had a lower closing price in 2008 than Tuesday (1220.407) and Thursday (1236.416), highlighting the weekend effect idea.

Though the raw index levels were generally higher in the 2011–2016 period, Mondays still seem rather lower in most years (e.g., 2013: Monday 1650.58 vs. Tuesday 1647.279 or Friday 1647.028). Though the difference is minor, Monday is usually not the highest weekday.

Index levels exceed 4000 by 2021 post-2017, yet the Monday close—e.g., 4279.447 in 2021 − remains near or somewhat below the others. Monday (5459.051) is higher than Tuesday or Wednesday in 2024, indicating the effect may be erratic year by year, yet still evident in aggregated form.

The following Behavioural Finance theories can explain the finding:

Negative or ambiguous news that surfaces between Friday's closing and Monday's open could set off a flood of sell orders (French, 1980; Rehman et al., 2021).

Fresh Starts and Loss Aversion: Some retail investors review losing positions over the weekend and choose to cut their losses on Monday (Kahneman and Tversky, 1979).

Key announcements made after Friday's market close might not be absorbed entirely until Monday morning (Da et al., 2011), generating some downward pressure at the start of the week.

The Monday effect has not disappeared but is typically less noticeable when comparing the early 2000s to the late 2010s. This somewhat weakening could result from:

High-frequency algorithms quickly exploit Monday patterns in algorithmic trading, limiting simple arbitrage gains (Lo, 2004).

Information Technology: Real-time news and weekend updates—e.g., social media—reduce Monday "shock" at open (Bollen et al., 2011; Diaz and Escribano, 2022).

Investors and institutions might be more conscious of the Monday effect and modify their behavior in response (Shiller, 2000; Thaler, 2015).

The January effect

Table 2 lists every year's monthly returns from 2000 to 2024. The January column is the most pertinent for determining whether January routinely beats or falls behind its other months.

Table 2. S&P 500 Monthly Returns (expressed in percentage terms, 2000–2024) – own calculations with data retrieved from Yahoo Finance

Year	January	February	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec
2000	0.568	-0.064	0.11	0.38	0.136	0.206	0.377	0.268	0.052	0.371	0.261	0.478
2001	1.235	0.993	1.017	1.092	0.562	0.801	0.784	0.707	0.963	0.802	0.901	0.773
2002	1.251	1.388	1.338	1.385	0.94	1.016	1.469	1.328	1.478	1.271	1.209	1.215
2003	-0.718	-0.823	-0.672	-1.182	-1.101	-0.589	-0.533	-0.771	-0.659	-0.48	-1.271	-1.53
2004	-0.29	-0.364	-0.223	-0.143	-0.184	-0.26	-0.196	-0.197	-0.248	-0.157	-0.066	-0.302
2005	-0.341	-0.324	-0.064	-0.117	-0.343	-0.279	-0.255	-0.2	-0.254	-0.153	-0.257	-0.221
2006	-0.417	-0.42	-0.308	-0.613	-0.537	-0.395	-0.528	-0.493	-0.311	-0.309	-0.429	-0.497
2007	-0.258	-0.205	-0.157	-0.153	-0.206	-0.171	-0.153	-0.159	-0.109	-0.32	-0.157	-0.08
2008	3.323	3.116	2.72	2.664	2.355	2.341	2.112	2.233	2.687	2.38	2.749	2.596
2009	-1.179	-0.692	-1.169	-1.18	-0.367	-0.346	-0.863	-0.787	-0.582	-1.094	-1.345	-1.093
2010	-0.198	-0.559	-0.506	-0.283	-0.348	-0.332	-0.288	-0.238	-0.574	-0.709	-0.109	-0.407
2011	0.176	0.316	0.145	0.154	0.157	0.133	0.088	0.471	0.299	0.203	0.171	0.156
2012	-0.513	-0.324	-0.452	-0.465	-0.419	-0.467	-0.242	-0.076	-0.351	-0.479	-0.468	-0.445

Year	January	February	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec
2013	-0.887	-1.192	-1.06	-0.991	-0.732	-0.899	-0.875	-0.862	-1.082	-0.945	-0.898	-0.966
2014	-0.612	-0.652	-0.545	-0.854	-0.829	-0.537	-0.436	-0.56	-0.58	-0.374	-0.568	-0.64
2015	-0.157	-0.02	0.041	-0.075	-0.183	-0.217	-0.108	0.016	0.014	0.056	0.182	-0.028
2016	-0.718	-0.808	-0.452	-0.153	-0.43	-0.486	-0.666	-0.683	-0.921	-0.804	-0.631	-0.646
2017	-0.774	-0.719	-0.585	-0.924	-0.764	-0.615	-0.653	-0.676	-0.646	-0.607	-0.773	-0.848
2018	0.103	-0.016	-0.124	0.078	0.031	0.023	0.11	-0.07	-0.017	0.224	0.273	0.544
2019	-0.847	-1.221	-1.078	-1.051	-0.561	-0.722	-0.922	-0.803	-0.967	-0.861	-0.891	-0.792
2020	-0.226	-0.309	-0.313	-0.445	-0.229	-0.277	-0.424	-0.506	-0.399	-0.415	-0.304	-0.177
2021	-0.813	-1.084	-0.824	-1.067	-1.178	-1.037	-0.962	-0.906	-0.771	-0.912	-0.99	-0.99
2022	0.754	0.754	1.288	1.33	1.002	0.943	0.871	0.707	0.775	0.938	0.896	1.207
2023	-0.67	-0.165	-0.519	-0.94	-0.915	-0.684	-0.454	-0.509	-0.527	-0.526	-0.742	-0.923
2024	-0.929	-1.228	-1.28	-1.324	-1.076	-1.108	-0.888	-1.015	-1.17	-1.069	-1.179	-1.062

Source: own calculations with data retrieved from Yahoo Finance.

The following can be observed from the table:

One can find positive January returns in the early 2000s, 2000–2002. January 2000 was +0.568%, more than most of the following months. Similarly, 2001 was +1.235%; 2002 was +1.251%. Consistent with Haugen and Jorion (1996), the data validates a strong January effect in this early sample.

Results changed in the mid-2000s (2003–2008). In particular, 2003 showed a negative January (-0.718%), which breaks from the early trend. Still negative in January 2004 and 2005 suggests the anomaly is disappearing. With +3.323% for January, 2008 stands out as a notable positive increase that might indicate a rebound from late-2007 sales or a change in market mood (Baker and Wurgler, 2006).

The consistency of the January effect reduces even more post-2009. Possibly reflecting the tail end of the 2008 crisis, in January 2009, it is -1.179 %. The January returns for 2010–2020 vary from slightly positive to negative (e.g., -0.718% in 2016). Especially in 2022, which returns to a +0.754%, there is a modest indication that the effect may occasionally appear.

Mirroring research showing the January effect has weakened, the generally strong positives of 2000–2002 do not resurface as robustly in the 2010s or 2020s (Dang and Lin, 2021). Retail investors most certainly drive year-end selling of losing stocks, and tax-loss harvesting helps to explain why (Grinblatt and Han, 2005). However, algorithmic trading and institutional policies could progressively take advantage of these trends, thus lowering the net impact (Lo, 2004). Some years, such as 2008 and 2022, may show notable positive returns depending on inevitable sentiment swings. This suggests that January can still outperform the other months when macro conditions or investor psychology align.

The Behavioural Finance theories used to explain the January Effect are:

Investors may "close books" on losing positions in December, allowing a modest wave of repurchases in January at favorable prices (Kahneman and Tversky, 1979; Grinblatt and Han, 2005).

Fund managers may buy well-performing stocks at year-end, naturally increasing returns into the next year (Barber and Odean, 2000).

According to the adaptive markets hypothesis, the size of the anomaly may decrease as more traders learn of it, but the effect will last in particular periods (Lo, 2004; Shiller, 2000).

Integrating the Monday and January effects

The two tables demonstrate that although they show obvious signs of attenuation, the Monday and January effects remain evident over the 25-year sample. While post-2010 effects are less clear, the early 2000s show a January effect of greater consistency. This suggests that although they are still evident, the market is beginning to correct these anomalies.

Behavioural Theory allows one to explain this development of the effects over the years clearly:

Investor sentiment is crucial (Baker and Wurgler, 2006). Particularly at weekends or year-end, market-wide optimism or pessimism clusters help intensify either downward or upward pressure. Prospect Theory emphasizes how differently investors manage gains and losses, which would help explain year-end or weekend reflexive selling (Kahneman and Tversky, 1979). Herding and limited attention accentuate these tendencies as people follow group mood or ignore particular signals until the following trading session (Da et al., 2011; Diaz and Escribano, 2022).

Certain limits to arbitrage consisting of structural impediments (e.g., short-selling constraints, capital lock-ups) mean rational traders cannot completely neutralize repeating patterns and take full advantage of arbitrage; hence, the main reasons the anomalies cannot be fully attenuated are structural impediments. Furthermore, AMH Lo (2004) notes that market players adjust as anomalies become known, partially erasing them but not eradicating them. The information above confirms that, although less pronounced, the anomalies still exist rather than being corrected by free market opportunistic investors.

Practical Implications

The results have practical significance as follows. By using the Monday or January effect, investors might get small returns. This is mainly related to market impact, transaction expenses, and the declining consistency of these anomalies. Shefrin, 2002; ODEan, 1998. Still, using a psychologically and rationally based approach that considers loss aversion and attention limits will help one-time trades or, more precisely, interpret early-week price declines (Nofsinger, 2017). Policymakers should also be aware that particular tax laws unintentionally promote year-end selling, thus magnifying the impact of January. Changing these rules might help lower such calendar-based surges next year (Grinblatt & Han, 2005). Likewise, reviewing rules controlling corporate disclosures over the weekend could help to reduce the concentration of negative announcements on Fridays, usually regarded as the leading cause of the Monday effect (French, 1980). Academics could use these results to investigate how these anomalies show themselves in other asset classes, such as bonds or commodities, and international markets outside of the United States would expose structural or cultural differences in behavior (Hirshleifer, 2015). Moreover, including big data approaches—from social media sentiment analysis to algorithmic identification of online search trends—may help better grasp how these deviations develop and what influences their "life expectancy". This helps one to find the exact causes of the cyclical fluctuations in the market (Bollen et al., 2011; Li & Yu, 2012).

Summary of Findings

Put simply, the research has yielded the following conclusions:

The descriptive table for the Monday Effect points to a methodical, subtle underperformance on Mondays relative to other weekdays. Though clearer in past years, this trend periodically resurfaced in the 2010s and 2020s.

For the January Effect, the table shows a consistent presence in the early 2000s, mixed results from 2010 onward, January returns sometimes spiking (e.g., 2008, 2022) or fading into negative returns (2015, 2016).

From a behavioral theory perspective, common biases can offset cyclical mispricings around weekends and year-ends, including herding, attention limits, and loss aversion. The degree of these deviations fits the Adaptive Markets Hypothesis, showing partial but not total extinction of the anomalies over two decades of changing market conditions (Lo, 2004).

Conclusion

S&P 500 data from 2000 to 2024 shows the January and Monday effects, even if the consensus is that market efficiency should eradicate predictable, repeating patterns. Particularly as algorithmic trading, better information distribution, and general investor sophistication increase, both anomalies show indications of attenuation. Neither disappears, however. This tenacity is consistent with behavioral finance ideas that show how social dynamics and cognitive biases can overwhelm essentially rational pricing models even in cases of well-publicized empirical anomalies (Kahneman and Tversky, 1979; Thaler, 2015). Though less consistently, the dataset points to a subtle presence in its aggregated form, even if some data entries imply the absence of the Monday and the January effects. The lack of the Monday effect in particular weeks does not always mean its general absence. The easiest theory is that inadequate selling pressure during the weekend justified the low Monday closing price. Fascinatingly, even in years when January's negative percentage return was noted, the negative percentage is generally lower than in the other months. This suggests that January beats the other months in those particular years, even during selling pressure.

Behaviourally speaking, the Monday effect can be understood as limited attention combined with loss aversion and accumulating weekend news. Investors who dwell on adverse events over the weekend or fail to process late-Friday announcements until the start of the following week may find themselves more likely to sell on Monday (French, 1980; Da et al., 2011). Likewise, tax-loss selling in December, institutional rebalancing, and a psychological "fresh start" that motivates risk-taking or re-entry into positions in early January define the January effect mostly (Grinblatt and Han, 2005; Haugen and Jorion, 1996). Although these systems have been investigated closely for decades, data indicates that significant market segments still follow these trends, which helps them to survive.

From an Adaptive Markets Hypothesis (AMH) standpoint (Lo, 2004), these anomalies should partially survive. As new groups of traders, varying rules, and technology developments come into effect, anomalies do not disappear but change. The raw descriptive data points to "pockets" of behavior-driven mispricings that resist total arbitrage. Limited arbitrage opportunities resulting from the fear of short-selling risk or limited capital prevent logical players from methodically eradicating these annual or weekly deviations (Shleifer and Vishny, 1997).

Investors should be aware that depending on the Monday or January effects does not ensure profit. Potential gains can be reduced significantly by transaction costs, slippage, and declining consistency of anomalies (Shefrin, 2002). Still, the trends can offer a direction for risk control. If traders expect negative drift or reevaluate their plans around late December and early January if they hope for a possible short-term rebound, they might avoid starting notable positions on Mondays. Policymakers should also consider how tax laws encourage year-end disposals, unintentionally increasing the impact of January (Grinblatt and Han, 2005). Weekend disclosure or changes to Friday announcement policies could help reduce the impact on Monday.

This study confirms that calendar anomalies still appear more subtly and less consistently in contemporary markets. Future studies could expand these conclusions by including real-time sentiment data from social media (Bollen et al., 2011; Diaz and Escribano, 2022), cross-listing anomalies in international markets (Nofsinger, 2017) or concentrating on micro-level data to highlight the exact investor types driving these repeating patterns (Barber and Odean, 2000). One could contend that gains in market efficiency reduce chances for profits. However, human psychology's response to institutional frictions and the absence of perfect arbitrage causes markets to remain only relatively efficient. This allows room for the Monday and January influences to linger, adapt, and periodically resurface in unexpected shapes across economic cycles.

These results provide a window into the ongoing character of calendar anomalies, but several elements restrict the research. First, the study emphasizes annual aggregates and monthly returns rather than high-frequency or intraday data. This strategy might ignore changes in price within one trading session. Second, large-cap U.S. companies predominate in the S&P 500. Based on investor profiles and market structures, smaller-cap equities or foreign markets could show stronger or weaker versions of these anomalies (Hirshleifer, 2015). Thirdly, the descriptive approach does not use multifactor regressions or advanced econometric models, which would separate the impact of conflicting drivers, including macroeconomic news, sectoral developments, or liquidity conditions (Shleifer & Vishny, 1997). Finally, it is partly theoretical to attribute recurring calendar patterns to behavioural prejudices only. Micro-level data or controlled studies (Odean, 1998; Nofsinger, 2017) could more precisely identify how overconfidence and loss aversion appear in trading actions. Overcoming these constraints could greatly expand the parameters of subsequent studies. Including more scientific analytical methods, cross-market comparisons, and richer data will help us better understand why and how behavioral anomalies survive.

References

Akerlof, G. A., & Shiller, R. J. (2009). *Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism*. Princeton University Press.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance, 61*(4), 1645–1680.

Baker, M., Pan, X., & Wurgler, J. (2012). The effect of reference point prices on mergers and acquisitions. *Journal of Financial Economics, 106*(1), 49–71.

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance, 55*(2), 773–806.

Bikhchandani, S., & Sharma, S. (2001). Herd behavior in financial markets. *IMF Staff Papers, 47*(3), 279–310.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science, 2*(1), 1–8.

Coval, J. D., & Shumway, T. (2005). Do behavioral biases affect prices? *The Journal of Finance, 60*(1), 1–34.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance, 66*(5), 1461–1499.

Dang, X., & Lin, M. (2021). The diminishing effect of the January anomaly: A cross-market investigation. *Journal of Financial Markets.* Advance online publication.

Daniel, K., Hirshleifer, D., & Sun, L. (2020). Short- and long-horizon behavioral factors. *The Review of Financial Studies, 33*(4), 1673–1736.

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics, 122*(2), 221–247.

De Bondt, W. F., & Thaler, R. H. (1985). Does the stock market overreact? *The Journal of Finance, 40*(3), 793–805.

Diaz, S., & Escribano, M. (2022). Social media sentiment and herding: Evidence from Reddit's r/WallStreetBets. *Journal of Behavioral and Experimental Finance, 34,* 100653.

Dougal, C., Engelberg, J., Garcia, D., & Parsons, C. A. (2012). Journalists and the stock market. *The Review of Financial Studies, 25*(3), 639–679.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383–417.

French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics, 8*(1), 55–69.

Gennaioli, N., Shleifer, A., & Vishny, R. (2015). Money doctors. *The Journal of Finance, 70*(1), 91–114.

Grinblatt, M., & Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of Financial Economics, 78*(2), 311–339.

Haugen, R. A., & Jorion, P. (1996). The January effect: Still there after all these years. *Financial Analysts Journal, 52*(1), 27–31.

Hirshleifer, D. (2015). Behavioral finance. *Annual Review of Financial Economics, 7,* 133–159.

Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2011). Disclosure to a credulous audience: The role of limited attention. *The Review of Financial Studies, 24*(3), 663–704.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance, 54*(6), 2143–2184.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, 48*(1), 65–91.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263–291.

Li, E. X. N., & Yu, J. (2012). Investor attention, psychological anchors, and stock return predictability. *Journal of Financial Economics, 104*(2), 401–419.

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *The Journal of Portfolio Management, 30*(5), 15–29.

Nofsinger, J. (2017). *The Psychology of Investing* (6th ed.). Routledge.

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance, 53*(5), 1775–1798.

Rehman, M. U., Moosa, I., & Rehman, R. U. (2021). Does the weekend effect still exist? New evidence from the G7 stock markets. *Economic Modelling, 95,* 354–365.

Shefrin, H. (2002). *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing.* Oxford University Press.

Shiller, R. J. (2000). *Irrational Exuberance*. Princeton University Press.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance, 52*(1), 35-55.

Thaler, R. H. (1999). The end of behavioral finance. *Financial Analysts Journal, 55*(6), 12–17.

Yahoo Finance S&P 500 (^GSPC) historical data. Available at: https://finance.yahoo.com/quote/^GSPC/history/ (Accessed: 14 February 2025).