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Revisiting Stock Price Bubbles: Behavioral Evidence from Pop Mart

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Abstract. This paper examines whether strong fundamental growth can coexist with speculative stock-price dynamics, using Pop Mart as a case study. With data from December 2020 to June 2026, I apply the supremum augmented Dickey–Fuller (SADF), generalized SADF (GSADF), and log-periodic power law singularity (LPPLS) methods and examine trading activity, public attention, and reactions to corporate announcements. GSADF identifies an explosive regime from October 2024 to October 2025, while rolling LPPLS indicators provide complementary evidence of nonlinear acceleration during the expansion. Bubble weeks exhibit higher returns, trading volume, and Google search attention. Lagged attention remains positively associated with bubble status across alternative specifications and measures. Event studies show positive abnormal returns around the 2024 interim results but negative reactions to the 2025 profit alert and 2026 annual-results announcement. These findings are consistent with fundamental improvement and speculative amplification occurring together, although they do not establish causal effects or directly measure mispricing.

Keywords: Stock Price Bubbles, Behavioral Finance, Investor Attention, GSADF, LPPLS

1. Introduction

Stock-price bubbles are often associated with prices becoming detached from fundamentals. A harder case arises when the underlying business is also improving: rapid appreciation may reflect genuine growth, increasingly optimistic expectations, or a speculative process in which the two reinforce one another. This distinction matters for firms whose valuations depend on intellectual property (IP), brand popularity, and uncertain future demand. Favorable operating results can support a revaluation while also providing the narrative around which investors form increasingly ambitious expectations. A large price increase alone cannot distinguish these possibilities.

Pop Mart provides a useful setting for examining this tension. Following a prolonged decline between 2021 and early 2023, its share price recovered in 2024 and accelerated through much of 2025. The expansion coincided with the international popularity of characters such as Labubu, stronger operating performance, and rising public attention. A substantial correction followed even as the company continued to report strong results. The case therefore raises a question that is not resolved by either stock returns or earnings growth alone: did a fundamentals-supported recovery develop into price dynamics consistent with speculative amplification?

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Theoretical and behavioral research explains how disagreement, overconfidence, resale incentives, and limited attention can sustain speculative demand [1-3]. Statistical methods, meanwhile, identify explosive or nonlinear price processes associated with bubbles. These perspectives address different parts of the problem. Price-based tests locate unusual dynamics but do not identify the surrounding behavioral mechanisms; measures of public attention describe interest in a firm but do not by themselves establish a bubble. Studying them together can clarify how an exceptional valuation episode differs from ordinary trading conditions.

This paper asks two related questions: whether Pop Mart experienced a statistically identifiable explosive regime, and which market and behavioral characteristics accompanied it. I use daily stock-market data from December 2020 through June 2026 and apply SADF and GSADF tests to identify and date explosive behavior. Rolling LPPLS indicators provide a complementary measure of nonlinear price dynamics. Weekly comparisons and regressions then examine Google search attention, trading volume, volatility, and market returns. Finally, event studies compare reactions to three major corporate announcements at different stages of the valuation cycle.

The analysis yields three findings. GSADF identifies an explosive regime from October 2024 to October 2025, with LPPLS positive-bubble signals concentrated in parts of the same expansion. Bubble weeks have higher company returns, trading volume, and search attention; attention remains positively associated with subsequent bubble status after controls and under the alternative LPPLS measure. Corporate announcements also receive different responses across the cycle: the 2024 interim results generate positive abnormal returns, whereas the 2025 profit alert and the March 2026 annual results receive negative responses. This contrast is consistent with changing expectations, although the event studies do not directly measure investors' prior forecasts.

The contribution is to connect bubble identification with behavioral and announcement evidence within one firm's valuation cycle. For an IP-driven consumer company, strong realized growth and speculative price dynamics need not be mutually exclusive. The analysis offers evidence on their coexistence, rather than a valuation model that separates fundamental value from a bubble component. Its conclusions are correspondingly limited: recursive tests and LPPLS identify price patterns, weekly regressions establish conditional associations, and three announcements provide case-specific evidence of possible expectation adjustment.

2. Background and related literature

2.1. Pop Mart and its valuation cycle

Pop Mart's valuation cycle combines a substantial business expansion with large changes in market prices. Figure 1 shows its stock price and trading volume over the sample. The stock declined from 2021 through early 2023, recovered during 2024, and appreciated rapidly in 2025 before correcting. Trading activity also increased during the expansion. These patterns provide context for the formal tests; neither the size of the price increase nor its coincidence with corporate developments is sufficient to establish a bubble or a causal explanation.

The recovery coincided with growing demand for Pop Mart's proprietary characters, including Labubu, and stronger reported operating performance. Its 2024 interim results documented growth in THE MONSTERS products and rapid expansion in the plush-toy segment.[1]These developments provided a business basis for more optimistic expectations. At the same time, valuations tied to the

[1] Pop Mart International Group Limited, 2024 Interim Results Announcement, August 20, 2024.

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future popularity of intellectual property remain sensitive to beliefs about how long growth can persist. The distinction between realized performance and expectations of future performance is therefore central to the case.

In July 2025, a positive profit alert projected first-half revenue growth of at least 200% and profit growth of at least 350% year-on-year.[2]The stock had already appreciated substantially by then. Pop Mart subsequently reported strong revenue and profit growth for 2025,[3]yet its share price fell by more than 20% following the March 2026 earnings release.[4]Section 5.3 examines the abnormal returns around these announcements and the 2024 interim results. The contrasting responses motivate an analysis of how the market assessed favorable operating information at different valuation stages, without assuming that reported growth exceeded expectations in every case.

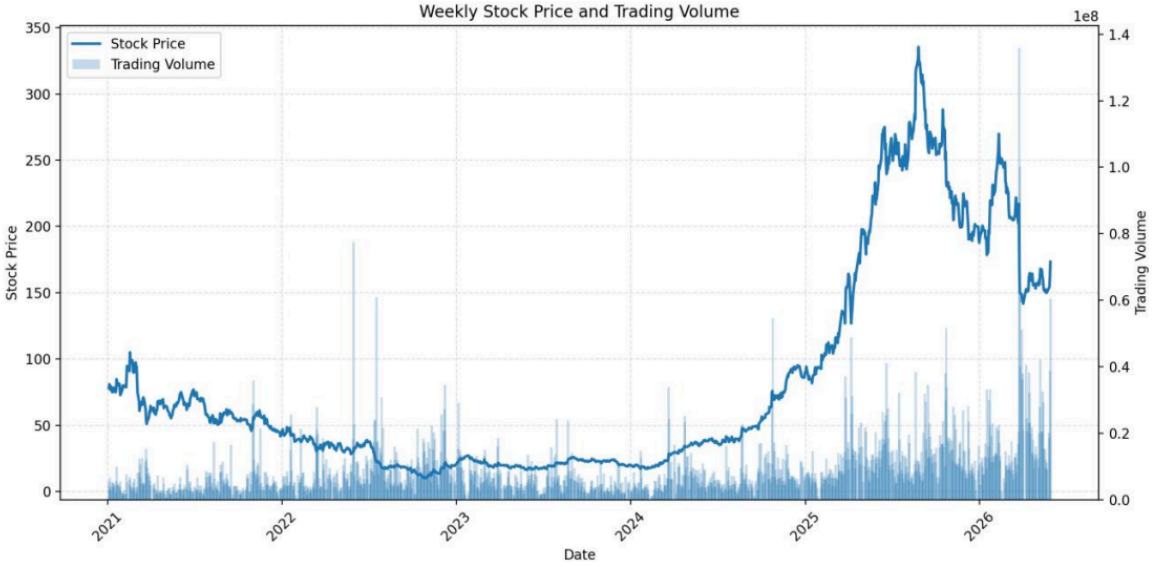


Figure 1. Market evolution of Pop Mart

Notes: Stock price and trading volume over the study period. Corporate announcements discussed in Section 2.1 are examined in Table 4.

2.2. Related literature and research motivation

Theoretical models explain why speculative demand can arise even when investors observe favorable information. Kreps [1] link heterogeneous beliefs to the option of reselling to more optimistic investors, while Blanchard and Watson [4] study bubble components that can persist before collapsing. Scheinkman and Xiong [2] combine overconfidence, disagreement, and short-sale constraints to explain bubbles and high trading volume. Behavioral models further connect biased beliefs to extrapolation of past information [5], while noise-trader risk can limit corrective arbitrage [6]. These mechanisms motivate attention to trading activity and expectations alongside prices.

Empirical identification is difficult because fundamental value is not directly observable. Shiller [7] examines volatility relative to dividends, and Diba and Grossman [8] study explosive rational bubbles. More recent methods identify unusual dynamics directly from prices. Phillips et al. [9]

[2] Pop Mart International Group Limited, Positive Profit Alert, July 2025.

[3] Pop Mart International Group Limited, Annual Results Announcement for the Year Ended December 31, 2025, March 25, 2026.

[4] Reuters, "Shares of Labubu Maker Pop Mart Plunge After Reporting Annual Earnings," March 25, 2026.

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introduce the SADF test, and Phillips et al. [10] extend it to GSADF, allowing both ends of the estimation window to vary. This flexibility supports the identification of multiple explosive episodes and their timing within a sample. Such tests diagnose statistical explosiveness; interpreting that behavior as mispricing requires additional economic evidence.

LPPLS offers a complementary approach based on accelerating price growth and log-periodic fluctuations [11, 12]. Rolling confidence indicators summarize support for these configurations across calibration windows [13, 14]. Negative-bubble configurations apply analogous dynamics to falling prices and potential rebounds [15]. Agreement with GSADF is informative because the methods examine different features of the price trajectory, although neither alone estimates the firm's fundamental value.

Attention research supplies the behavioral link. Sentiment has stronger effects on securities that are difficult to value and subject to limits to arbitrage [3], while limited attention affects the processing of financial information [16]. Barber and Odean [17] find that individuals disproportionately buy attention-grabbing stocks. Da, Engelberg, and Gao [18] connect Google search activity to short-run price pressure and subsequent reversals. For Pop Mart, search intensity provides a measure of public interest that may accompany speculative demand, but it can also reflect consumer interest in its products. It is therefore treated as an attention proxy rather than a direct measure of investor sentiment.

These literatures motivate examining price dynamics, attention, and corporate news together. The Pop Mart case allows the analysis to ask whether an explosive valuation regime coincided with stronger fundamentals and unusually high attention, and whether market responses to favorable operating disclosures varied across that regime.

3. Data and empirical methodology

3.1. Data and variables

The daily sample covers Pop Mart International Group Limited (9992.HK) from its Hong Kong listing on December 11, 2020 through June 2026. Closing prices and trading volume are obtained from Investing.com.[5]Daily stock returns are log differences in closing prices, and Hang Seng Index returns provide the market benchmark. Volatility is the rolling standard deviation of daily log returns over 20 trading days, annualized using 252 trading days. Bubble tests use the log closing-price series. Weekly returns aggregate daily log returns, weekly volume is the logarithm of average daily trading volume, and weekly volatility averages the daily rolling measure.

Weekly Google Trends search intensity for the keyword "Pop Mart" measures public attention. The index ranges from 0 to 100 within the selected sample.[6]The search series is aligned with weekly stock and market observations. Because its coverage ends before the daily price sample, the behavioral analysis uses their available intersection. Table 2 reports 261 observations for most variables and 258 for volatility. Table 3 reports 260 observations in the baseline regression, 257 with the additional controls, and 237 in the LPPLS specification. Search intensity does not distinguish investors from consumers, and its regression coefficient is interpreted accordingly.

[5] Source: https://www.investing.com/. The historical data include daily closing prices and trading volume for Pop Mart International Group Limited.

[6] Observations reported by Google Trends as "" are assigned a value of 0.5.

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Corporate announcements and financial reports supply the dates and content of the three events examined: the 2024 interim results, the July 2025 positive profit alert, and the March 2026 annual-results announcement. The same disclosures provide the operating context in Section 2.1.

3.2. Bubble detection models

SADF and GSADF identify statistically explosive prices, while LPPLS examines nonlinear acceleration. I use the recursive tests to date the main regime and rolling LPPLS confidence as a complementary indicator and an alternative outcome in the behavioral regressions.

3.2.1. SADF and GSADF tests

The recursive right-tailed ADF regression is

$$\Delta y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{k} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

where y_t is the log stock price and k is the lag order. The unit-root null is tested against the explosive alternative $\beta > 0$. SADF takes the supremum of the ADF statistic over expanding windows with a fixed starting point [9]:

$$SADF(r_0) = \sup_{r_2 \in [r_0, 1]} \{ADF_0^{r_2}\} \tag{2}$$

Here r_0 is the minimum fractional window size and r_2 is the window endpoint. GSADF also varies the starting point r_1, allowing greater flexibility when multiple episodes occur [10]:

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}} \{ADF_{r_1}^{r_2}\} \tag{3}$$

At each endpoint, the backward SADF sequence is

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \{ADF_{r_1}^{r_2}\} \tag{4}$$

Test statistics are compared with simulated right-tailed critical values. An episode begins when the BSADF sequence rises above its corresponding critical-value sequence and ends when it falls below. The full-sample SADF and GSADF statistics establish evidence of explosiveness, while BSADF supplies the date-stamping sequence. Distinguishing the overall test from the endpoint-specific sequence is necessary when interpreting the plotted regime.

3.2.2. LPPLS model

The LPPLS model represents expected log prices as

$$lnP(t) = A + B(t_c - t)^{\beta} + C(t_c - t)^{\beta} cos[\omega ln(t_c - t) + \phi] \tag{5}$$

where P_t is the stock price, t_c is the estimated critical time, β governs acceleration, and ω and ϕ govern the frequency and phase of the log-periodic component. For a positive bubble, the relevant parameter region includes

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$$B < 0,\ 0 < \beta < 1 \tag{6}$$

These restrictions imply faster-than-exponential growth as the trajectory approaches t_c. The critical time represents a potential regime transition, not a deterministic crash forecast. Rolling calibration windows produce confidence indicators equal to the proportion of windows satisfying the restrictions for positive- or negative-bubble configurations. Positive confidence measures support for accelerating upward dynamics; negative confidence concerns analogous downward dynamics. They are not classifications based only on the sign of returns, and the confidence values are not probabilities of a future crash.

Following Johansen, Ledoit, and Sornette [11] and Zhang et al. [13], I use these indicators to assess whether nonlinear acceleration accompanies the GSADF regime. The behavioral robustness analysis uses positive-bubble confidence as a continuous alternative to the binary GSADF classification.

3.3. Behavioral and event-study design

The subsequent analysis compares bubble and non-bubble weeks, relates lagged market characteristics to bubble status, and examines corporate-announcement returns. These exercises describe associations and changes in market response; they do not identify causal effects of attention or news.

3.3.1. Bubble characteristics and behavioral regressions

A week is classified as a GSADF bubble week when at least half of its trading days belong to an identified episode. All behavioral variables use the weekly definitions in Section 3.1. I first compare their means between bubble and non-bubble weeks, using heteroskedasticity and autocorrelation consistent (HAC) standard errors with four weekly lags for the differences.

The weekly linear probability model is

$$Bubble_t = \alpha + \beta Attention_{t-1} + \gamma_1 Volume_{t-1} + \gamma_2 Volatility_{t-1} \tag{7}$$
$$+\gamma_3 MKTReturn_{t-1} + \delta Trend_t + \varepsilon_t$$

$Bubble_t$ equals one for a GSADF bubble week and zero otherwise. Attention, log volume, volatility, and Hang Seng Index returns are standardized to zero mean and unit variance and lagged by one week. Their coefficients therefore measure the association between a one-standard-deviation change in a regressor and next week's bubble probability. Specifications progressively add volume and volatility, market returns, and a linear time trend; inference uses HAC standard errors with four weekly lags.

Lagging the regressors reduces the mechanical contemporaneous relationship between market variables and a classification constructed from the same week's prices. It does not remove reverse causality or common influences on prices and attention. As a robustness check, I replace the binary outcome with LPPLS positive-bubble confidence, retaining the controls and inference procedure. Consistent signs across the two outcomes indicate that the association is not confined to one bubble definition.

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3.3.2. Event-study design

Event studies follow Brown and Warner [19] and MacKinlay [20]. Expected returns are estimated using the market model

$$R_t^{PM} = \alpha + \beta R_t^{HSI} + \varepsilon_t \tag{8}$$

where R_t^{PM} and R_t^{HSI} are the daily Pop Mart and Hang Seng Index returns. The estimation window comprises trading days [−120, −21] relative to each reaction date, or 100 observations. Abnormal and cumulative abnormal returns are

$$AR_t = R_t^{PM} - (\widehat{\alpha} + \widehat{\beta} R_t^{HSI}) \tag{9}$$

$$CAR_{[\tau_1,\tau_2]} = \sum_{t=\tau_1}^{\tau_2} AR_t \tag{10}$$

I report reaction-day AR and CAR over [−1, +1], [−3, +3], and [−5, +5] trading days. The reaction date is the following trading day for announcements released after the Hong Kong market closes, and the announcement date for releases during trading hours. The CAR plots cover [−10, +10] to show the surrounding return path. With three events, the evidence is case-specific; positive operating growth need not be a positive surprise relative to prior expectations, which are not directly measured.

4. Bubble identification

Table 1 and Figures 2–3 report the recursive-test and LPPLS evidence. The interpretation focuses on the timing and form of unusual price dynamics rather than an estimated gap between price and fundamental value.

4.1. SADF and GSADF evidence

Both recursive tests reject the no-explosiveness null at the 1% level. The SADF statistic is 5.300 against a 99% critical value of 2.100; the GSADF statistic is 6.420 against 2.810. Rejection under both window structures indicates that the finding is not confined to one recursive specification.

Table 1. SADF and GSADF tests for explosive behavior

Test	Test Statistic	90% CV	95% CV	99% CV	Result
SADF	5.300	1.330	1.600	2.100	Reject H_0 at 1%
GSADF	6.420	2.180	2.350	2.810	Reject H_0 at 1%

Notes: Tests use Pop Mart's log stock price. CV denotes a simulated upper-tail critical value. The unit-root null is rejected when the test statistic exceeds the relevant critical value.

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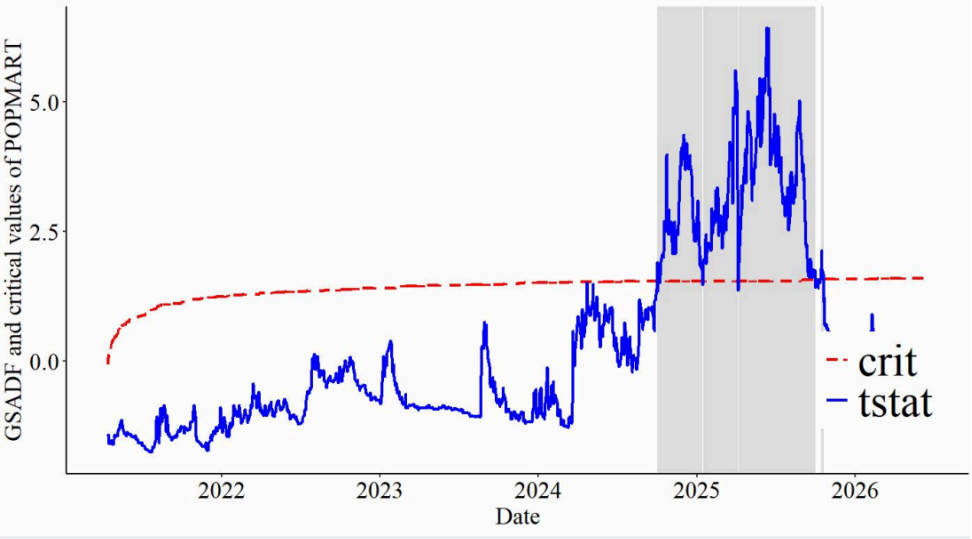


Figure 2. Recursive test and bubble date stamping for Pop Mart

Notes: The backward SADF sequence and its critical-value sequence identify the explosive intervals used in the weekly analysis.

Figure 2 shows the date-stamping sequence. Persistent explosiveness is limited before late 2024. The identified intervals are October 9, 2024–January 15, 2025; January 16–April 7, 2025; and April 8–October 2, 2025. Their adjacency makes it useful to interpret them as stages of a broader regime spanning October 2024–October 2025, rather than as three economically separate bubbles. The statistic rises especially strongly during the rapid appreciation in 2025 and subsequently falls below its critical threshold. This timing gives the weekly behavioral analysis a price-based classification that is defined independently of search attention.

4.2. LPPLS evidence

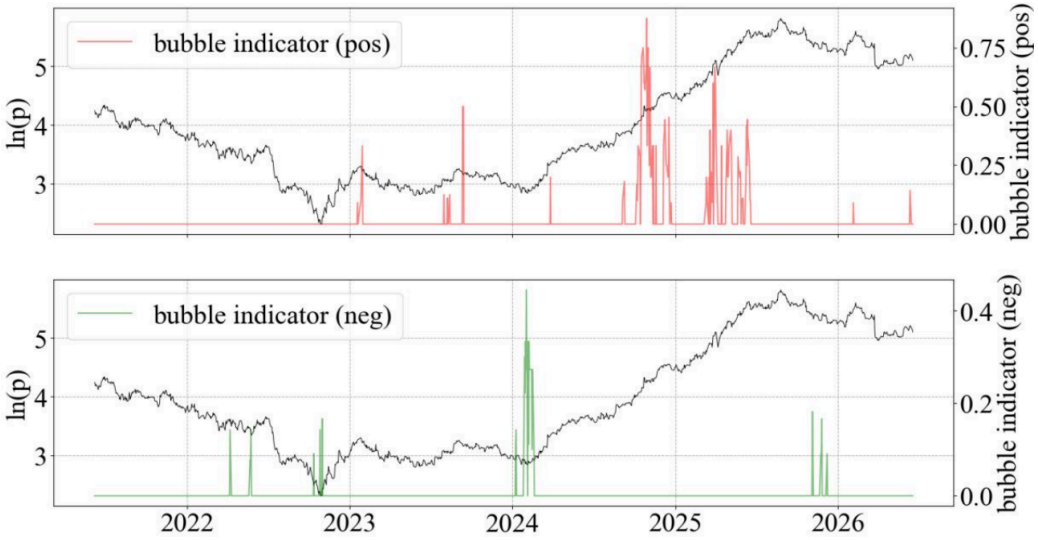


Figure 3. LPPLS positive and negative bubble indicators

Notes: Positive and negative confidence summarize the proportion of calibration windows satisfying the respective LPPLS restrictions. The black line is the log stock price.

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The rolling LPPLS indicators in Figure 3 provide complementary evidence on the price trajectory. Positive confidence becomes more pronounced in late 2024 and parts of 2025, overlapping the GSADF expansion. The signals are intermittent rather than a continuous classification of the entire GSADF interval. This distinction is expected because GSADF tests persistence in a recursive autoregression, whereas LPPLS evaluates accelerating growth with a log-periodic component. The two measures can therefore support a similar interpretation of the expansion without identifying identical start and end dates.

The negative-bubble panel supplies context for downward dynamics. It contains signals in earlier declining periods and again in late 2025. These signals do not imply that every price decline is a negative bubble or that a rebound is certain. Nor do they independently establish an exact termination date for the positive regime. The subsequent regressions use only the positive-confidence series, so the main behavioral result does not depend on interpreting the negative signals as a separate episode.

The comparison supports a narrower conclusion than a direct finding of overvaluation. Pop Mart experienced an explosive price regime during 2024–2025, and parts of that expansion also displayed nonlinear acceleration captured by LPPLS. Neither procedure observes or estimates the firm's fundamental value. Strong earnings growth may have supported the rise while speculative feedback amplified it, but the tests cannot quantify those contributions separately. This boundary matters particularly for Pop Mart, whose operating performance was improving during the price expansion.

The methods also differ in how their outputs enter the analysis. GSADF date-stamping produces the binary weekly classification used in the main comparisons and regressions; LPPLS positive confidence is a continuous outcome used for robustness. A positive attention association in both specifications would show that the behavioral result extends beyond one statistical representation of the price process. It would not, by itself, identify attention as the cause of either process. Section 5 examines this association and then turns to the market's response to corporate information.

5. Behavioral evidence and corporate announcements

This section examines the market environment surrounding the identified regime. Table 2 compares weekly characteristics, Table 3 reports lagged behavioral regressions, and Table 4 compares reactions to corporate announcements. Together they address which features accompanied the expansion and whether favorable operating disclosures received similar responses at different valuation stages.

5.1. Bubble characteristics

Bubble weeks combine stronger stock returns, heavier trading, and much higher public attention. Average weekly returns are 2.93%, compared with −0.29% in non-bubble weeks; the 3.22-percentage-point difference has a HAC t-statistic of 2.86. Average Google search intensity rises from 5.92 to 50.38, a difference of 44.47 index points ($t = 7.38$). Log trading volume is also significantly higher. These comparisons show that the explosive regime coincides with changes in both market activity and public interest, rather than simply a larger cumulative price increase.

Figure 4 shows the timing of search attention. Interest begins rising before the strongest price acceleration and reaches its largest values during the GSADF regime. The elevation extends over multiple weeks, so the difference in means is not solely the product of one isolated search spike. Attention remains a descriptive proxy: searches may respond to product popularity, financial news,

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or prior price increases. The figure cannot establish whether search activity initiated the expansion or followed it.

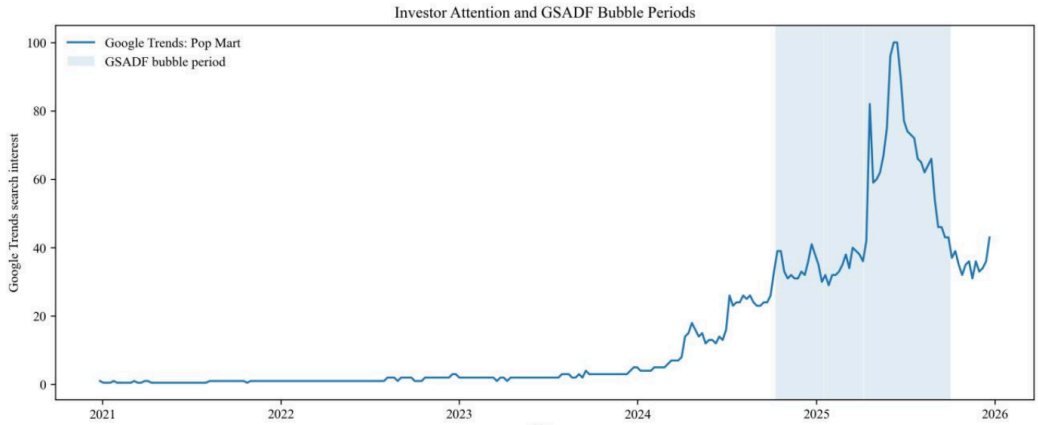


Figure 4. Public attention and GSADF bubble episodes

Notes: Weekly Google Trends search intensity for "Pop Mart," normalized to 0–100. Shading marks GSADF episodes; search data end before the daily price sample.

Neither rolling volatility nor Hang Seng Index returns differs significantly between the two groups. This means the comparison does not show a corresponding increase in these measures of risk and broad market performance. It does not rule out wider market influences or other omitted conditions. Table 2 is therefore a description of the episode, while Table 3 asks whether attention remains associated with bubble status after the observed market variables are considered jointly.

Table 2. Characteristics of bubble and non-bubble periods

Variable	Bubble	Non-Bubble	Difference	HAC t -stat	N
Weekly Return (%)	2.929	-0.289	3.219***	2.863	261
Log Trading Volume	16.152	15.587	0.565***	4.604	261
20-day Rolling Volatility (%)	59.292	60.855	-1.562	-0.265	258
Google Search Attention	50.385	5.919	44.466***	7.378	261
Hang Seng Market Return (%)	0.340	-0.101	0.441	0.805	261

Notes: A bubble week has at least half its trading days in a GSADF episode. Returns and annualized volatility are reported in percent; return differences are percentage points. Volume is the log of average daily volume, and attention is the weekly Google Trends index. Difference equals the bubble mean minus the non-bubble mean. HAC t-statistics use four weekly lags. ***, **, and * denote 1%, 5%, and 10% significance.

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5.2. Behavioral correlates and robustness

Table 3 estimates the weekly specifications in Section 3.3.1. All market regressors are lagged one week and standardized. Column (1) includes attention alone; subsequent columns add volume and volatility, market returns, and a time trend. Column (5) uses LPPLS positive confidence in place of GSADF bubble status. Sample sizes differ across specifications and are reported with the estimates.

Attention is the most stable correlate in these specifications. The baseline coefficient is 0.330 (t = 9.49), corresponding to a 33.0-percentage-point difference in fitted bubble probability for a one-standard-deviation increase in lagged attention. With all controls and a linear trend, the coefficient is 0.336 (t = 6.52). Lagged volume, volatility, and market returns are not individually significant once attention is included. The close attention estimates across columns indicate that these particular controls do not account for the observed association.

This finding is consistent with research linking attention to investor demand [17, 18], but it does not demonstrate a causal effect. Past appreciation may attract searches, and both variables may respond to information about demand for Pop Mart's products. The search measure also includes interest from people who do not trade the stock. A one-week lag and HAC inference address timing and residual dependence in specific ways; they do not resolve these identification problems. The coefficient is consequently interpreted as a conditional association within this valuation cycle.

Table 3. Behavioral factors associated with bubble episodes

	GSADF Bubble Dummy				LPPLS Positive Confidence
	(1)	(2)	(3)	(4)	(5)
Lagged Attention	0.330***	0.339***	0.339***	0.336***	0.026**
	(9.49)	(9.60)	(9.62)	(6.52)	(2.31)
Lagged Log Volume		-0.015	-0.015	-0.016	0.007
		(-0.57)	(-0.54)	(-0.60)	(0.79)
Lagged Volatility		0.023	0.023	0.024	0.004
		(1.27)	(1.27)	(1.23)	(0.44)
Lagged Market Return			-0.003	-0.003	-0.002
			(-0.19)	(-0.20)	(-0.33)
Time Trend				0.015	0.004
				(0.08)	(0.13)
Observations	260	257	257	257	237
R^2	0.678	0.680	0.680	0.680	0.126

Notes: Columns (1)–(4) are linear probability models for GSADF bubble status; column (5) uses LPPLS positive confidence. Attention, log volume, volatility, and market returns are standardized and lagged one week. Parentheses report HAC t-statistics with four weekly lags. ***, **, and * denote significance at 1%, 5%, and 10%.

The LPPLS regression provides a useful check on the choice of outcome. Lagged attention remains positive and significant, with a coefficient of 0.026 (t = 2.31). Because positive confidence is continuous, this coefficient is a change in the confidence indicator rather than a change in the

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probability of the binary GSADF state. The result supports the attention association under a second measure of price dynamics. Its smaller sample of 237 observations, compared with 257 in the full GSADF specification, also means the two coefficients are not a like-for-like comparison of effect sizes.

The regressions establish attention as a recurring feature of the identified expansion. They leave open how investors assessed new operating information as the valuation evolved. The announcement analysis addresses this separate question by comparing abnormal returns around three favorable corporate disclosures.

5.3. Corporate announcements and expectation correction

Table 4 reports abnormal returns around the 2024 interim results, July 2025 positive profit alert, and March 2026 announcement of the 2025 annual results. Each disclosure reports favorable operating performance, but they occur before, during, and after the GSADF regime. Figure 5 plots CAR from ten trading days before to ten trading days after each reaction date. The table summarizes selected windows, while the figure shows whether movements are concentrated on the reaction date or extend around it.

The 2024 interim results receive a positive response: reaction-day AR is 9.92% and CAR[−1, +1] is 12.14%. Although CAR[−5, +5] declines to 5.48%, it remains positive. During this earlier recovery stage, the response is consistent with operating news improving the market's assessment of the business. By July 2025, the pattern reverses. The profit alert produces AR of −4.60% and CAR[−1, +1] of −8.33%, with larger negative CAR over the wider windows. Strong reported growth therefore does not translate into a positive return surprise during the explosive regime.

The March 2026 annual-results announcement is associated with a still larger decline: reaction-day AR is −26.31% and CAR[−1, +1] is −30.70%. One interpretation of the contrast across events is that the benchmark for favorable news became more demanding as expectations rose. Extrapolative beliefs provide a possible mechanism [5], but the data do not directly measure expected earnings or isolate that mechanism. The wider-window losses may also include other information and market developments. The announcement evidence is thus consistent with expectation correction rather than a causal test of it.

The event paths also warrant caution about timing. The July 2025 series already declines before day 0, so its wider-window CAR should not be attributed entirely to the profit alert. The three disclosures occur in different conditions and are not interchangeable treatments. Their value here is to document contrasting responses within the same company's cycle: favorable realized operating performance accompanied positive abnormal returns early in the recovery and negative returns at later stages. This evidence complements the price and attention results without establishing that either attention or expectations alone caused the reversal.

Table 4. Stock price reactions to major corporate announcements

Event	Reaction Date	AR[0]	CAR[-1,+1]	CAR[-3,+3]	CAR[-5,+5]
2024 Interim Results	2024-08-21	9.92	12.14	12.72	5.48
2025 Positive Profit Alert	2025-07-16	-4.60	-8.33	-19.77	-28.43
2025 Annual Results	2026-03-25	-26.31	-30.70	-32.61	-36.35

Notes: Returns are in percent. AR[0] is reaction-day abnormal return; CAR[a, b] cumulates abnormal returns over trading days a to b. Expected returns use the Hang Seng market model estimated over [−120, −21], with 100 observations. For announcements after

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market close, day 0 is the next trading day. Window returns describe each event and are not reported as causal effects.

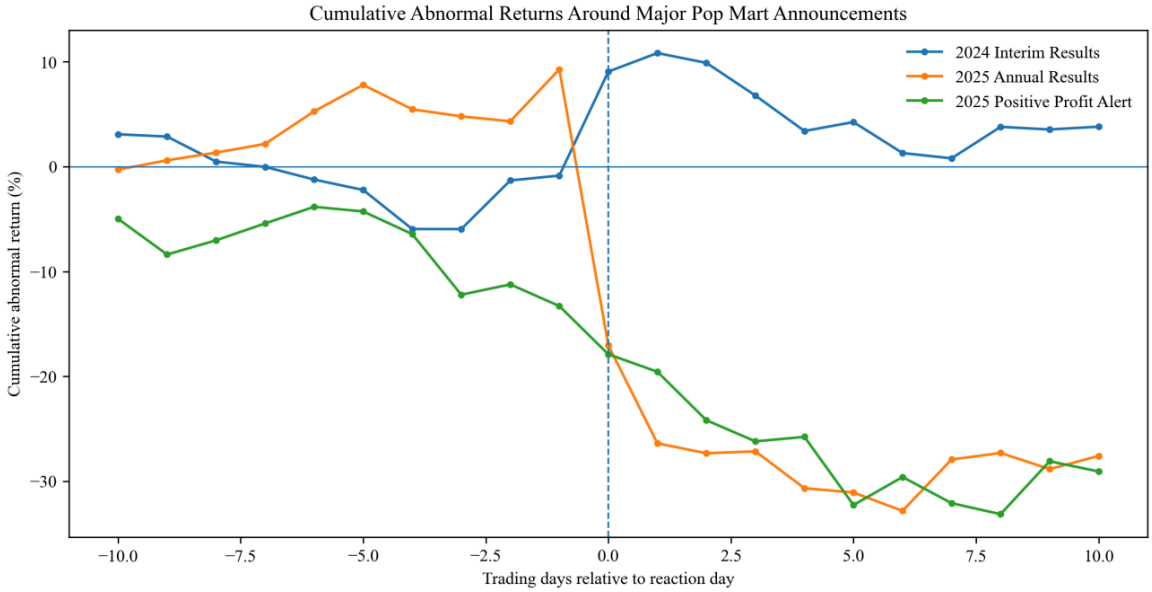


Figure 5. Cumulative abnormal returns around corporate announcements

Notes: CAR over [−10, +10] trading days, with day 0 the reaction date. Expected returns use the Hang Seng market model estimated over [−120, −21].

6. Conclusion

Pop Mart's valuation cycle shows how strong business growth can accompany speculative price dynamics. GSADF identifies an explosive regime from October 2024 to October 2025, while rolling LPPLS indicators show nonlinear acceleration during parts of the expansion. Bubble weeks exhibit higher returns, trading volume, and public attention. Lagged Google search intensity remains positively associated with both GSADF bubble status and LPPLS positive confidence after the reported controls.

The announcement evidence adds a change in market response: positive abnormal returns around the 2024 interim results contrast with negative reactions to the 2025 profit alert and the March 2026 annual results. This pattern is consistent with expectations becoming harder to exceed as valuation rises, although prior expectations are not directly observed. Strong realized growth can therefore coexist with an eventual downward reassessment of the stock.

The conclusions remain specific to the evidence. Price-based diagnostics do not measure the size of mispricing, attention regressions do not establish causality, and three events cannot identify a general announcement effect. Within those limits, the case connects statistical bubble detection with attention and corporate-news responses, illustrating how improving fundamentals and speculative amplification may coexist in an IP-driven consumer company.

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