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论文题目： Revisiting Stock Price Bubbles:
Behavioral Evidence from Pop Mart

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. Using data from December 2020 to June 2026, I apply the SADF, GSADF, and LPPLS methods to identify bubble-like price dynamics and examine trading activity, public attention, and market reactions to major corporate announcements. The results identify a pronounced explosive regime from late 2024 through much of 2025, accompanied by unusually high trading activity and Google search attention. Attention remains the most robust behavioral correlate across alternative bubble measures. Event-study evidence further shows that favorable corporate news generated positive abnormal returns early in the valuation cycle but increasingly negative reactions as expectations became more demanding. Overall, the findings suggest that fundamental improvement and speculative amplification can coexist.

Keywords: Stock Price Bubbles; Behavioral Finance; Investor Sentiment; GSADF; LPPLS

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1 Introduction

Stock-price bubbles are often associated with prices becoming detached from fundamentals. Yet the more difficult case is when fundamentals themselves are improving. A rapidly rising stock may reflect genuine growth, increasingly optimistic expectations, or a speculative process in which the two reinforce one another. This distinction is especially important for firms whose valuations depend heavily on intangible assets, brand popularity, and expectations of future demand. For such firms, strong fundamentals do not necessarily rule out a bubble; they may instead provide the initial narrative around which speculative expectations develop.

Pop Mart offers a particularly useful setting for studying this tension. After declining substantially between 2021 and early 2023, its share price recovered in 2024 and accelerated sharply through much of 2025. The run-up coincided with the international popularity of characters such as Labubu, rapidly improving financial performance, and a surge in public attention. Yet the stock later experienced a major correction even as the company continued to report strong operating results. This unusual combination creates the central question of the paper: when strong fundamentals and rising expectations coexist, how can we distinguish fundamental revaluation from speculative amplification?

A large literature provides reasons why speculative dynamics may emerge even when investors observe favorable fundamentals. Heterogeneous beliefs, overconfidence, resale incentives, and limits to arbitrage can sustain prices above levels justified by common expectations (Harrison and Kreps 1978; Blanchard and Watson 1982; Scheinkman and Xiong 2003). Behavioral-finance research further shows that sentiment and limited attention matter especially for difficult-to-value securities (Baker and Wurgler 2006; Hirshleifer and Teoh 2003). Attention may be particularly relevant once an asset becomes salient: individual investors disproportionately buy attention-grabbing stocks, while increases in Google search activity are associated with short-run price pressure and subsequent reversals (Barber and Odean 2008; Da, Engelberg, and Gao 2011). In parallel, the SADF and LPPLS literatures develop statistical tools for identifying explosive and nonlinear price dynamics associated with bubbles (Phillips, Wu, and Yu 2011; Phillips, Shi, and Yu 2015; Sornette and Cauwels 2015).

These literatures, however, are often studied separately. Bubble-detection methods can identify when unusual price dynamics occur, but say relatively little about the behavioral

environment surrounding them. Attention-based studies, meanwhile, may document heightened investor interest without establishing whether it coincides with a statistically identifiable bubble regime. Pop Mart allows these perspectives to be brought together within a single valuation cycle. By combining bubble detection with measures of attention, trading activity, and reactions to fundamental news, this paper examines not simply whether Pop Mart experienced a bubble, but how fundamental improvement, investor attention, and increasingly demanding expectations evolved together as the valuation expanded and eventually corrected.

Against this background, this paper addresses two related research questions. First, did Pop Mart's stock price experience a statistically identifiable speculative bubble, and when did this episode begin and end? Second, what market and behavioral factors were associated with the identified bubble period, particularly investor attention, trading activity, and reactions to fundamental corporate information? These questions allow the analysis to move beyond documenting a large price increase and instead examine both the statistical characteristics of the price process and the economic conditions surrounding its development.

To answer these questions, I use Pop Mart's stock-market data from its listing in December 2020 through June 2026. I apply the SADF and GSADF procedures to test for explosive price behavior and date-stamp the corresponding episodes. I then use the LPPLS model as a complementary method for examining whether the price trajectory exhibits nonlinear acceleration and log-periodic behavior associated with speculative dynamics. To investigate the characteristics of the identified episode, I compare bubble and non-bubble periods and analyze whether Google search attention, trading volume, volatility, and broader market returns are associated with bubble status. Finally, I conduct event studies of three major corporate announcements to examine how the market's reaction to favorable fundamental information changed across different stages of the valuation cycle.

The analysis produces three main findings. First, the SADF, GSADF, and LPPLS results provide convergent evidence that Pop Mart experienced an explosive price regime beginning in late 2024 and continuing through much of 2025. The agreement between the recursive explosiveness tests and the nonlinear LPPLS indicators suggests that the episode was characterized by both unusually persistent price growth and accelerating price dynamics. Second, the bubble period was associated with stronger returns, heavier trading, and exceptionally high Google search attention, while broader market performance did not differ significantly between bubble and non-bubble periods. Investor attention remains the most stable behavioral correlate when other market conditions are considered and when the

alternative LPPLS bubble measure is used. Third, the market's reaction to favorable corporate information changed as the valuation cycle progressed. Strong operating news generated a positive response during the earlier recovery stage but increasingly negative reactions after the stock price and investor expectations had risen substantially. Taken together, these results suggest that improving fundamentals initially supported Pop Mart's valuation, while rising attention and increasingly optimistic expectations amplified the subsequent expansion and contributed to a later expectation correction.

This paper contributes to the existing literature in two ways. First, it connects statistical bubble identification with behavioral-finance evidence by showing that an explosive price regime can be examined together with investor attention, trading activity, and market reactions to new information. This provides a more complete account of a bubble episode than price-based detection alone. Second, the Pop Mart case illustrates that fundamental growth and speculative amplification are not mutually exclusive. A company may experience genuine improvements in operating performance while its valuation is simultaneously strengthened by attention-driven demand and increasingly optimistic expectations. The findings therefore extend the understanding of bubble formation in IP-driven consumer companies, where fundamental value is especially sensitive to expectations about brand popularity and future growth.

The remainder of the paper is organized as follows. Section 2 describes Pop Mart's stock-price evolution and reviews the related literature, while Section 3 presents the data and empirical methodology. Section 4 reports the bubble-identification results, Section 5 examines the characteristics and behavioral correlates of the identified episode, and Section 6 concludes.

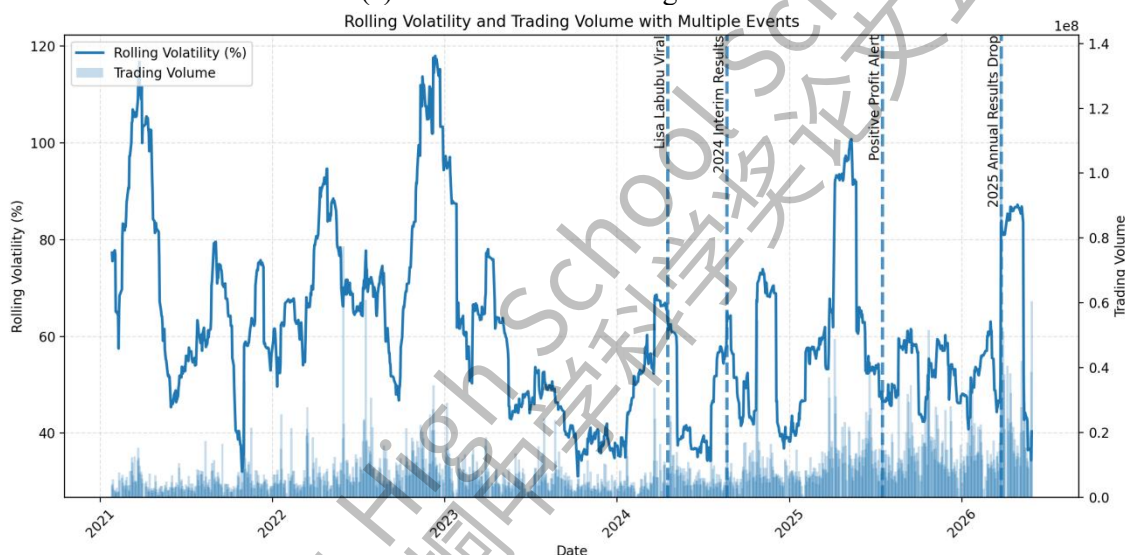
2 Background and Related Literature

2.1 Pop Mart and Its Valuation Cycle

Before formally identifying stock-price bubbles, it is useful to understand the economic and market developments surrounding Pop Mart's valuation cycle. Figure 1a summarizes the evolution of the company's stock price, trading volume, and volatility over the full sample, while Figure 2 highlights several major developments during the 2024–2026 period. The purpose of this discussion is descriptive rather than causal: the figures document how corporate developments, market activity, and investor expectations evolved together before the formal empirical analysis.



(a) Stock Price and Trading Volume



(b) Stock Volatility and Trading Volume

Figure 1. Market Evolution of Pop Mart, 2021–2026

Notes: Panel A reports Pop Mart's stock price and trading volume over the full sample period.

Panel B reports rolling stock-return volatility together with trading volume. Event markers provide descriptive context for major developments discussed in the text.

Pop Mart's early post-listing period was characterized by a prolonged decline in its share price. As shown in Figure 1a, the stock fell substantially from 2021 through early 2023, while trading activity remained relatively subdued apart from several short-lived volume spikes. Figure 1b also shows intermittent increases in volatility. One possible interpretation is that investors became increasingly uncertain about whether the rapid growth associated with Pop Mart's early blind-box business model could be sustained. This interpretation should

nevertheless remain cautious, since the decline may also have reflected broader market conditions rather than company-specific expectations alone.

A noticeable change in the valuation trajectory emerged during 2024. Figure 2 highlights the period surrounding the increasing popularity of Labubu, including widely reported celebrity exposure through figures such as Lisa from Blackpink.¹ Pop Mart's stock subsequently continued to recover from its earlier lows, accompanied by greater trading activity. A plausible interpretation is that investors increasingly began to view Pop Mart not simply as a blind-box retailer, but as an IP-driven consumer company whose valuation depended on the commercial potential and future popularity of its proprietary characters.

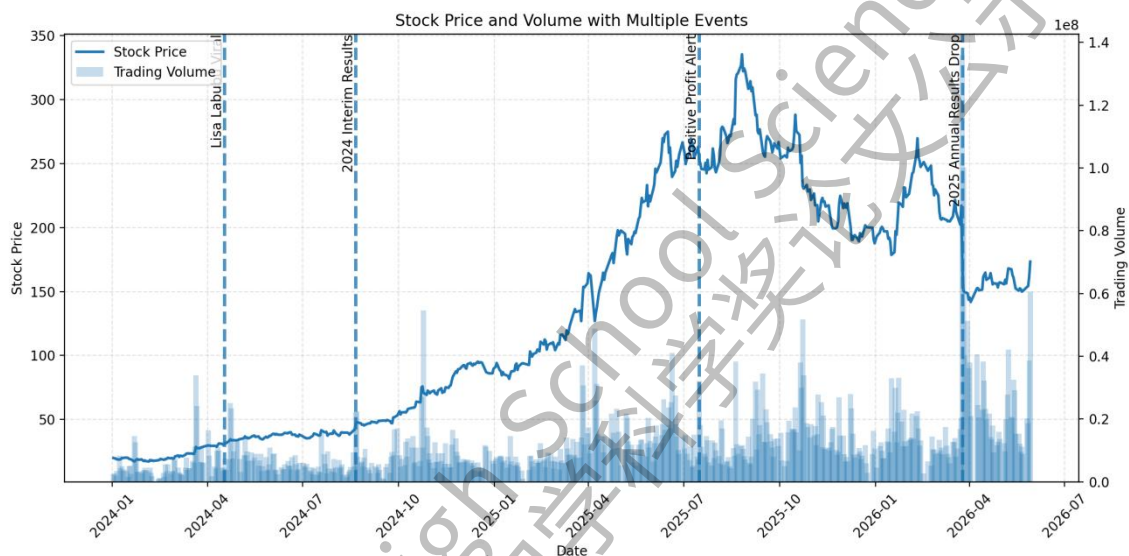


Figure 2. Major Events and Pop Mart's Stock Price, 2024–2026

Notes: This figure presents Pop Mart's stock-price evolution around selected corporate and product-related developments between 2024 and 2026. The event markers provide descriptive context and should not be interpreted as causal estimates of their effects on stock prices.

Importantly, the improvement in market expectations was accompanied by stronger reported fundamentals. Pop Mart's 2024 interim results documented substantial growth in proprietary products, including THE MONSTERS, together with rapid expansion in the plush-toy segment.² As Figure 2 shows, the stock-price trend remained positive around and after this period. The recovery in valuation therefore cannot be attributed solely to online

¹ [Business Insider](#), "Inside the Meteoric Rise of Labubu," November 2024.

² [Pop Mart International Group Limited](#), 2024 Interim Results Announcement, August 20, 2024.

popularity or investor attention: stronger operating performance also provided fundamental support for increasingly optimistic expectations.

Optimism intensified further during 2025. In July 2025, Pop Mart issued a positive profit alert stating that first-half revenue was expected to increase by no less than 200% year-on-year, while profit was expected to increase by no less than 350%.³ By this point, however, the share price had already appreciated substantially, and Figure 1b indicates active trading and elevated volatility during the broader upswing. Thus, improving fundamentals increasingly coincided with high valuations and strong expectations about future growth.

The subsequent correction provides an important contrast. Pop Mart reported strong financial performance for 2025, with both revenue and profit increasing sharply.⁴ Nevertheless, its share price fell by more than 20% following the earnings release as investors focused on the sustainability of future growth.⁵ The sharp decline is visible in Figure 2. Rather than reflecting weak realized performance, the reaction is more consistent with a reassessment of expectations after a period in which anticipated growth had become exceptionally strong.

Taken together, these developments reveal a useful tension for studying stock price bubbles. Pop Mart's valuation expansion coincided with genuine improvements in operating performance, but also with rapidly increasing product popularity, investor attention, and expectations about future growth. Strong fundamentals and speculative amplification are therefore not necessarily mutually exclusive. Pop Mart provides a particularly useful setting in which to examine whether an initially fundamentals-supported revaluation can develop into statistically explosive price dynamics as expectations become increasingly optimistic.

2.2 Related Literature and Research Motivation

2.2.1 Theoretical Foundations of Asset Price Bubbles

A large literature in financial economics studies why asset prices may depart from fundamental values and generate speculative bubbles. Early theoretical models emphasize heterogeneous beliefs and speculative incentives. Harrison and Kreps (1978) show that

³ [Pop Mart International Group Limited, Positive Profit Alert, July 2025.](#)

⁴ [Pop Mart International Group Limited, Annual Results Announcement for the Year Ended December 31, 2025, March 25, 2026.](#)

⁵ [Reuters, "Shares of Labubu Maker Pop Mart Plunge After Reporting Annual Earnings," March 25, 2026.](#)

disagreement among investors can generate speculative demand because investors may be willing to purchase an asset at a high price when they expect to resell it to more optimistic investors. Blanchard and Watson (1982) characterize bubbles as stochastic deviations from fundamentals that can persist before eventually collapsing, while Tirole (1985) establishes conditions under which rational bubbles may arise in general equilibrium.

Subsequent research introduces information frictions and behavioral forces into the analysis of bubble formation. Allen, Morris, and Postlewaite (1993) show that asymmetric information can generate speculative trading even in the absence of changes in fundamentals. Barberis, Shleifer, and Vishny (1998) demonstrate how investor sentiment and biased beliefs about past information can generate predictable departures from fully rational expectations. Scheinkman and Xiong (2003) further show that overconfidence, heterogeneous beliefs, and short-sale constraints can jointly produce speculative bubbles and unusually high trading volume. More broadly, disagreement and limits to information processing may prevent prices from immediately incorporating all available information (Hong and Stein 2007).

2.2.2 Empirical Identification of Bubbles

Empirically identifying bubbles is challenging because fundamental value is not directly observable. Early studies therefore examine whether stock prices display movements that appear excessive relative to observable fundamentals. Shiller (1981) documents stock-price volatility that is difficult to reconcile with subsequent dividend movements. Related studies develop alternative tests for bubble components and explosive behavior in asset prices (West 1987; Diba and Grossman 1988), while Froot and Obstfeld (1991) introduce the concept of intrinsic bubbles linked to fundamental variables.

More recent research develops methods that identify bubble episodes directly from the statistical dynamics of prices. Phillips, Wu, and Yu (2011) introduce the Supremum Augmented Dickey–Fuller (SADF) test for detecting periods of explosive price behavior. Phillips, Shi, and Yu (2015) extend this framework through the Generalized SADF (GSADF) procedure, which allows recursive estimation windows to vary more flexibly and is therefore capable of identifying multiple bubble episodes within the same sample.

A complementary literature focuses on nonlinear price acceleration. Johansen, Ledoit, and Sornette (2000) develop the log-periodic power-law framework, in which speculative bubbles are characterized by accelerating price growth and log-periodic fluctuations as the market approaches a potential regime change. Subsequent work develops the Log-Periodic Power Law Singularity (LPPLS) framework and related indicators for identifying historical

episodes of speculative acceleration (Sornette and Cauwels 2015; Zhang et al. 2016). Together, these approaches provide complementary methods for identifying both statistical explosiveness and nonlinear bubble-like price dynamics.

2.2.3 Behavioral Finance, Sentiment, and Attention

A related behavioral-finance literature explains why speculative price movements may be amplified even when rational investors remain active in the market. De Long et al. (1990) show that noise-trader risk can prevent arbitrageurs from fully eliminating mispricing. Baker and Wurgler (2006) document that investor sentiment has particularly strong effects on securities that are difficult to value and subject to greater limits to arbitrage. These arguments are especially relevant when valuation depends heavily on uncertain expectations about future growth rather than on readily observable current cash flows.

Investor attention provides an additional channel through which beliefs may affect prices and trading demand. Hirshleifer and Teoh (2003) emphasize the role of limited attention in information processing, while Peng and Xiong (2006) show that investors allocate their attention selectively across information sources. Tetlock (2007) documents a relationship between media sentiment and subsequent market activity. Barber and Odean (2008) show that individual investors disproportionately purchase attention-grabbing securities, including stocks experiencing extreme returns, unusually high trading volume, or intensive news coverage. Using Google search volume as a more direct measure of attention, Da, Engelberg, and Gao (2011) find that increases in search activity are associated with short-run price pressure followed by subsequent reversal. These studies suggest that heightened attention can accompany and potentially amplify speculative demand when an asset becomes increasingly salient to investors.

Motivation. Existing research therefore provides rich theories of speculative bubbles, increasingly sophisticated methods for detecting them, and substantial evidence that sentiment and attention affect asset prices. Less clear, however, is how these forces evolve when unusually strong fundamental growth occurs simultaneously with rapidly increasing popularity and investor expectations. This distinction is important because statistically explosive prices need not imply that the underlying business improvement is unreal; fundamental revaluation and speculative amplification may coexist.

Pop Mart provides a useful setting in which to examine this interaction. Its valuation depends heavily on intangible IP value, consumer popularity, and expectations about future growth, making beliefs about future demand especially important. I therefore combine

SADF/GSADF and LPPLS bubble-detection methods with measures of investor attention, trading activity, and event-study evidence to examine both whether bubble-like dynamics emerged and how the surrounding behavioral and expectation environment evolved over the valuation cycle.

3 Data and Empirical Methodology

3.1 Data and Variables

This study examines the stock-price dynamics of Pop Mart International Group Limited (stock code: 9992.HK), which has been listed on the Main Board of the Hong Kong Stock Exchange since December 11, 2020. The sample begins from the company's listing and extends through June 2026. Daily stock-market data are obtained from Investing.com,⁶ including the closing price and trading volume. The closing price is used as the primary price series for bubble detection, while daily stock returns are calculated as log differences in closing prices. To account for broader market conditions, I additionally collect daily observations for the Hang Seng Index and construct corresponding market returns. Furthermore, stock-price volatility is measured as the 20-trading-day rolling standard deviation of daily log returns, annualized using 252 trading days. Trading activity is measured using daily trading volume and, in the weekly analysis below, the logarithm of average daily trading volume within each week.

To capture behavioral factors potentially associated with bubble episodes, I collect weekly Google Trends search intensity for the keyword "Pop Mart." Following Da, Engelberg, and Gao (2011), internet search activity provides a relatively direct measure of active public attention toward a firm. Google Trends normalizes search interest to a scale from 0 to 100 within the selected sample, with higher values indicating greater search intensity.⁷ Because Google Trends is available at the weekly frequency, the behavioral analysis is conducted using weekly observations. The weekly search series is aligned with the corresponding stock-market variables. Since Google Trends coverage ends earlier than the daily stock-price sample, the behavioral regressions use the intersection of the available weekly series.

⁶ Source: <https://www.investing.com/>. The historical data include daily closing prices and trading volume for Pop Mart International Group Limited.

⁷ Observations reported by Google Trends as "< 1" are assigned a value of 0.5.

Finally, I collect information on major Pop Mart-related corporate events from the company's official announcements and financial reports. These events include earnings announcements, profit alerts, and other major disclosures that may have affected investor expectations. The event information is used both to provide descriptive context for the evolution of Pop Mart's valuation and to examine stock-price reactions around clearly dated corporate announcements.

3.2 Bubble Detection Models

To identify potential stock-price bubbles, I employ two complementary methodological frameworks. The first consists of the Supremum Augmented Dickey–Fuller (SADF) and Generalized Supremum Augmented Dickey–Fuller (GSADF) tests, which detect statistically explosive price behavior (Phillips, Wu, and Yu 2011; Phillips, Shi, and Yu 2015). The second is the Log-Periodic Power Law Singularity (LPPLS) model, which characterizes the nonlinear acceleration and log-periodic dynamics associated with speculative bubbles (Johansen, Ledoit, and Sornette 2000; Zhang et al. 2016). These approaches are complementary rather than interchangeable: SADF and GSADF test for statistical explosiveness, whereas LPPLS examines the dynamic structure of bubble-like price acceleration.

3.2.1 SADF and GSADF Tests

The SADF approach of Phillips, Wu, and Yu (2011) is based on a recursive right-tailed Augmented Dickey–Fuller regression:

$$\Delta y_t = \alpha + \beta y_{t-l} + \sum_{i=1}^k \phi_i \Delta y_{t-i} + \varepsilon_t, \quad (1)$$

where y_t denotes the logarithm of the stock price. The null hypothesis corresponds to a unit-root process, whereas the right-tailed alternative, $\beta > 0$, represents explosive behavior. Unlike the conventional ADF test, the objective is therefore not to establish stationarity but to identify periods in which the persistence of the price process becomes unusually high.

The SADF statistic repeatedly estimates the right-tailed ADF regression using an expanding window with a fixed initial observation:

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

where r_0 denotes the minimum fractional window size and r_2 denotes the endpoint of the recursive sample. A sufficiently large SADF statistic relative to its simulated critical value provides evidence of explosive price behavior.

Because SADF uses a common starting point, it may have limited power when multiple bubbles occur within the same sample. Phillips, Shi, and Yu (2015) therefore develop the GSADF test, which allows both the starting and ending points of the estimation window to vary:

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

This flexible-window structure searches over a much larger set of subsamples and is therefore particularly useful when several explosive episodes may occur within the same price series.

The timing of individual episodes is identified using the backward SADF (BSADF) sequence:

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

A bubble is dated when the BSADF statistic rises above its corresponding right-tailed critical value, while its subsequent fall below the critical value indicates the termination of the explosive episode. This procedure allows the analysis to identify both the existence and timing of recurrent bubble periods in Pop Mart's stock price.

3.2.2 LPPLS Model

The LPPLS model provides a complementary perspective by focusing on the nonlinear structure of a rapidly accelerating price trajectory. Following the log-periodic power-law literature (Johansen, Ledoit, and Sornette 2000; Zhang et al. 2016), the expected log price can be represented as

$$\ln P(t) = A + B(t_c - t)^\beta + C(t_c - t)^\beta \cos[\omega \ln(t_c - t) + \phi], \quad (5)$$

where $P(t)$ is the asset price, t_c denotes the estimated critical time, β governs the rate of acceleration, and ω and ϕ determine the frequency and phase of the log-periodic component.

For a positive bubble, the economically relevant parameter region generally requires

$$B < 0, \quad 0 < \beta < 1. \quad (6)$$

Under these conditions, the price trajectory grows at an accelerating, faster-than-exponential rate as t approaches t_c . The oscillatory component captures fluctuations whose frequency increases as the critical point approaches. LPPLS therefore identifies bubble-like behavior from the shape of the price trajectory rather than solely from the magnitude of accumulated returns.

The estimated critical time t_c should not be interpreted as a deterministic forecast of a market crash. Instead, it represents a potential transition point at which the existing accelerating price regime may become increasingly unstable. In addition to the fitted price path, I use rolling LPPLS estimates to construct positive- and negative-bubble confidence indicators. These continuous measures provide an alternative characterization of bubble intensity and are later used to assess the robustness of the GSADF-based results.

3.3 Behavioral and Event-Study Design

The bubble-detection procedures identify when Pop Mart exhibits explosive price dynamics, but they do not explain the market environment associated with these episodes. I therefore conduct three additional analyses. First, I compare market characteristics between bubble and non-bubble weeks. Second, I estimate weekly regressions to examine whether behavioral and market variables are associated with subsequent bubble status. Third, I use an event-study framework to examine how investors responded to major announcements at different stages of the valuation cycle.

3.3.1 Bubble Characteristics and Behavioral Regressions

Because Google Trends data are observed weekly, all variables in the behavioral analysis are aggregated to the weekly frequency. A week is classified as a bubble week if at least half of its trading days fall within a GSADF bubble episode. Weekly stock returns are constructed by aggregating daily log returns. Trading activity is measured as the logarithm of average daily trading volume, while volatility is measured as the weekly average of the 20-day rolling annualized volatility. Google Trends search intensity for “Pop Mart” captures public attention, and weekly Hang Seng Index returns capture broader market conditions.

I first compare the means of these variables between bubble and non-bubble weeks. Statistical inference for the mean differences is based on heteroskedasticity and autocorrelation consistent (HAC) standard errors with four weekly lags. This comparison provides a descriptive characterization of the market environment associated with the bubble episodes.

I then examine whether behavioral and market variables are associated with subsequent bubble status using the following weekly linear probability model:

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

The dependent variable equals one if week t is classified as a GSADF bubble week and zero otherwise. Attention, log trading volume, volatility, and Hang Seng Index returns are standardized prior to estimation, so that the associated coefficients capture the change in bubble probability corresponding to a one-standard-deviation change in each explanatory variable.

All explanatory variables are lagged by one week. This temporal ordering reduces the mechanical contemporaneous relationship that would arise from using current market conditions to explain a bubble classification constructed from the same week's price dynamics. The specifications progressively add trading volume and volatility, market returns, and a linear time trend. Statistical inference is again based on HAC standard errors with four weekly lags.

As a robustness check, I replace the binary GSADF bubble indicator with the continuous LPPLS positive-bubble confidence measure. Because GSADF identifies statistical explosiveness whereas LPPLS captures nonlinear bubble-like price dynamics, consistency across the two measures reduces the concern that the results depend on a particular definition of a bubble. These regressions are interpreted as conditional associations rather than causal estimates.

3.3.2 Event-Study Design

Finally, I examine stock-price reactions to major corporate announcements using the standard event-study framework of Brown and Warner (1985) and MacKinlay (1997). For each event, expected Pop Mart returns are estimated using the market model

$$R_t^{PM} = \alpha + \beta R_t^{HSI} + \varepsilon_t, \quad (8)$$

where R_t^{PM} denotes Pop Mart's daily return and R_t^{HSI} denotes the daily return on the Hang Seng Index. The model is estimated over trading days $[-120, -21]$ relative to the event reaction date.

The abnormal return on day t is defined as

$$AR_t = R_t^{PM} - (\hat{\alpha} + \hat{\beta} R_t^{HSI}), \quad (9)$$

and cumulative abnormal returns are calculated as

$$CAR_{[\tau_1, \tau_2]} = \sum_{t=\tau_1}^{\tau_2} AR_t. \quad (10)$$

The analysis reports the abnormal return on the reaction day and cumulative abnormal returns over $[-1, +1]$, $[-3, +3]$, and $[-5, +5]$ trading-day windows. For announcements released

after the Hong Kong market closes, the following trading day is treated as the reaction date. For announcements released during trading hours, the announcement date itself is used.

The event-study analysis complements the bubble and behavioral tests by examining whether the market's response to new fundamental information changed across different stages of Pop Mart's valuation cycle. Because only a small number of major corporate events are examined, the resulting evidence is interpreted as case-specific evidence on expectation adjustment rather than as a general causal estimate of announcement effects.

4 Bubble Identification

This section examines whether Pop Mart's stock price exhibited dynamics consistent with speculative bubble behavior during the sample period. We combine two complementary approaches. The SADF and GSADF procedures test for and date-stamp episodes of statistically explosive price behavior, while the Log-Periodic Power Law Singularity (LPPLS) model examines whether the price path displays the nonlinear acceleration and log-periodic fluctuations commonly associated with self-reinforcing speculative dynamics. The two approaches therefore capture distinct dimensions of bubble-like behavior: statistical explosiveness and nonlinear price dynamics.

4.1 SADF and GSADF Evidence

Table 1 reports the SADF and GSADF statistics together with their simulated critical values. Both tests provide strong evidence of explosive price behavior. The SADF statistic is 5.300, exceeding its 99% critical value of 2.100, while the GSADF statistic is 6.420, well above the corresponding 99% critical value of 2.810. The null hypothesis of no explosive behavior is therefore rejected at the 1% level under both procedures.

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: This table reports the SADF and GSADF test statistics for Pop Mart's stock price and their simulated 90%, 95%, and 99% critical values. The null hypothesis H_0 is that the price series does not exhibit explosive behavior. Rejection occurs when the test statistic exceeds the corresponding upper-tail critical value.

The two tests differ primarily in how they search for explosiveness over time. The SADF procedure recursively expands the estimation window from a fixed starting point (Phillips, Wu, and Yu 2011), whereas the GSADF procedure allows both the starting and ending points of the window to vary (Phillips, Shi, and Yu 2015). This additional flexibility makes GSADF particularly useful when multiple episodes of exuberance may occur within the same sample. The rejection obtained from both procedures therefore indicates that the evidence of explosiveness is robust to alternative recursive-window specifications.

Figure 3 provides the corresponding date-stamping evidence. The recursive statistic remains largely below its critical-value sequence from 2021 through mid-2024, suggesting little evidence of persistent explosiveness over this period. A pronounced change occurs in late 2024. The procedure identifies three adjacent explosive intervals: October 9, 2024 to January 15, 2025; January 16 to April 7, 2025; and April 8 to October 2, 2025. Because these intervals are contiguous, it is more economically meaningful to interpret them as successive stages of a broader explosive regime rather than as three independent bubbles. On this interpretation, Pop Mart entered an explosive price regime in October 2024 that persisted until October 2025. The statistical evidence becomes particularly pronounced during the rapid appreciation in 2025, before the recursive statistic eventually falls below its critical threshold. The GSADF evidence therefore points to a clearly defined transition into, and subsequently out of, an unusually persistent period of price explosiveness.

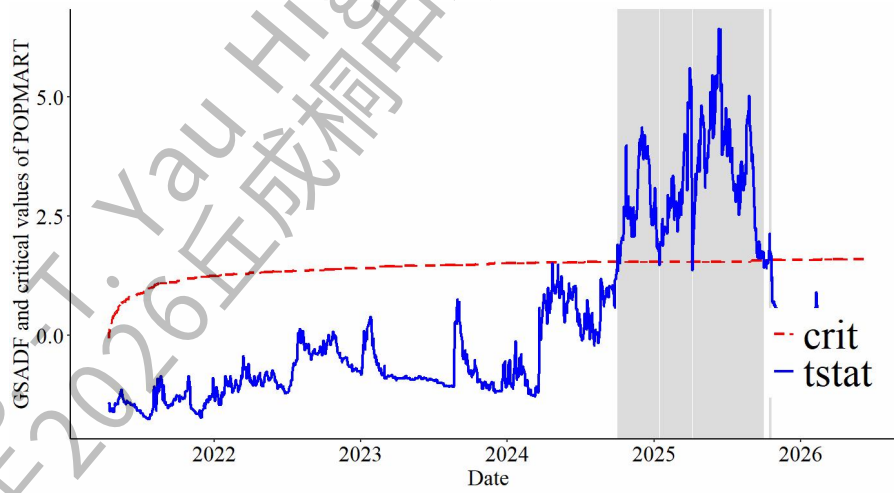


Figure 3. Recursive GSADF Test and Bubble Date-Stamping for Pop Mart

4.2 LPPLS Evidence

The GSADF results identify when Pop Mart's price dynamics became statistically explosive, but they reveal less about the form of the price trajectory within that regime. The LPPLS

model provides a complementary perspective. It characterizes speculative bubbles as periods of faster-than-exponential price growth accompanied by accelerating log-periodic fluctuations (Sornette and Cauwels 2015; Shu and Song 2024). In the LPPLS framework, these patterns arise from self-reinforcing feedback mechanisms, including imitation and herding, that can cause price growth to become increasingly unstable as the market approaches a potential regime change.

Figure 4 illustrates the LPPLS fit to Pop Mart's log stock price. The fitted trajectory is relatively subdued during the weak-price period between 2021 and 2023, begins to turn upward in 2024, and steepens markedly into 2025. The resulting curvature is consistent with an accelerating price process rather than a continuation of the more moderate dynamics observed earlier in the sample. The LPPLS fit should nevertheless be viewed primarily as a visualization of the nonlinear price trajectory; stronger evidence comes from the rolling bubble indicators examined below.

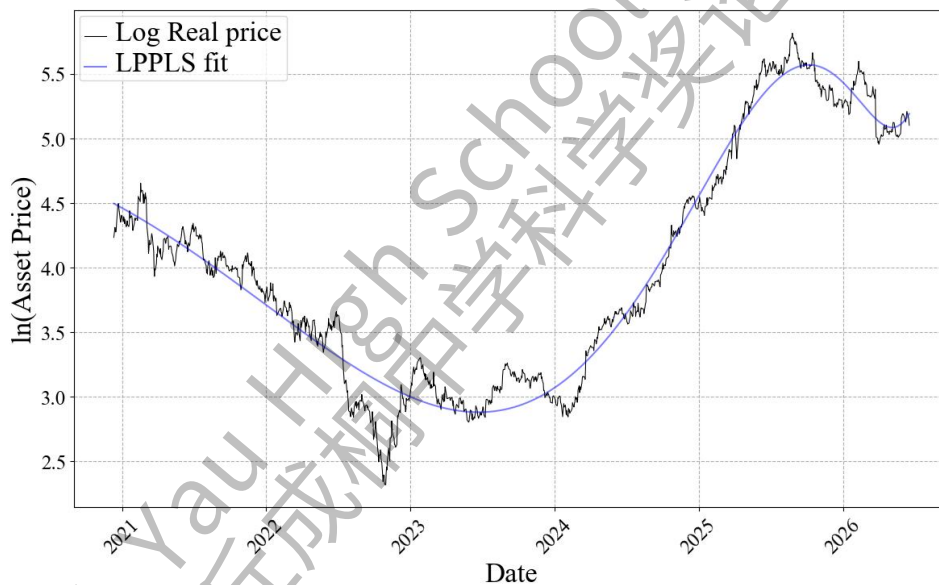


Figure 4. LPPLS Fit to Pop Mart's Stock Price

Importantly, this evidence does not imply that Pop Mart's stock price necessarily exceeded its fundamental value. Fundamental value is neither observed nor estimated by the LPPLS model. Rather, the model identifies a particular pattern of nonlinear price acceleration that the literature associates with speculative and self-reinforcing market dynamics. The evidence should therefore be interpreted as showing that Pop Mart's 2024–2025 price appreciation displayed characteristics consistent with a speculative bubble regime, rather than as demonstrating that the increase was entirely disconnected from fundamentals.

Figure 5 provides a more systematic view through the positive and negative LPPLS bubble indicators. A positive bubble corresponds to an accelerating upward price trajectory, whereas a negative bubble describes an accelerating downward trajectory generated by analogous positive-feedback dynamics and is often associated with an eventual rebound (Yan, Woodard, and Sornette 2010; Zhang et al. 2016). These indicators are not simple classifications of positive and negative returns. Instead, they summarize the proportion of rolling calibration windows that satisfy the parameter restrictions associated with the corresponding LPPLS configuration. Higher indicator values therefore imply broader support across estimation windows for a positive or negative bubble regime.

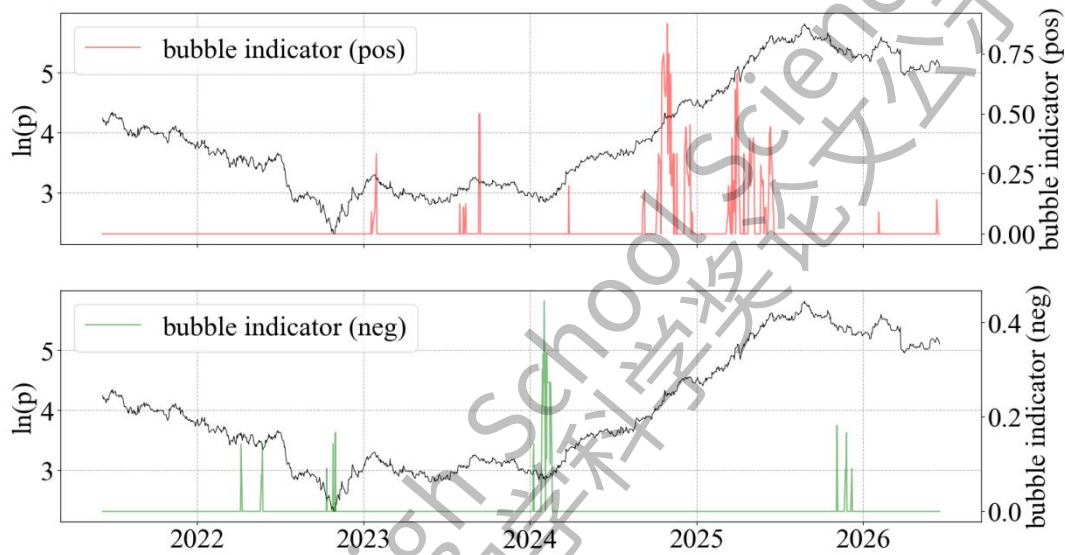


Figure 5. LPPLS Positive and Negative Bubble Indicators

The positive-bubble indicator is relatively weak before 2024 but becomes substantially more pronounced from late 2024 through 2025, overlapping closely with the explosive regime identified by GSADF. By contrast, negative-bubble signals become more visible during the subsequent correction from late 2025 into early 2026. The shift from predominantly positive-bubble signals during the appreciation phase toward stronger negative-bubble signals during the decline is consistent with a transition from self-reinforcing price acceleration to a corrective regime.

4.3 Comparing the Two Bubble Measures

Taken together, the GSADF and LPPLS results provide convergent evidence from two conceptually distinct approaches. GSADF identifies a statistically explosive regime beginning in October 2024 and ending in October 2025. Over approximately the same period, the LPPLS analysis reveals a steepening price trajectory and a marked increase in positive-

bubble signals. The two measures also provide broadly consistent evidence around the end of the episode: the GSADF statistic falls below its critical threshold after October 2025, while LPPLS signals subsequently shift toward the negative-bubble regime. The unusual 2024–2025 price episode is therefore visible both in the statistical persistence of price growth and in the nonlinear structure of the price trajectory.

At the same time, neither approach establishes that Pop Mart’s price appreciation was entirely driven by mispricing. Strong fundamental growth and speculative amplification may coexist, particularly for firms experiencing rapid changes in consumer attention and market expectations. The evidence in this section therefore supports a deliberately narrower conclusion: Pop Mart experienced an unusually persistent and rapidly accelerating price regime from late 2024 through 2025 that is consistently detected by two different bubble-identification frameworks. This finding motivates the next section, which examines whether investor attention, trading activity, and other behavioral factors were systematically associated with the evolution of this episode.

5 What Is Associated with Pop Mart’s Bubble Episodes?

Section 4 establishes that Pop Mart experienced a statistically unusual period of explosive price dynamics from late 2024 through 2025. The next question is what distinguished this episode from normal trading periods. The literature on speculative bubbles suggests that rapid price appreciation may be accompanied by unusually active trading, investor disagreement, trend-chasing behavior, and heightened investor attention (Scheinkman and Xiong 2003; Greenwood and Nagel 2009; Barber and Odean 2008; Da, Engelberg, and Gao 2011). Motivated by these mechanisms, this section first characterizes the identified bubble periods, then examines their behavioral correlates, and finally studies how market reactions to fundamental information changed over the valuation cycle.

5.1 Bubble Characteristics

Table 2 compares the weeks identified by GSADF as bubble periods with the remaining weeks in the sample. Because investor attention is measured at the weekly frequency, all variables are aggregated accordingly. The comparison reveals three particularly clear differences. First, Pop Mart earns an average weekly return of 2.93% during bubble weeks, compared with -0.29% otherwise, yielding a statistically significant difference of 3.22 percentage points ($t = 2.86$). Second, trading activity is substantially higher: average log trading volume rises from 15.59 to 16.15 ($t = 4.60$). Third, and most strikingly, average

Google search intensity increases from 5.92 during non-bubble weeks to 50.38 during bubble weeks, with a difference of 44.47 index points ($t = 7.38$).

Figure 6 shows that the increase in attention is not driven solely by a few isolated observations. Search activity rises sharply during the 2024–2025 valuation expansion and is concentrated around the GSADF bubble regime. This pattern is consistent with evidence that attention-grabbing securities attract greater investor demand (Barber and Odean 2008) and that Google search intensity captures active information acquisition by market participants (Da, Engelberg, and Gao 2011). In the case of Pop Mart, therefore, the explosive price episode coincided not only with stronger returns and heavier trading, but also with an exceptional increase in public interest surrounding the company.

Importantly, neither volatility nor broad market performance differs significantly across the two regimes. Average 20-day rolling volatility is 59.29% during bubble weeks and 60.85% otherwise, while the difference in Hang Seng Index returns is also statistically insignificant ($t = 0.81$). These results help distinguish the Pop Mart episode from a general period of high market risk or unusually favorable Hong Kong equity-market performance. The defining features of the bubble regime are therefore primarily company-specific: strong price appreciation, heavier trading, and unusually elevated attention. The descriptive evidence, however, does not reveal whether attention contains information about bubble status beyond these contemporaneous market characteristics. This motivates the multivariate analysis that follows.

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: This table compares weekly market characteristics during GSADF-identified bubble and non-bubble periods. A week is classified as a bubble week when at least half of its trading days fall within a GSADF bubble episode. Weekly Return and Hang Seng Market Return are expressed in percentage points. Trading volume is measured as the logarithm of average daily trading volume. Volatility is the weekly average of 20-day rolling annualized volatility. Google Search Attention is the weekly Google Trends index for “Pop Mart.” The Difference column reports the bubble-period mean minus the non-bubble-period mean. t -statistics are based on HAC standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

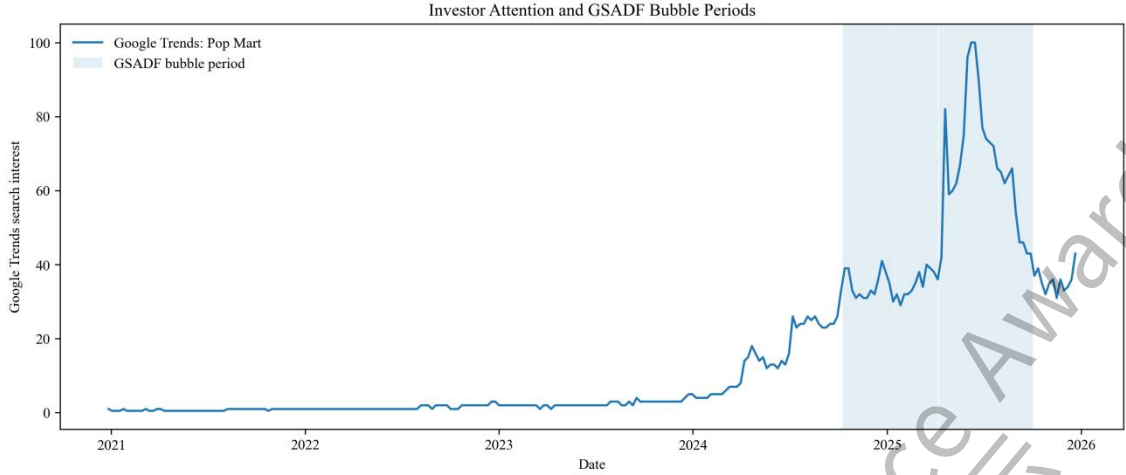


Figure 6. Investor Attention and GSADF Bubble Episodes

Notes: This figure plots weekly Google Trends search intensity for “Pop Mart.” Shaded regions indicate bubble episodes identified by the GSADF date-stamping procedure. Google Trends search intensity is normalized between 0 and 100 over the sample period.

5.2 Behavioral Correlates and Robustness

Table 3 examines whether the behavioral characteristics documented above remain associated with subsequent bubble status after controlling for other market conditions. Using the specification described in Section 3, all explanatory variables are lagged by one week and standardized before estimation. The regressions progressively control for trading volume, volatility, Hang Seng Index returns, and a linear time trend. This design does not establish causality, but it reduces the mechanical contemporaneous relationship between current price explosiveness and market variables measured over the same week.

Investor attention emerges as the most stable correlate of subsequent GSADF bubble status. In the baseline specification, a one-standard-deviation increase in lagged Google search attention is associated with a 0.330 increase in the probability that the following week is classified as a bubble week ($t = 9.49$). The coefficient changes little as trading volume, volatility, and market returns are introduced. Even after controlling for a linear time trend, the estimated coefficient remains 0.336 and highly significant ($t = 6.52$). By contrast, lagged trading volume, volatility, and market returns do not provide significant additional explanatory power once attention is included.

This result is consistent with behavioral-finance evidence that limited attention affects investor demand and that highly visible securities are more likely to attract individual investors (Barber and Odean 2008; Da, Engelberg, and Gao 2011). Nevertheless, the coefficient should be interpreted as an association rather than a causal effect. Rising prices

may themselves attract searches, while both attention and valuation may respond to changes in expectations about Pop Mart's fundamentals. The results therefore indicate that elevated attention is a particularly robust behavioral feature of the bubble episode, rather than demonstrating that attention independently caused the bubble.

The final column of Table 3 provides a robustness test using LPPLS positive-bubble confidence instead of the binary GSADF indicator. This is useful because the two approaches define bubbles differently: GSADF detects statistically explosive price dynamics, whereas LPPLS focuses on nonlinear acceleration and log-periodic behavior (Phillips, Shi, and Yu 2015; Zhang et al. 2016). Lagged attention remains positive and statistically significant in the LPPLS specification, with a coefficient of 0.026 ($t = 2.31$). The consistency across two conceptually different bubble measures therefore reduces the concern that the main result is driven by a particular statistical definition of a bubble.

The preceding evidence shows that attention rose alongside the bubble and remained associated with its subsequent development even after observable market conditions were controlled for. A related question is whether the market's interpretation of new fundamental information also changed as valuations and expectations increased. To examine this dimension of the bubble cycle, I next study stock-price reactions to major corporate announcements.

Table 3. Behavioral Factors Associated with Bubble Episodes

	GSADF Bubble Dummy				LPPLS Positive Confidence
2-5 (lr)6-6	(1)	(2)	(3)	(4)	(5)
Lagged Attention	0.330*** (9.49)	0.339*** (9.60)	0.339*** (9.62)	0.336*** (6.52)	0.026** (2.31)
Lagged Log Volume		-0.015 (-0.57)	-0.015 (-0.54)	-0.016 (-0.60)	0.007 (0.79)
Lagged Volatility		0.023 (1.27)	0.023 (1.27)	0.024 (1.23)	0.004 (0.44)
Lagged Market Return			-0.003 (-0.19)	-0.003 (-0.20)	-0.002 (-0.33)
Time Trend				0.015 (0.08)	0.004 (0.13)
Observations	260	257	257	257	237
R^2	0.678	0.680	0.680	0.680	0.126

Notes: Columns (1)–(4) report linear probability regressions in which the dependent variable equals one if week t is classified as a GSADF bubble week and zero otherwise. Column (5) replaces the GSADF indicator with LPPLS positive-bubble confidence. Attention, log trading volume, volatility,

and Hang Seng Index returns are standardized to have zero mean and unit standard deviation. All explanatory variables are lagged by one week. HAC t -statistics with four weekly lags are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

5.3 Corporate Announcements and Expectation Correction

Table 4 reports event-study results for three major corporate announcements at different stages of Pop Mart's valuation cycle: the 2024 interim results, the July 2025 positive profit alert, and the March 2026 annual results. Following standard event-study methodology (e.g., see Brown and Warner 1985; MacKinlay 1997), abnormal returns are measured relative to a market model estimated using the Hang Seng Index. The events provide a useful comparison because all contain favorable information about the company's operating performance, but occur under very different valuation conditions. Figure 7 complements the table by plotting cumulative abnormal returns from ten trading days before to ten trading days after each announcement, allowing the timing and persistence of market reactions to be observed more directly.

The 2024 interim results produced a strongly positive response. The reaction-day abnormal return was 9.92%, while $CAR[-1, +1]$ and $CAR[-3, +3]$ reached 12.14% and 12.72%, respectively. At this relatively early stage of the valuation recovery, stronger operating performance therefore appears to have provided favorable information that had not yet been fully incorporated into the stock price. Although $CAR[-5, +5]$ subsequently declined to 5.48%, the overall response remained positive.

The response changed markedly by July 2025. Despite the exceptionally strong revenue and profit growth announced in the positive profit alert, the reaction-day abnormal return was -4.60% , while $CAR[-1, +1]$, $CAR[-3, +3]$, and $CAR[-5, +5]$ fell to -8.33% , -19.77% , and -28.43% , respectively. This announcement occurred within the GSADF bubble regime, after both the stock price and investor attention had already risen substantially. One interpretation is that expectations of continued rapid growth had become increasingly embedded in the valuation. Behavioral models of extrapolative expectations suggest that, after extended periods of strong performance, investors may place excessive weight on the continuation of recent growth (Barberis, Shleifer, and Vishny 1998). Under such conditions, objectively strong results need not generate a positive price surprise if expectations are already exceptionally demanding. The March 2026 annual results provide even stronger evidence of expectation correction. Despite strong realized performance, the reaction-day abnormal return was -26.31% , and $CAR[-1, +1]$, $CAR[-3, +3]$, and $CAR[-5, +5]$ were

−30.70%, −32.61%, and −36.35%, respectively. By this point, the GSADF explosive regime had ended and the LPPLS evidence had shifted away from strong positive-bubble dynamics. The sharp negative response is therefore consistent with a broader reassessment of the optimistic growth expectations formed during the preceding valuation expansion.

Taken together, the three analyses describe a coherent valuation cycle. Pop Mart's bubble periods were characterized by unusually strong company-specific returns, heavier trading, and exceptionally high public attention rather than by stronger aggregate market performance. Attention remained the most robust behavioral correlate across both GSADF and LPPLS measures. At the same time, the event-study results suggest that the market's benchmark for evaluating new information became progressively more demanding: strong operating news generated positive surprises early in the cycle but increasingly negative reactions after expectations had risen substantially. The evidence does not imply that Pop Mart's price expansion was detached from fundamentals. Rather, it is consistent with a process in which improving fundamentals and increasingly optimistic expectations initially reinforced one another, followed by an eventual reassessment once realized performance was no longer sufficient to exceed the market's elevated expectations.

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: This table reports abnormal returns and cumulative abnormal returns around three major Pop Mart corporate announcements. Returns are expressed in percentage points. Expected returns are obtained from a market model using the Hang Seng Index as the market benchmark. The model is estimated over trading days $[-120, -21]$ relative to the reaction date, using 100 trading-day observations. For announcements released after market close, the following trading day is treated as the reaction date. AR[0] denotes the abnormal return on the reaction day, while CAR[a, b] denotes the cumulative abnormal return from trading day a through trading day b .

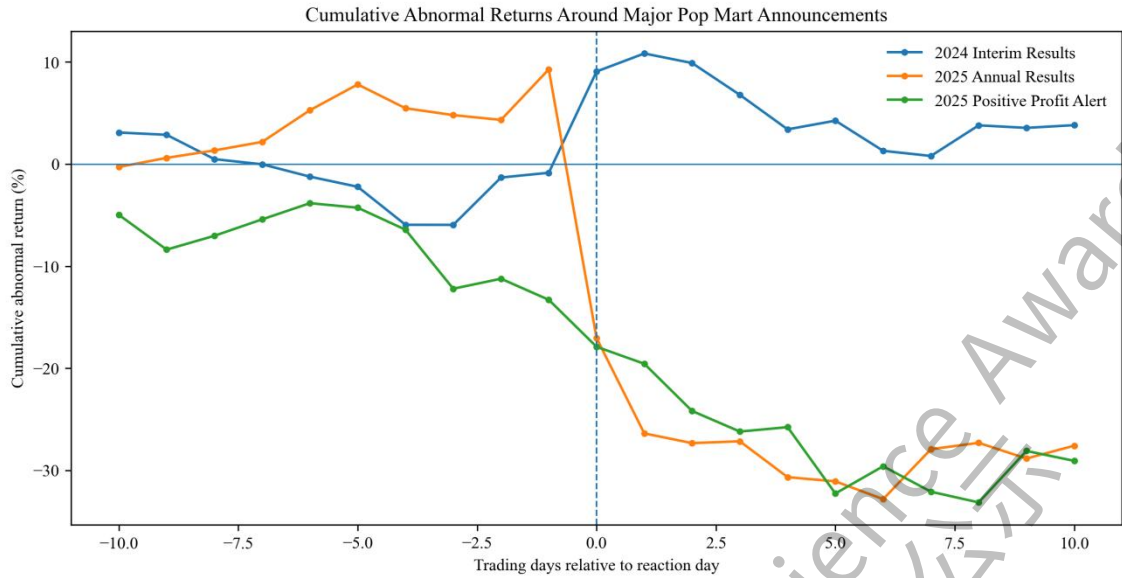


Figure 7. Cumulative Abnormal Returns around Major Corporate Announcements

Notes: This figure plots cumulative abnormal returns from ten trading days before to ten trading days after each corporate announcement. Day 0 denotes the reaction trading day. Expected returns are estimated using the Hang Seng Index market model over the pre-event estimation window $[-120, +21]$.

6 Conclusion

This paper asks a broader question through the case of Pop Mart: can strong fundamentals and speculative price dynamics coexist? Pop Mart provides a useful setting for addressing this question because its rapid improvement in operating performance was accompanied by rising product popularity, increasing investor attention, and an unusually strong expansion in market valuation. Combining SADF/GSADF and LPPLS bubble-detection methods with behavioral indicators and event-study evidence, I examine not only whether bubble-like price dynamics emerged, but also how the surrounding market environment evolved over the valuation cycle.

Three findings stand out. First, both GSADF and LPPLS identify a pronounced period of explosive price dynamics from late 2024 through much of 2025. Second, these bubble periods were characterized by stronger Pop Mart-specific returns, heavier trading, and substantially higher public attention, with investor attention remaining the most robust behavioral correlate across both bubble measures. Third, the event-study results show that strong corporate news generated positive abnormal returns early in the valuation cycle but

increasingly negative reactions once market expectations had become substantially more demanding.

Taken together, the results suggest that fundamental improvement and speculative amplification need not be mutually exclusive. In Pop Mart's case, stronger business performance appears to have supported the initial revaluation, while rising attention and increasingly optimistic expectations may have amplified the subsequent price expansion. As expectations became elevated, however, even strong realized performance was no longer sufficient to generate positive surprises. This case therefore highlights a broader feature of speculative markets: bubbles may emerge not simply from weak fundamentals, but from the interaction between genuine growth, investor attention, and increasingly demanding expectations.

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I've been a fan of Pop Mart ever since I was a kid. What drew me in at first was the simple thrill of blind boxes — the surprise of opening a new figure, the fun of collecting different series. For years, I was just a regular customer enjoying the culture around designer toys. Then Labubu blew up. I watched it go from a niche character to a viral phenomenon, taking over social feeds, popping up in stores everywhere, and driving huge crowds to shop. As a fan, I was excited by the hype. But I also started noticing something else: Pop Mart's stock price seemed to swing up and down almost in lockstep with how hot the brand felt in daily life. That got me thinking: how much of a stock's value is actually built on real business results, and how much is just fed by public excitement and speculation? It was a question I couldn't shake. When we started learning about market behavior and valuation in my high school microeconomics class, I realized I could turn that casual curiosity into a proper research project. That's how this paper got its start.

My deepest thanks go to Mr. Zhang, my high school microeconomics teacher. Thank him for providing me with help without charge. When I first went to him with this idea, I had nothing but a handful of observations and a lot of questions. He didn't dismiss it as just a student's passing interest. Instead, he stayed after class with me more than once to talk through my thoughts, helped me narrow down a clear research question, and walked me through the core theories behind stock market bubbles. He taught me where to find reliable public financial data, how to read market reports critically, and how to structure an argument that holds up. He read every draft I sent him, marked up places where my logic was weak, and pushed me to back up every point with evidence. Most importantly, he never just gave me the answers. He asked questions that made me work through the problems myself. That's the part that has mattered most — getting to practice thinking like a researcher, not just writing a paper. I'm truly grateful for all the time he put into guiding me, all on his own time.

I also owe thanks to the researchers whose work I cited throughout this paper. Their studies on asset bubbles, behavioral finance and consumer markets gave me the theoretical foundation to build on. Publicly available company filings, stock data and industry reports also gave me the raw material I needed for my analysis. This paper wouldn't exist without that prior work.

I know this study has its limits. I only had access to public information, and I don't yet have the technical skills to run more advanced quantitative models to measure the bubble exactly. Some parts of my analysis are more descriptive than precise. I hope to keep studying economics and finance in the future, build stronger research skills, and dig deeper into questions like this.

In the preparation of this manuscript, I have used Doubao (version 2.1 Turbo) — an artificial intelligence model developed by ByteDance — as the sole AI-assisted tool.ⁱ Its use is strictly limited to language polishing, sentence structure refinement, and academic phrasing optimization, with the sole purpose of improving the fluency, clarity, and formal consistency of the written presentation. All core academic work underlying this paper was completed independently by the author. This includes the formulation of the research question, study design, data collection and processing, empirical analysis and result derivation, and all core arguments and conclusions. The AI tool did not participate in the creation of any core academic content, data interpretation, or research judgment. I take full and sole responsibility for the originality, academic integrity, and factual accuracy of all content, data, and conclusions presented in this work.

Finally, thank you again to everyone who encouraged me along the way.

ⁱSource: [Details of AI tool usage](#)