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Conditional demand for lottery-type stocks: Information spillovers and asset prices comovement[☆]

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ABSTRACT

Previous literature has shown that investors' demand for lottery-type stocks is conditional on a number of factors, and that these stocks underperform in the long run compared to non-lottery-type stocks. We document that investors' demand for lottery-type stocks is conditional on days with information spillovers. Specifically, on macroeconomic news days, the demand for lottery-type stocks depends on information content, and their prices more closely follow the market index movements. This comovement tends to persist on FOMC announcement days and for firms without overlapping earnings announcements. We provide an information-based theory to explain the empirical pattern.

1. Introduction

Literature has well-documented that investors have lottery demands, and thus, assets with strong lottery features tend to be overvalued on average, leading to future underperformance relative to their non-lottery-type counterparts (see e.g., Bali et al., 2011; Kumar, 2009; Liu et al., 2020).[1] Recent emerging studies find that investors' demand for lottery-type stocks is conditional and has various dependencies. For example, Fong and Toh (2014) shows that investors strongly demand lottery-type investments during high sentiment periods. An et al. (2020) shows the strong and robust underperformance of lottery-type stocks when investors have previously lost money. The lottery demand is also conditional upon the presence of events, with Liu et al. (2020) reporting that there is a time-varying demand for the lottery ahead of the firm's quarterly earnings announcements. The cumulative return of these lottery-type stocks appears to be an inverted-V-shaped pattern in the pre- and post-event periods. Guo et al. (2024) documents that there is a flight-to-lottery pattern in the pre-event period of FOMC announcements.

While there is a rich set of prior studies in this regard, there is limited knowledge about whether and how investors' lottery stock demand is influenced by news content. Investigating this research question can yield several benefits. First, investors who demand lottery-type stocks might face constraints in subscribing to professional newswire services. Therefore, it would be helpful to understand whether they will learn on days with information spillovers to revise their expectations of lottery-like payoffs. Second, the existing literature generally believes that demand for lottery-type stocks is mainly driven by less well-diversified investors who can hold only a few assets at once. It would be useful to know whether other investor clientele also engage with this type of asset.

To examine this, we design an empirical setting where we look at macronews content and study whether and how it impacts investor demand for lottery-type stocks.[2] To quantify the news content in a simple manner, we utilise the price change of the most prominent market assets—the market index—and perform the analysis on macronews days. Previous literature has documented that important information tends to be released on those days, which has significant asset pricing implications (e.g., Cieslak et al., 2019; Hu et al., 2022; Lucca & Moench, 2015; Savor & Wilson, 2013, 2014). We follow Hirshleifer and Sheng

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[1] Lottery-type stocks are those stocks displaying right-skewed payoffs: low probability of winning enormous rewards. These stocks also show high idiosyncratic volatility (Kumar, 2009).

[2] For simplicity, we use macronews in this paper to represent macroeconomic news.

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(2022) (HS) to define the macronews days as the days releasing information about one of the Federal Open Market Committee meetings' interest rate decisions (FOMC), Manufacturing Purchasing Managers Index (PMI), Employment Status (EMP) and Personal Consumption (PC). HS found that these events considerably impacted the US stock market by examining 40 different macronews announcements. To measure stocks' reaction surrounding the macronews day t, we follow HS to construct market-model based cumulative abnormal returns (CAR) over windows of [t-5,t-1], [t, t+1], and [t+2, t+6], denoted as the pre-event, during-event and post-event CAR, respectively, reflecting the demand for the stocks in different periods.

The main finding of this paper is that the investors' demand for lottery-type stocks is strongly affected by macronews content during and following the macronews days. Specifically, we show that the market excess returns are positively correlated with the cumulative abnormal returns on lottery-type stocks over during-event and post-event windows. Notably, the impact is more pronounced when the stock's lottery feature is stronger. These findings are robust to the choice of measures capturing macronews content, including S&P 500 index, the market index excluding focal stocks, and the event surprises. Also, the main conclusion is not affected by the methods for measuring the stock's cumulative abnormal returns, including being adjusted by Fama–French-3 factors and Carhart-4 factors. In addition, we perform portfolio analysis. A portfolio strategy of buying (selling) the decile portfolio of stocks with the most lottery features, when the market excess returns indicate positive (negative) news content, generates 45 basis points (bps) (t-statistics = 6.23) of abnormal returns over the during-event window using a value-weighted scheme. Furthermore, it generates 52 bps (t-statistics = 4.07) abnormal returns over the post-event window. Collectively, our analysis empirically confirms that the macronews content affects investors' demand for lottery-type stocks.

We then investigate the mechanism behind it. Since literature has revealed that lottery-type stocks are more likely to exhibit information asymmetry issues (see Barinov, 2018; Tao et al., 2020), we conjecture that the relation between lottery-type stocks and the market index may be related to information spillovers (see e.g., Ben-Rephael et al., 2021). This idea also follows the information market theory proposed by Veldkamp (2006). Assuming that information covers many assets and can be observed by many investors, asset return comovement is more likely to occur when investors price one asset using the common subset of the information concerning many other assets. When surrounding the macroenews days, information is important, rich, and less costly for investors to obtain, and it has considerable implications for asset prices across different stocks. For those lottery-type stocks, which exhibit strong information asymmetry, investors tend to learn from the common source of information and price the value of these specific assets. When information drives an increase (or decrease) in the pay-offs of the given assets (i.e., the market index), the valuation of other assets also increases (or decreases). We refer to this phenomenon as *information-driven comovements*.

Furthermore, we extend the idea by Zhang and Zhao (2023), which shows that the quality of the information environment influences investors' learning effectiveness (e.g., a poor information environment hampers it), in the context of Veldkamp (2006)'s theory. We propose that investors in lottery-type stocks, who already face heightened information asymmetry, are particularly sensitive to the quality of the information environment. In settings with poor information quality, these investors may struggle to fully incorporate the information-driven payoffs of benchmark assets into their valuation of other stocks, thereby weakening return comovement. In contrast, when the information environment is rich and accessible, investors can more effectively process shared signals, leading to stronger information-driven comovement. Consistent with this hypothesis, we find that comovement among lottery-type stocks and the market index is significantly stronger in high-quality information environments. On the other hand, we observe no such comovement under poor information conditions. This evidence reinforces the notion of information-driven comovement.

Veldkamp (2006)'s theory predicts that the comovement falls when more signals can be observed or more investors are attentive and informed. Consistently, we find that the comovement pattern tends to be more persistent among those lottery-type stocks, which are also non-announcing firms for their quarterly earnings, than those announcing firms. A subsample analysis shows that the comovement tends to be short-lived for the recent sample period when the overall information environment is more efficient, and information technology has made information collection relatively easier. In addition, when examining each announcement type separately, FOMC days are the most attentive and influential announcement series to investors, reporting a more persistent comovement. Moreover, splitting the sample into high/low investor sentiment periods, we find that the comovement is more likely to appear and last longer in the optimistic period, when retail investors tend to be more active in the market.

To see how persistent the comovement between the two types of assets lasts after the macronews day, we conduct a long-run performance test. The result suggests that the demand for lottery-type stocks is unlikely to be affected after one week. This pattern is consistent with the finding of Patton and Verardo (2012): it is less likely that investors will learn across assets and use the common signals to revise their expectations when they are reasonably certain about the valuation of the given asset, which further supports the *information-driven comovements* explanation.

In addition, we rule out other possibilities, such as *retail attention-induced spillover* (see e.g., Hoberg & Phillips, 2018; Huang et al., 2022, 2021). Using Google searching volume index as a proxy of retail attention and Bloomberg news readership index as a proxy of institutional attention (see Ben-Rephael et al., 2017; Da et al., 2011), we observe that a consistently high level of institutional attention appears on those lottery-type stocks around macroeconomic news days (i.e., [−5,+5]). In contrast, retail attention reports relatively few changes. All in all, the evidence is more consistent with *an information-driven comovement* theory.

Our result is also robust to mechanical effects that the comovement of lottery-type stocks with the market index could be driven by the fact that those stocks are high-beta assets in nature (see e.g., Bali et al., 2017). As such, it is not surprising to observe that those lottery-type stocks can strongly covary with the market. By controlling for individual stocks' market beta, we find no evidence that high-beta stocks drive the comovement in the regression and bivariate-sorted portfolios analyses.

This paper contributes to two strands of literature. First, we extend the literature on lottery-like stocks by suggesting that investors' demand for lottery-like stocks is conditional on information spillover, especially macronews, which is rich, free and easily accessible. Existing literature has shown that investors' demand for lottery-type stocks is conditional, with various dependencies, such as sentiment periods and events (see, e.g., An et al., 2020; Fong & Toh, 2014; Guo et al., 2024; Liu et al., 2020). We demonstrate that this demand is not only influenced by pre-scheduled events, such as a firm's quarterly earnings or FOMC announcements, but is also significantly affected by the content of information released on major news events. More importantly, our placebo test downplays the significance of the presence of events in lottery-type stocks (see Guo et al., 2024; Liu et al., 2020) but highlights the importance of information content to this type of stock in the subsequent period.

Second, our work contributes to the asset price comovement literature by suggesting that assets comovement occurs when there are information spillovers. The empirical literature on comovement or lead–lag return effects has uncovered many economic linkages at the firm level, such as supplier-customer link (Cohen & Frazzini, 2008), product rivals (Hoberg & Phillips, 2016), and firms mentioned in the shared analyst reports (Ali & Hirshleifer, 2020). We demonstrate that asset price comovement does not need to be based on factual linkages. Between the market asset and individual stocks in the cross-section, comovement can also occur when there are information spillovers among these lottery-type stocks, exhibiting strong information asymmetry. Investors learn from macro news and price these lottery-type stocks, generating predictable returns.

The rest of the paper is organised as follows. Section 2 presents our data and methodology, while Section 3 reports the results. Section 4 examines the channels that may explain why investors' demand for lottery-type stocks is affected by macronews, while Section 5 explores alternative explanations for our findings. Finally, Section 6 summarises our work and presents conclusions.

2. Data and methodologies

2.1. Constructing stock-level variables

We collect the individual US stock data from the Center for Research in Security Prices (CRSP), where the sample consists of all common stocks listed on the NYSE, AMEX and NASDAQ stock exchanges and, consistent with the literature, we exclude penny stocks with a share price below $1 at the most recent month's end. The sample period is from January 1996 to December 2023.

2.1.1. Lottery measures

We follow the literature to construct five proxies measuring the lottery-like level of a stock, including maximum daily returns (MAX) from Bali et al. (2011), expected idiosyncratic skewness (SKEWEXP) based on Boyer et al. (2010), idiosyncratic volatility (IVOL) by Ang et al. (2006), stock price (PRC) following Kumar (2009), and a composite Z-score (ZSCORE) based on these four variables (Liu et al., 2020). To ensure that the proxies are comparable, we further cross-sectionally standardise the lottery-like level for each proxy.

2.1.2. Return performance measures

Following Hirshleifer and Sheng (2022), we construct cumulative abnormal returns (CAR), conditional upon macronews days, using the market model. On day t, the CAR on stock i over the period of $[t+h, t+H]$ is defined as follows:

$$CAR[h,H]_{i,t} = \left[\prod_{j=t+h}^{t+H}(1+R_{i,j}) - 1\right] - \hat{\beta}_{i,t}\left[\prod_{j=t+h}^{t+H}(1+R_{m,j}) - 1\right] \tag{1}$$

where $R_{i,j}$ is the return on stock i on day j, $R_{m,j}$ is the market return on day j, and $\hat{\beta}_{i,t}$ is obtained from the market model via the regression $R_{i,t} = \alpha_{i,t} + \beta_{i,t}R_{m,t} + \epsilon_t$ with a rolling window from $t-300$ to $t-46$. We use CAR[−5,−1], CAR[0,1], and CAR[2,6] to observe the stock price reaction before, during, and after the macronews days.[3]

2.1.3. Control variables

To control for firm characteristics that may affect the main results in this paper, the baseline regression includes the following control variables. High value firms generally outperform low value firms, which is well known Caglayan et al. (2018), Fama and French (1993, 1995) and Pontiff and Schall (1998). We follow the literature to capture the value with book-to-market ratio (BM). Known as size effects, investors are believed to require a higher premium on holding stocks with smaller market cap (Fama & French, 1993; Van Dijk, 2011; Zakamulin, 2013). Building upon it, we therefore take the natural logarithm of market cap (log(ME)) as one of the control variables. Moreover, stocks with past up-trends are believed to outperform stocks with past downtrends, and it is termed as the momentum effect (MOM) (Jegadeesh & Titman, 1993). To capture such an effect, we take the returns over the past twelve months, skipping the most recent one as it has reverse predictive power on the future stock returns, which is termed the reversal effects (REV). It is well documented that investors require a higher premium on holding stocks with less liquidity to compensate for the illiquidity risk (Amihud, 2002; Amihud & Noh, 2021; Cakici & Zaremba, 2021), we then measure one's illiquidity (ILLIQ) with the absolute monthly returns on a stock divided by the respective monthly trading volume in dollars. In addition to the characteristics of general stocks, lottery-like stocks are found to be sensitive to the turnover, as Kumar (2009) document that stocks with high monthly turnover (TURN) are more likely to be attention-grabbing. We therefore also take the turnover as one of the control variables. More details can be found in Appendix A.

2.2. Macronews days

We obtain a list of macroeconomic announcement days, including the Federal Open Market Committee (FOMC) interest rate decision meeting, Employment Status (EM), ISM PMI (PMI) and Personal Consumption (PC) from Bloomberg Economic Calendar for the US market, respectively. Due to data precision and availability, the sample starts in 1997 and ends in 2023. As shown in Hirshleifer and Sheng (2022), these macro events tend to have considerable asset pricing implications for the financial market.[4] The details of these macro events can be found in Appendix A.

2.3. Data summary

Table 1 reports the summary statistics of the data. In Panel A, there are 1109 pre-scheduled macroeconomic events, and 1063 macronews days in total, among which 216 days are FOMC announcement days, 307 are PMI days, 231 are PC days, and 305 are UM days, respectively.[5] Panel B presents summary statistics for stock performance surrounding macronews days. It includes Cumulative Abnormal Returns (CAR) over three windows surrounding macronews days: [−5, −1], [0, 1], and [2, 6]. The mean CAR is relatively small across all three windows, with slightly positive returns (0.19%) in the pre-event (CAR[−5,−1]), and almost negligible returns around the event day (CAR[0,1]), and post-event (CAR[2,6]). This statistic is generally consistent with Lucca and Moench (2015), which documents that stocks tend to have return drifts ahead of macronews days.

In Panel C, we further examine the return performance of lottery-type stocks in the three periods, respectively. All stocks are sorted into ten deciles based on the ZSCORE measure at the most recent month's end. The bottom (top) decile portfolio of stocks is denoted as the (lottery-type) Non-lottery-type stocks. A hedging portfolio is constructed by taking the difference between the two decile types. Interestingly, the mean returns of $CAR[-5,-1]$ of the hedging portfolios are 0.91% and 1.02% in equal-weighted and value-weighted schemes, respectively, which are statistically significant at the 1% level. In sharp contrast, we find that both the mean returns on $CAR[0,1]$ and $CAR[2,6]$ of the same portfolios are insignificant from zero in the value-weighted scheme. Our results are consistent with the findings of Guo et al. (2024) – there is a flight-to-lottery pattern prior to macro announcements. However, they do not find evidence of return drifts or reversals after the event. Taking Panel B and C together, our results confirm that lottery-type stock prices can be significantly affected by the macronews, mainly in the pre-event rather than the post-event

[3] For example, CAR[0,1] measures the cumulative abnormal returns over a two-trading-day window.

[4] Gilbert et al. (2017) document macro-announcements' importances, including FOMC, employment status, ISM PMI and Personal Consumption regarding the financial market. Similarly, by examining 40 different macroeconomic news announcements, Hirshleifer and Sheng (2022) find the considerable impacts of these macronews in the US stock market.

[5] There are cases where different macronews events happen on the same trading days. As such, we end up with 1063 macronews days.

Table 1
Summary statistics.

Panel A: Macro-announcement events						
	Total macro days		FOMC	ISM PMI	PC	EMP
#_of_events	1064		216	323	249	321
Panel B: Stock performance (Time-series average of cross-sectional statistics)						
	#_of_stocks	Mean (%)	Std. (%)	25th Decile (%)	Median	75th Decile (%)
CAR[−5,−1]	3777.37	0.19	8.03	−3.08	−0.11	2.92
CAR[0,1]	3845.49	0.06	5.34	−2.05	−0.10	1.87
CAR[2,6]	3771.19	0.05	8.05	−3.27	−0.21	2.86
Panel C: Lottery-type stocks VS. non-lottery-type stocks						
	Equal-weighted			Value-weighted		
	CAR[−5,−1]	CAR[0,1]	CAR[2,6]	CAR[−5,−1]	CAR[0,1]	CAR[2,6]
Decile 1	0.04*	0.03*	0.03	0.00	0.00	0.07***
	(1.89)	(1.92)	(1.53)	(0.17)	(0.17)	(3.61)
Decile 10	0.95***	0.18***	0.16	1.02***	0.09	−0.02
	(8.26)	(3.05)	(1.43)	(7.46)	(1.19)	(−0.15)
10 - 1	0.91***	0.15**	0.13	1.02***	0.09	−0.09
	(7.59)	(2.46)	(1.07)	(6.87)	(1.04)	(−0.66)

This table reports the summary statistics of macronews events and stock return performance. Panel A provides the number of different event observations used in this paper. In Panel B, the summary statistics of average individual stocks' cumulative abnormal return (CAR) are provided before, during, and after the macronews days. In Panel C, the average return performance of lottery-type stocks (Decile 10), non-lottery-type stocks (Decile 1), and their hedged return performance (Decile 10-1) around the macronews days, respectively. Macronews events include the FOMC interest rate decisions meeting (FOMC), Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). The lottery-type stock is identified using ZSCORE at the end of the most recent month, which is computed by taking the mean standardised value of the ranking index based on the portfolio sorted on maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (PRC), individually. The higher the ZSCORE, the higher the lottery feature a stock has. The details of variable construction can be found in Appendix A. Our sample includes common stocks publicly listed on NYSE, Amex, and NASDAQ stock exchanges and stock prices below $1 are excluded. The sample period is between January 1997 and December 2023. The t-statistics, reported in parentheses, are based on Newey and West (1987) standard errors with the six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

period. This, however, cannot rule out the possibility that the content of macronews may influence investors' demand for lottery-type stocks.

To explore this possibility, we regress the aforementioned CARs on market returns for each lottery decile. The coefficient on the market return measures the sensitivity of CAR to market movements. A statistically significant and positive coefficient suggests that when the market performs well, abnormal returns around the event tend to be more positive — possibly indicating that the firm's returns move with the market during the event window.

Fig. 1 visualises the estimated coefficients on the market return term across lottery deciles. Two key insights emerge from the figure. First, both the during-event and post-event CARs (represented by the green and blue lines, respectively) exhibit upward trends, indicating that the correlation between CARs and market returns becomes stronger for stocks with more lottery-like characteristics. Second, there is no clear evidence of this pattern in the pre-event CAR (shown as the red line), as the coefficients are statistically and insignificantly different from zero, despite a slight upward trend.

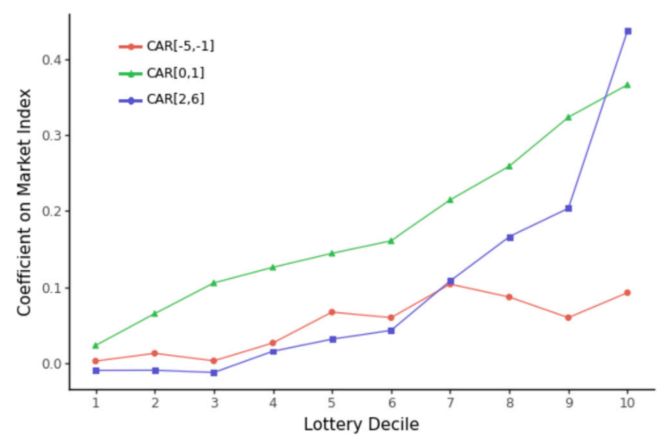

Fig. 1. Sensitivity of lottery stocks to market returns surrounding macronews days
This figure visualises how strongly cumulative abnormal returns (CAR) on lottery portfolios around macro news days are associated with the market's return on the macro news day itself. Inspired by Hirshleifer and Sheng (2022), we measure the pre-event, during-event and post-event reaction of stocks to macronews with CAR[−5,−1], CAR[0,1] and CAR[2,6]. Stocks are sorted into deciles on the lottery characteristics. We measure the lottery level of a stock at the end of the most recent month, with the maximum daily returns, idiosyncratic volatility, expected idiosyncratic skewness, and negative stock prices. We further construct a proxy as the average z-score on the aforementioned proxies (ZSCORE). See Appendix A for details. We then perform the following regression for each lottery decile:

$$CAR_t = \alpha + \beta MNews_t + \epsilon$$

where $MNews_t$ is the market returns on a macronews day t. For brevity, we report only the results related to ZSCORE. The sample period is between January 1997 and December 2023.

3. Empirical results

In this section, we document that investors' demand for lottery-type stocks is conditional on the macronews content, as evidenced by both regression and portfolio analyses. This finding is robust in alternative methods measuring macronews content and cumulative abnormal returns. We also examine the role of high-beta assets and demonstrate that their influence does not drive our main conclusion.

3.1. Baseline results

We investigate whether the content of important information in the market influences investors' demand for lottery-type stocks. To start, we use the market index's price change on macronews days as a proxy for macronews information content ($MNews$). We then regress each stock's CAR against its lottery measures ($Lottery$), $MNews$, and an interaction term between $Lottery$ and $MNews$. As mentioned above, the

$Lottery$ quantifies the extent of a stock's lottery-like features: The higher the $Lottery$ measure, the stronger these features are. The interaction term aims to examine how lottery-type stocks respond to changes in the market index's price. The regression model is detailed as follows:

$$CAR[h,H]_{i,t} = \beta_0 + \beta_1 Lottery_{i,m-1} MNews_t + \beta_2 Lottery_{i,m-1} + \beta_3 MNews_t + \lambda' X_{i,m-1} + \epsilon_{i,t}, \tag{2}$$

where $CAR[h,H]_{i,t}$ is the cumulative abnormal return using the market model over a holding window h days and H days after a macronews day t. For example, CAR[0,1] measures the cumulative abnormal returns over a window spanning both the macroenews day (t) and the following day ($t+1$). $MNews_t$ captures the information content revealed on the macronews day t, proxied by the CRSP-value-weighted market index less one-month T-bill rate. $Lottery$ is the most recent month's stock-level lottery measures, including the maximum daily return (MAX), expected idiosyncratic skewness (SKEWEXP), idiosyncratic volatility (IVOL), negative stock price (PRC) and ZSCORE. A higher level in proxy indicates a stronger lottery feature of a stock. X is a vector of lagged-one-month control variables, including book-to-market ratio (BM), market equity (ME), momentum (MOM), reversal (REV), turnover (TURN), and illiquidity (ILLIQ). The regression includes both firm, year, month and day of week fixed effects. Standard errors are clustered by macronews days. If information content indeed influences the demand for lottery-type stocks, we should expect the β_1 coefficient to be statistically significant.

Table 2 reports the above regression results for different lottery proxies. Focusing on the coefficient on the interaction term (β_1), we find evidence that macronews contents influence lottery demand. In the last panel associated with the proxy of ZSCORE of the table, β_1 regarding CAR[−5,−1], CAR[0,1] and CAR[2,6] are 0.41 (t-statistic: 0.10), 10.84 (t-statistic: 5.15) and 11.68 (t-statistic: 3.05), respectively. We can gain two insights from that: (i) the news content has no influence on the pre-event performance of lottery-like stocks, which makes sense since the information has not been revealed before the event; (ii) investors' demand for lottery-like stocks is positively impacted by the information content. When market excess returns are larger on a macronews day, there is a stronger demand for lottery-type stocks, leading to price increases immediately and up to 6 days after the event day. So, how strong is the correlation? By observing column (14) and (15) of Table 2, we find that a one standard deviation increase in ZSCORE increases the responsiveness of CAR[0,1] and CAR[2,6] to market movements by 10.84 bps and 11.68 bps, respectively, for every 1% increase in the market return.

This pattern is robust in the other lottery proxies. Still observing β_1 but on the other four proxies, we find that the coefficients regarding CAR[0,1] are all statistically significant at the 1% level and their average is 8.23%, and the coefficients regarding CAR[2,6] are both statistically significant at either the 1% or 5% level with the average coefficient of 9.78%. These findings further support the information-driven theory. Overall, it can be concluded that the demand for lottery-type stocks positively correlates with the market index's price change following macro announcements.

3.2. Portfolio analysis

While the regression analysis provides an overview of the conditional performance of lottery-type stocks during and after macronews days, it is interesting to understand further how investors' demand for lottery-type stocks is affected by different market conditions. To examine this, we conduct a portfolio analysis sorting the stocks on lottery measures and study their performance after the macronews days. In line with the baseline analysis, the portfolio is constructed as follows: First of all, on each macronews day, we rank all the stocks into decile portfolios using each of the five different lottery proxies measured in the most recent month. The bottom decile exhibits the most lottery-like features, while the top decile exhibits the least. Next, we focus on decile ten (the lottery-type stocks) only and buy (sell) the decile portfolio of stocks when the market excess returns are positive (negative). The average cumulative abnormal returns over both [0,+1] and [+2,+6] windows are traced and reported in Table 3. If the demand for the lottery-type stock is positively influenced by macronews content, we should expect that CAR[0,1] and CAR[2,6], on average, are positive and statistically significant on both long- and short-legs.

Panel A of Table 3 reports the average cumulative abnormal returns on stocks using different lottery measures over two different time periods. On both equally- and value-weighted schemes, it can be observed that lottery-type stocks, on average, generate positive cumulative abnormal returns. The gap between the average returns on the long leg and short leg is virtually small. For instance, the equally-weighted (EW) portfolio sorting CAR[0,1] on ZSCORE yields 35 bps (t-statistics: 3.98) and 53 bps (t-statistics: 7.26) on the short and long legs, respectively, while this gap is close to zero in the value-weighted (VW) scheme: 46 bps on the short leg vs. 45 bps on the long leg. Moving to the post-event period, where the return performance is measured by CAR[2,6], we observe a similar pattern: 49 bps and 59 bps on the EW short and long legs, and 67 bps and 42 bps on the VW short and long legs. With these findings, we conclude that the investors' demand for lottery-type stocks is affected by the market conditions when key releases are announced and being digested. That is, when the macronews releases positive signals, the benchmark asset (the market index incorporating the news content immediately) yields positive changes, and would trigger the increasing demand for lottery-type stocks and increasing stock prices as investors price the stocks with the payoffs of the given assets. However, if the macronews releases negative signals, it displays an opposite pattern.

The mean cumulative abnormal returns seem reasonable, so how about the reward-to-risk ratios? Panels B and C report the Sharpe and Sortino ratios of lottery-type stock portfolios. We summarise these panels from different dimensions. First, the gap between the short and long leg ratios is small, which is similar to the portfolio mean returns. Second, the value-weighted scheme diminishes the ratios but not too much, compared with the equal-weighted scheme, suggesting that part of the returns can be absorbed by stocks' market cap, which is consistent with our baseline regression analysis. Third, the ratios are much larger for CAR[0,1] than CAR[2,6]. Combined with the mean returns, this indicates that the post-event CAR is more risky or more volatile than the CAR[0,1]. The mean Sharpe and Sortino ratios for VW CAR[0,1] are 1.49 and 2.40, which are comparable to 0.55 and 0.81 for VW CAR[2,6]. Panel D also suggests that among the total of 1064 macronews days, there are 424 days (40%) when we short the lottery-type portfolios, while we hold the long leg for 640 days (60%).

3.3. Robustness checks

We examine the robustness of our baseline results against various empirical choices concerning variables. One issue with our empirical design is that any individual stock analysed on the left-hand side of the regression is also included in the CRSP value-weighted market index, capturing the macronews content (MNews), on the right-hand side as a constituent. This raises concerns that the price changes of lottery-type stocks could be influenced by their own movements as constituents of the market index. To address this issue, we exclude the focal stock from the CRSP VW index and reconstruct the market index whenever the stock is the subject of the regression on the left-hand side. This revised approach yields similar findings: the coefficients on CAR[0,1] and CAR[2,6] are both positive and statistically significant. We then substitute the market index with the S&P 500 to determine if our results are sensitive to the choice of the market benchmark. The robust outcome indicates that using a different market index to capture macronews content is effective. Moreover, one may argue that the market index changes may not fully capture the macronews content.

Table 2
Demand for lottery-type stocks and macronews content: Regression analysis.

Proxy =	IVOL			MAX			PRC			EXPSKEW			ZSCORE		
	(1) CAR[−5,−1]	(2) CAR[0,1]	(3) CAR[2,6]	(4) CAR[−5,−1]	(5) CAR[0,1]	(6) CAR[2,6]	(7) CAR[−5,−1]	(8) CAR[0,1]	(9) CAR[2,6]	(10) CAR[−5,−1]	(11) CAR[0,1]	(12) CAR[2,6]	(13) CAR[−5,−1]	(14) CAR[0,1]	(15) CAR[2,6]
Proxy × MNews	**−0.39**	**10.74*****	**8.97****	**0.43**	**6.24*****	**6.29****	**−0.05**	**8.20*****	**13.37*****	**1.76**	**7.74*****	**10.47*****	**0.41**	**10.84*****	**11.68*****
	(−0.06)	**(5.51)**	**(2.51)**	**(0.08)**	**(3.59)**	**(2.58)**	**(−0.01)**	**(3.88)**	**(3.73)**	**(0.58)**	**(3.96)**	**(3.12)**	**(0.10)**	**(5.15)**	**(3.05)**
Proxy	0.06	−0.00	−0.06**	0.15**	−0.03*	−0.09***	−0.18***	0.03	−0.02	−0.10**	−0.01	−0.09**	0.02	−0.04	−0.10**
	(1.23)	(−0.03)	(−1.99)	(2.52)	(−1.78)	(−2.82)	(−3.01)	(1.12)	(−0.37)	(−2.39)	(−0.52)	(−2.06)	(0.60)	(−1.60)	(−2.42)
MNews	2.50	19.57***	12.25**	−0.86	14.96***	10.11**	2.49	19.72***	13.07**	2.09	17.91***	8.06*	2.17	18.38***	9.83**
	(0.43)	(7.40)	(2.27)	(−0.18)	(6.90)	(2.45)	(0.43)	(7.26)	(2.36)	(0.35)	(7.16)	(1.65)	(0.37)	(7.34)	(1.98)
MOM	0.04	0.01	−0.02	0.03	0.00	−0.04	0.03	0.02	−0.02	0.03	0.03	−0.02	0.04	0.02	−0.02
	(1.16)	(0.58)	(−0.59)	(0.76)	(0.21)	(−1.11)	(0.95)	(0.83)	(−0.57)	(0.72)	(0.93)	(−0.41)	(1.18)	(0.75)	(−0.47)
REV	8.73***	−0.14	0.23	7.39***	0.14	0.33	8.77***	−0.10	0.21	8.22***	0.01	0.30	8.17***	−0.02	0.25
	(14.55)	(−1.10)	(1.03)	(12.39)	(1.13)	(1.55)	(14.57)	(−0.78)	(1.00)	(17.23)	(0.07)	(1.33)	(17.09)	(−0.14)	(1.19)
TURN	−0.37	−0.03	−0.46***	−4.00*	0.19	−2.35***	−0.34	−0.02	−0.50***	−0.25	−0.07	−0.51***	−0.28	−0.04	−0.50***
	(−1.26)	(−0.55)	(−4.61)	(−1.71)	(0.33)	(−3.38)	(−1.16)	(−0.31)	(−4.82)	(−0.82)	(−1.34)	(−4.84)	(−0.92)	(−0.79)	(−4.95)
BM	0.06***	0.06***	0.15***	0.12***	0.12***	0.27***	0.07***	0.06***	0.15***	0.08***	0.09***	0.24***	0.08***	0.09***	0.25***
	(3.25)	(3.98)	(4.34)	(4.54)	(6.49)	(9.44)	(3.33)	(3.98)	(4.33)	(3.30)	(6.75)	(10.41)	(3.61)	(7.20)	(11.01)
ILLIQ	1.31*	0.02	−0.33	1.62	−0.31	1.06**	1.39*	0.11	−0.39	1.56	−0.24	0.10	1.41	−0.31	0.64
	(1.69)	(0.04)	(−0.90)	(1.20)	(−1.13)	(2.07)	(1.81)	(0.26)	(−1.06)	(0.68)	(−0.44)	(0.15)	(1.18)	(−1.07)	(1.35)
log(ME)	−0.35***	−0.27***	−0.62***	−0.32***	−0.27***	−0.55***	−0.46***	−0.24***	−0.60***	−0.36***	−0.25***	−0.55***	−0.32***	−0.26***	−0.58***
	(−9.45)	(−12.83)	(−17.30)	(−8.09)	(−13.15)	(−15.48)	(−10.87)	(−11.45)	(−13.99)	(−8.59)	(−9.84)	(−13.60)	(−8.26)	(−12.04)	(−16.02)
Adj. R^2 (%)	4.50	0.80	1.04	4.84	1.18	1.57	4.51	0.79	1.06	3.92	0.66	0.82	4.43	0.91	1.11
Observations	3,569,458	3,541,474	3,554,476	2,088,146	2,077,988	2,081,287	3,569,314	3,541,654	3,554,383	2,753,926	2,733,131	2,750,334	3,152,546	3,131,195	3,144,271

This table tests whether the investor's demand for lottery-type stocks is affected by the macronews content, quantified by the price change of the market index on the macronews days, in a panel regression model. The regression equation is detailed as follows:

$$CAR[h,H]_{i,t} = \beta_0 + \beta_1 Lottery_{i,m-1} MNews_t + \beta_2 Lottery_{i,m-1} + \beta_3 MNews_t + \lambda' X_{i,m-1} + \epsilon_{i,t},$$

where $CAR[h,H]_{i,t}$ is the cumulative abnormal return using the market model over a holding window h days and H days after a macronews day t. Macronews events include the FOMC interest rate decisions meeting (FOMC), Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). *Lottery* is the lottery-like level measured at the end of the most recent month, using one of the five proxies, including idiosyncratic volatility (IVOL), the maximum daily returns in a month (MAX), the negative stock price (PRC), the expected idiosyncratic skewness (EXPSKEW) and the mean z-score on the front four proxies (ZSCORE) (See Appendix A for their detailed construction). A higher level indicates a stronger lottery feature of a stock. $MNews$, capturing the information content revealed on the macro-news days, is the CRSP value-weight market excess returns on the macronews day t. The control set X includes Momentum (MOM), Reversal (REV), Turnover (TURN), Book-to-Market ratio (BM), Illiquidity (ILLIQ), and the natural logarithm of market capitalisation (log(ME)) calculated at the end of the most recent month. Standard errors are clustered by macronews days and adjusted T-statistics are reported in parentheses. Both firm, year, month and day of week fixed effects are included. Intercepts are not reported for brevity. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Our sample includes common stocks publicly listed on NYSE, Amex, and NASDAQ stock exchanges and stock prices below $1 are excluded. The sample period is between January 1997 and December 2023. Reported coefficients are in percentage.

Table 3
Demand for lottery-type stocks and macronews content: Portfolio analysis.

	CAR[0,1]						CAR[2,6]					
	EW			VW			EW			VW		
	Short	Long	Total	Short	Long	Total	Short	Long	Total	Short	Long	Total
Panel A: Portfolio return (%)												
IVOL	0.39***	0.44***	0.42***	0.25**	0.16**	0.20***	0.49***	0.35**	0.40***	0.21	0.14	0.17
	(4.77)	(6.60)	(8.13)	(2.48)	(1.97)	(3.09)	(3.00)	(2.55)	(3.86)	(1.24)	(0.93)	(1.49)
MAX	0.34***	0.30***	0.32***	0.17**	0.02	0.08	0.39***	0.23**	0.29***	0.01	0.07	0.05
	(4.60)	(5.34)	(7.06)	(2.16)	(0.24)	(1.49)	(2.99)	(2.01)	(3.41)	(0.08)	(0.65)	(0.56)
PRC	0.22**	0.57***	0.43***	0.31***	0.48***	0.41***	0.43**	0.71***	0.60***	0.49**	0.50***	0.50***
	(2.55)	(7.82)	(7.71)	(3.16)	(5.22)	(6.09)	(2.57)	(5.19)	(5.66)	(2.56)	(2.89)	(3.85)
SKEW	0.28***	0.54***	0.44***	0.34***	0.31***	0.32***	0.39**	0.60***	0.52***	0.49***	0.13	0.27**
	(3.17)	(7.41)	(7.74)	(3.52)	(3.38)	(4.79)	(2.32)	(4.39)	(4.86)	(2.82)	(0.99)	(2.57)
ZSCORE	0.35***	0.53***	0.46***	0.46***	0.45***	0.45***	0.49***	0.59***	0.55***	0.67***	0.42**	0.52***
	(3.98)	(7.26)	(8.15)	(4.43)	(4.51)	(6.23)	(2.80)	(4.12)	(4.97)	(3.49)	(2.47)	(4.07)
Panel B: Sharpe ratio												
IVOL	2.60	2.93	2.80	1.35	0.87	1.06	1.03	0.72	0.84	0.43	0.26	0.32
MAX	2.42	2.40	2.41	1.11	0.13	0.50	1.04	0.54	0.73	0.04	0.16	0.12
PRC	1.39	3.47	2.65	1.72	2.32	2.09	0.89	1.46	1.23	0.88	0.81	0.84
SKEW	1.73	3.29	2.66	1.92	1.50	1.65	0.80	1.23	1.06	0.97	0.28	0.56
ZSCORE	2.17	3.22	2.80	2.41	2.00	2.14	0.97	1.16	1.08	1.20	0.69	0.89
Panel C: Sortino ratio												
IVOL	4.58	5.76	5.25	1.87	1.19	1.46	1.24	1.16	1.20	0.47	0.46	0.46
MAX	4.04	4.14	4.10	1.56	0.17	0.68	1.45	0.87	1.11	0.05	0.24	0.15
PRC	1.86	7.31	4.42	2.26	4.50	3.47	1.03	2.68	1.81	0.99	1.67	1.31
SKEW	2.70	5.96	4.51	2.61	2.71	2.67	0.95	1.92	1.45	1.16	0.44	0.78
ZSCORE	3.26	6.14	4.77	3.56	3.78	3.70	1.14	2.06	1.58	1.43	1.24	1.34
Panel D: Number of days triggering tradings												
#	424	640	1064	424	640	1064	424	640	1064	424	640	1064

This table reports the performance of strategies of buying (selling) and holding the lottery-type stocks over periods of [t+0, t+1] and [t+2, t+6], triggered by the information content released on a macronews day t: long them if the market excess returns on day t are positive, and short otherwise. Both equal (EW) and value-weighted (VW) schemes are applied to the strategies. The universe stocks are sorted into ten deciles on their lottery measures at the end of the previous month, including the maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL), low price (PRC), and ZSCORE (see Appendix A for details). This table only reports results related to the lottery-type stock, which is the bottom decile and exhibits the most lottery-like features. In Panel A, the average cumulative abnormal returns (CAR) on portfolios using each lottery measure are reported on the short leg, long leg, and the total (combining both long and short legs), respectively. The t-statistics, reported in parentheses, are based on Newey and West (1987) standard errors with the six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Panel B and C calculate the Sharpe Ratio and Sortino Ratio, which are both annualised. The number of long-leg, short-leg, and total trading days are provided in Panel D. Macronews events include the FOMC interest rate decisions meeting (FOMC), Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). Our sample includes common stocks publicly listed on NYSE, Amex, and NASDAQ stock exchanges and stock prices below $1 are excluded. The sample period is between January 1997 and December 2023.

Addressing this concern, we measure it with the event surprises (SUP), which is the absolute value of the difference between the expected outcome by economists and the real outcome, divided by the standard deviation of the difference. The estimated and real outcomes of events are obtained from the Bloomberg economic calendar. We then replaced the MNews with SUP, and the results were robust, which did not affect our main conclusions. While dealing with SUP, we notice that the coefficients are much smaller than the market return due to the unit of the market returns and the surprises.

Finally, we switch from using the CAR based on the market model to Fama–French 3-factor adjusted return as the measure of an individual stock's abnormal return performance, aiming to account for the instantaneous impact of size and book-to-market ratio on price drifts. The interaction term $ZSCORE \times MNews$ remains positive and statistically significant in the specification of CAR[0,1] and CAR[2,6]. Overall, our analysis suggests that the conditional demand for lottery-type stocks on information content is consistent across various empirical settings (see Table 4).

3.4. High-beta assets?

Another possible explanation of the above pattern is that it could be mechanical. Previous literature has found that lottery-type stocks tend to be high-beta assets (see, e.g., Bali et al., 2017), so it may not be surprising to observe that lottery-type stocks can strongly covary with the market index. To investigate this explanation, we measure each stock's beta at the end of the most recent month by regressing its daily excess returns against market excess returns over a one-year rolling window for each day. We then rerun the baseline regression, adding lagged-one-month beta as an additional control variable.

The results in Panel A of Table 5 remain quantitatively similar to the baseline Table 2 after controlling for the beta, suggesting that, under the regression analysis, the relation between the information-driven co-movement between market index and lottery-like stocks remain robust after controlling for the high beta characteristics.

Furthermore, we conduct a bivariate-sorted portfolio analysis. We first sort all stocks by the most recent month's beta into quintiles. Within each beta quintile, we further sort the stocks into lottery quintiles with the aforementioned five lottery proxies. As for the return calculation, we assign the signs of market returns upon the macronews days to the cumulative abnormal returns (CAR) for each stock, termed the market conditional CAR (MCCAR). Specifically, we long (short) the CAR if market returns are positive (negative).

For brevity, Panel B of Table 5 reports the mean returns with respective t-statistics for each lottery quintile across different beta quintiles. We gain two insights from this panel. First, both MCCAR[0,1] and MCCAR[2,6] display an upward trend along with the increasing lottery characteristics after controlling for the beta. For instance, MCCAR[0,1] on the ZSCORE quintiles are 3, 11, 16, 25 and 38 bps from the less-lottery-like quintile to the most-lottery-like one. Second, the mean MCCAR[0,1] and MCCAR[2,6] on lottery-hedging portfolios (labelled as "5 - 1") across different beta quintiles are statistically significant and positive across different proxies, further suggesting that the high-beta assets do not drive our findings. Collectively, our results are robust to mechanical effects and unlikely to be driven by high-beta assets.

Table 4
Robustness checks.

Panel A: Robust on MNews

	MNews = S&P500			MNews = Mkt exclude focal stocks			MNews = abs(SUP)		
	(1) CAR[−5,−1]	(2) CAR[0,1]	(3) CAR[2,6]	(4) CAR[−5,−1]	(5) CAR[0,1]	(6) CAR[2,6]	(7) CAR[−5,−1]	(8) CAR[0,1]	(9) CAR[2,6]
ZSCORE × MNews	**0.28**	**7.67*****	**10.55*****	**0.40**	**10.88*****	**11.68*****	**0.12*****	**0.10****	**0.14****
	(0.07)	**(3.98)**	**(2.89)**	**(0.10)**	**(5.17)**	**(3.04)**	**(2.77)**	**(2.16)**	**(2.24)**
ZSCORE	0.03	−0.03	−0.10**	0.02	−0.04	−0.10**	−0.08	−0.07*	−0.14**
	(0.62)	(−1.35)	(−2.35)	(0.58)	(−1.61)	(−2.42)	(−1.44)	(−1.93)	(−2.58)
MNews	3.75	13.71***	8.53*	2.17	18.30***	9.81**	0.11*	0.11***	−0.03
	(0.63)	(5.63)	(1.72)	(0.37)	(7.32)	(1.98)	(1.67)	(4.00)	(−0.45)
Control X	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2 (%)	4.43	0.79	1.1	4.44	0.91	1.11	4.46	0.71	1.08
Observations	3,152,546	3,131,195	3,144,271	3,148,765	3,131,195	3,140,756	3,139,680	3,118,574	3,131,410

Panel B: Robust in CAR

	FF3F-adjusted CAR			C4F-adjusted CAR		
	(10) CAR[−5,−1]	(11) CAR[0,1]	(12) CAR[2,6]	(13) CAR[−5,−1]	(14) CAR[0,1]	(15) CAR[2,6]
ZSCORE × MNews	**0.70**	**7.71*****	**16.24*****	**−0.57**	**5.64*****	**13.41*****
	(0.22)	**(3.33)**	**(5.11)**	**(−0.20)**	**(2.73)**	**(4.53)**
ZSCORE	0.09***	0.03	−0.07**	0.09***	0.03*	−0.05*
	(2.69)	(1.61)	(−2.29)	(3.07)	(1.76)	(−1.93)
MNews	−0.64	9.56***	9.05***	−0.86	6.64***	6.99***
	(−0.18)	(5.80)	(3.59)	(−0.26)	(4.99)	(3.08)
Control X	YES	YES	YES	YES	YES	YES
Adj. R^2 (%)	4.96	0.73	1.16	4.8	0.68	1.1
Observations	3,171,559	3,155,018	3,169,627	3,171,559	3,155,018	3,169,627

This table reports the robustness checks of Table 2 exercise. In Panel A, we conduct the robustness check on the measure of macronews content. Instead of using the value-weighted CRSP market index, we utilise the S&P500 index, the CRSP market index excluding the focal stock, and the absolute value of the macronews surprises. Panel B provides an alternative measure of CAR by using the Fama–French three-factor (FF3F) model (Fama & French, 1993) and the Carhart four-factor (C4F) model (Carhart, 1997). Note that all the other specifications of the regression model and the dataset align with the baseline Table 2.

4. Information-based explanation

We now turn our attention to exploring the possible explanations for why investors' demand for lottery-type stocks can be affected by macro news content. The literature has well documented that lottery-type assets tend to be those stocks which exhibit strong information asymmetry (see, e.g., Barinov, 2018; Tao et al., 2020). We conjecture that the comovement between lottery-type stocks and the market asset may be related to investors' information consumption (see, e.g., Ben-Rephael et al., 2021).

The information-based theory, proposed by Veldkamp (2006), predicts that asset prices co-move when investors price one asset using a common subset of information concerning many other assets. On days when macro news is released, the information may affect the payoffs of many assets and can be observed by many investors. Consequently, investors are likely to price these lottery-type stocks (i.e., stocks with strong information asymmetry) based on macro news content. When the price change of the market index indicates positive payoffs, the valuation of these lottery-type assets also increases, and vice versa. We refer to it as *information-driven comovement*. The following subsections will empirically test this theory.

4.1. Announcing firms and non-announcing firms

Following the *information-driven comovement* theory by Veldkamp (2006), if investors consume a common subset of information and use it to price lottery-type stocks, the comovement should be more persistent among those lottery-type stocks with stronger information asymmetry. Empirically, we categorise all individual stocks into announcing and non-announcing firms, depending on whether the firm discloses its quarterly earnings surrounding the macronews days. If investors can observe firm-specific news from quarterly earnings announcements and learn about the future payoffs of the stocks, the comovement between the two types of assets should be weaker and short-lived because investors will rely much less on the common information to price the asset.

To start with, we introduce an earnings-announcing dummy variable (EA) to identify if a firm announces its quarterly earnings in a window $[t-1, t+1]$ surrounding a macronews day t. We then add EA to the baseline regression model (2) and form a triple interaction term.

The left sub-panel of Panel A of Table 6 aligns with the prediction by the information theory and supports our conjecture, which can be seen from two perspectives. First, triple interactions (when EA = 1), indicating the comovement between lottery-type announcing stocks and the market index, show no statistically significant coefficients. Second, the interaction term $ZSCORE \times MNews$ (when EA = 0), indicating the comovement between lottery-type non-announcing stocks and the market index, retains its statistically significant and positive, e.g., 10.91 bps and 11.92 bps regarding CAR[0,1] and CRA[2,6], with t-statistics of 5.19 and 3.06, respectively. Collectively, we find that such a comovement is more persistent among non-announcing firms, which aligns with our conjecture.

4.2. Poor information environment

In the prior section, we discussed the channel from the macronews content to the valuation of lottery-type stocks: investors consume a common subset of information, such as the payoff of a well-observed asset (market index changes) affected by the macronews content, to price the lottery-type stocks, leading to the comovement. Building on the theory – a poor information environment hampers investors' learning effectiveness by Zhang and Zhao (2023), and information-driven comovement theory, we expect that the comovement should be weaker in an inferior information quality environment. In a poor information quality environment, investors' learning effectiveness is hampered, which affects the aforementioned channel, leading to no or weaker comovement, and vice versa.

We follow Zhang and Zhao (2023) to measure the information environment, and introduce a dummy variable (PoorEnv) displaying

Table 5
Lottery-type stocks and high-beta assets.

Panel A: Regression analysis after controlling for beta

	(1) CAR[−5,−1]	(2) CAR[0,1]	(3) CAR[2,6]
ZSCORE × MNews	**0.19**	**10.62*****	**11.63*** **
	(0.05)	**(5.05)**	**(3.03)**
ZSCORE	0.09**	−0.02	−0.10**
	(2.18)	(−0.68)	(−2.34)
MNews	2.02	18.13***	9.74**
	(0.35)	(7.27)	(1.96)
Beta	**−0.27*****	**−0.11****	**−0.01**
	(−3.71)	**(−2.23)**	**(−0.08)**
Control X	YES	YES	YES
Adj. R^2	4.47	0.89	1.12
Observations	3,117,813	3,096,775	3,109,633

Panel B: Bivariate-sorted lottery portfolios (Beta controlled)

	IVOL	EXPSKEW	MAX	PRC	ZSCORE
Panel B.1: MCCAR[0, 1]					
1	0.03	0.08***	0.02	0.08***	0.03**
	(1.54)	(4.78)	(1.24)	(5.86)	(2.35)
2	0.12***	0.11***	0.09***	0.12***	0.11***
	(5.78)	(5.79)	(4.56)	(5.75)	(5.60)
3	0.19***	0.16***	0.14***	0.18***	0.16***
	(7.74)	(6.06)	(6.03)	(6.80)	(6.43)
4	0.26***	0.23***	0.22***	0.25***	0.25***
	(8.48)	(7.26)	(7.80)	(7.71)	(7.90)
5	0.37***	0.36***	0.29***	0.35***	0.38***
	(8.61)	(8.02)	(7.64)	(7.64)	(8.25)
5 - 1	0.35***	0.27***	0.27***	0.27***	0.35***
	(8.46)	(6.66)	(7.72)	(6.13)	(7.81)
Panel B.2: MCCAR[2, 6]					
1	0.05**	−0.01	0.05**	0.01	0.01
	(1.98)	(−0.24)	(1.97)	(0.32)	(0.32)
2	0.11***	0.05*	0.10***	0.06*	0.06*
	(3.32)	(1.81)	(3.34)	(1.68)	(1.92)
3	0.15***	0.10**	0.15***	0.13***	0.11**
	(3.51)	(2.46)	(3.79)	(2.91)	(2.54)
4	0.22***	0.16***	0.20***	0.23***	0.21***
	(3.80)	(2.88)	(4.02)	(3.96)	(3.63)
5	0.33***	0.37***	0.27***	0.44***	0.38***
	(3.79)	(4.37)	(3.64)	(4.97)	(4.26)
5 - 1	0.27***	0.37***	0.22***	0.44***	0.37***
	(3.31)	(4.79)	(3.12)	(5.22)	(4.24)

This table reports the robust baseline results after controlling for individual stocks' market beta, which is measured at the end of the most recent month by following Bali et al. (2017). Panel A adds the beta as one of the control variables to the baseline regression. Panel B reports the mean Market-Conditional Cumulative Abnormal Returns (MCCAR) for the bivariate-sorted portfolios. Stocks are first sorted into quintiles based on their beta, then within each beta quintile, further sorted into quintiles based on one of the five lottery proxies, including high idiosyncratic volatility (IVOL), high expected idiosyncratic skewness(EXPSKEW), the maximum daily return in a month (MAX), low stock price (PRC) and the mean z-score on the front four proxies (ZSCORE). See Appendix A for the proxy details. This results in 25 portfolios, but only the average returns across the five lottery quintiles (averaged over all beta quintiles) are reported for brevity. The MCCAR is constructed following the same methodology as the baseline CAR, but with an added market-timing component: the sign of the daily market return on day t determines the long or short position taken on the CAR. In other words, MCCAR captures the abnormal return that would be earned by going long on the CAR when the market return is positive, and short when it is negative. Note that all the regressions and dataset specifications align with the baseline.

1 for poor and 0 for good information quality environment. Then we repeat the exercise related to the earnings announcement, but replace EA with PoorEnv.

The right sub-panel of Panel A presents the regression results that are consistent with our expectations. The triple interactions (when PoorEnv = 1) show negative but statistically insignificant coefficients, suggesting weak or no evidence that the persistence of comovement is in a poor information environment. However, the double interaction $ZSCORE \times MNews$ (when PoorEnv = 0) still remain statistically positive and significant. It suggests that the comovement is more persistent in a better information environment. This further supports our information-based explanation for the demand for lottery-type stocks.

4.3. FOMC vs. non-FOMC days

Suppose investors use macronews content to price lottery-type stocks and therefore cause the comovement. In that case, the impact should be more pronounced and more persistent on days when the news release is more informative, attentive, and intensive to investors. Among the four different macronews events, the FOMC announcement is one of the most influential events in the market (see, e.g., Lucca & Moench, 2015). If *information-driven comovement* theory explains our finding, we should expect that the comovement will be more persistent during the FOMC days rather than any other macronews days.

Panel B separates the baseline analysis into FOMC days and non-FOMC days, which are the days announcing the other three events. The coefficients on $ZSCORE \times MNews$ appear positive and statistically significant regarding both CAR[0,1] and CAR[2,6] on FOMC days and non-FOMC days. However, by comparing column (3) and column (6), we find that the comovement is much stronger and more persistent on FOMC days. Specifically, the coefficients are 22.83 bps (t-statistic: 2.92) and 8.37 bps (t-statistic: 1.97) on FOMC days and non-FOMC days, respectively. Collectively, the evidence is consistent with *information-driven comovement* explanation.

4.4. Recent sample period

Veldkamp (2006) further predicts a decrease in comovement over time, as advances in information technology have simplified the process of collecting information. Additionally, the declining cost of information leads to a more diverse set of signals for investors when pricing assets with information asymmetry. Therefore, the information-driven comovement should be weaker and tends to be short-lived in recent years, given the increased efficiency of the overall information environment. By dividing the sample into two subperiods, we observe a positive and statistically significant coefficient for $ZSCORE \times MNews$ (coefficient = 11.97 and t-statistics = 4.21) during the [0,+1] window between 1997 and 2010. However, the coefficient for the interaction term over the same window period is 9.02 (t-statistics = 2.96) from 2011 to 2023, which is smaller in magnitude. It can also be noted that the coefficient for $ZSCORE \times MNews$ remains positive and statistically significant at the 1% level in the early period, whereas it becomes insignificant in the recent period.

4.5. High investor sentiment period

Moreover, we test whether the comovement is conditional upon different sentiment periods. If the *attention-induced spillover* explains our findings, the comovement should be stronger and more persistent during periods of high sentiment when more retail investors are actively trading in the market and mispricing is more likely to occur. To investigate this, we divide the sample into high and low sentiment periods using (Baker & Wurgler, 2007) sentiment index based on the full-sample median and rerun the baseline exercise for both periods. Panel D of Table 6 shows that comovement occurs in both sub-samples, and becomes more persistent during high sentiment periods when most retail investors are in the market. Specifically, the interaction coefficients in columns (3) and (6) are 17.61 bps and 6.78 bps for the high and low sentiment periods, with t-statistics of 2.53 and 1.87, respectively. Collectively, this sentiment analysis supports our conjecture. Overall, the five sets of results align with the theoretical prediction that investors' information consumption drives the comovement between lottery-type stocks and the market index.

4.6. Long-run performance

Patton and Verardo (2012) argue that investors learn across assets and use the common signals to revise their expectations about the given assets. When they are reasonably certain about the valuation of the

Table 6
Information-based explanation.

Panel A: Earnings announcements/information environment

	EA			PoorEnv		
	(1) CAR[−5,−1]	(2) CAR[0,1]	(3) CAR[2,6]	(1) CAR[−5,−1]	(2) CAR[0,1]	(3) CAR[2,6]
ZSCORE × MNews	**0.30**	**10.91*****	**11.92*****	**3.78**	**12.95*****	**13.75*****
	(0.07)	**(5.19)**	**(3.06)**	**(0.72)**	**(3.75)**	**(2.92)**
ZSCORE × MNews × Dummy	2.05	−0.73	−4.52	0.33	−4.69	−7.38
	(0.37)	(−0.15)	(−0.84)	(0.04)	(−0.97)	(−1.00)
ZSCORE × Dummy	0.09*	−0.15***	−0.23***	0.18**	0.04	0.11
	(1.70)	(−3.64)	(−4.15)	(2.19)	(0.98)	(1.33)
Dummy × MNews	1.48	4.33	−4.36	3.24	−8.80	−19.21*
	(0.21)	(0.81)	(−0.67)	(0.23)	(−1.41)	(−1.71)
ZSCORE	0.02	−0.03	−0.09**	−0.13**	−0.08*	−0.11*
	(0.50)	(−1.26)	(−2.15)	(−2.09)	(−1.96)	(−1.69)
MNews	2.11	18.15***	10.03**	7.21	20.47***	16.16**
	(0.36)	(7.37)	(2.01)	(1.40)	(5.33)	(2.07)
Dummy	0.08	0.00	−0.09	0.25	−0.07	0.24
	(1.61)	(0.09)	(−1.60)	(1.46)	(−0.63)	(1.14)
Control *X*	YES	YES	YES	YES	YES	YES
Adj. R^2 (%)	4.43	0.91	1.12	4.16	1.03	1.39
Observations	3,152,546	3,131,195	3,144,271	2,021,148	2,006,628	2,015,106

Panel B: FOMC days & other event days

	FOMC			Non-FOMC		
	(1) CAR[−5,−1]	(2) CAR[0,1]	(3) CAR[2,6]	(4) CAR[−5,−1]	(5) CAR[0,1]	(6) CAR[2,6]
ZSCORE × MNews	**0.55**	**10.58****	**22.83*****	**0.66**	**10.96*****	**8.37****
	(0.09)	**(2.34)**	**(2.92)**	**(0.14)**	**(4.59)**	**(1.97)**
ZSCORE	−0.06	−0.02	−0.17*	0.04	−0.04	−0.09*
	(−0.74)	(−0.43)	(−1.71)	(0.90)	(−1.54)	(−1.93)
MNews	8.28	16.43***	17.90**	−0.64	17.52***	5.12
	(1.19)	(3.80)	(2.06)	(−0.09)	(5.60)	(0.94)
Control *X*	YES	YES	YES	YES	YES	YES
Adj. R^2 (%)	2.15	2.14	2.02	6.04	1.02	1.17
Observations	657,049	652,519	656,419	2,494,745	2,477,901	2,487,129

Panel C: Subsample period analysis

	1997:2010			2011:2023		
	(1) CAR[−5,−1]	(2) CAR[0,1]	(3) CAR[2,6]	(4) CAR[−5,−1]	(5) CAR[0,1]	(6) CAR[2,6]
ZSCORE × MNews	**−1.45**	**11.97*****	**14.06*****	**2.80**	**9.02*****	**7.55**
	(−0.28)	**(4.21)**	**(2.69)**	**(0.46)**	**(2.96)**	**(1.39)**
ZSCORE	0.09	−0.08**	−0.20***	0.05	−0.03	−0.04
	(1.55)	(−2.29)	(−3.36)	(0.90)	(−1.08)	(−0.81)
MNews	−1.72	21.47***	14.32**	9.14	12.34***	2.75
	(−0.28)	(6.70)	(2.32)	(0.84)	(3.17)	(0.34)
Control *X*	YES	YES	YES	YES	YES	YES
Adj. R^2 (%)	5.53	1.24	1.40	3.34	0.71	1.17
Observations	1,646,687	1,630,105	1,641,239	1,505,842	1,501,078	1,503,016

Panel D: Subsample of high/low sentiment periods analysis

	High sentiment			Low sentiment		
	(1) CAR[−5,−1]	(2) CAR[0,1]	(3) CAR[2,6]	(4) CAR[−5,−1]	(5) CAR[0,1]	(6) CAR[2,6]
ZSCORE × MNews	**0.21**	**10.66*****	**17.61****	**0.63**	**11.00*****	**6.78***
	(0.03)	**(2.94)**	**(2.53)**	**(0.12)**	**(4.53)**	**(1.87)**
ZSCORE	−0.01	−0.06	−0.20***	0.07	−0.02	−0.02
	(−0.09)	(−1.54)	(−3.16)	(1.35)	(−0.59)	(−0.34)
MNews	4.29	19.32***	26.20***	2.53	17.69***	−1.99
	(0.79)	(5.78)	(3.53)	(0.29)	(5.27)	(−0.37)
Control X	YES	YES	YES	YES	YES	YES
Adj. R^2 (%)	5.39	1.22	1.74	4.35	1.2	1.38
Observations	1,570,612	1,556,362	1,566,754	1,581,825	1,574,715	1,577,385

This table provides extensive analysis following the Table 2 exercise. Panel A introduces a dummy variable and forms a triple interaction term into the baseline regression model, controlling for either earnings-announcing (EA) firms or periods in a poor information environment. Specifically, we divide individual stocks into announcing firms for their quarterly earnings in a [t−1, t+1] window around the macronews day, and non-announcing firms, respectively. The dummy variable, EA, would be one if firm *i* has an earnings announcement during the window, and zero otherwise. We then follow Zhang and Zhao (2023) to measure whether the information environment is poor (PoorEnv). Panel B categorises macronews days further into FOMC days and the other three types of event days. Panel C splits the sample into 1997–2009 and 2010–2021 periods. Panel D splits the sample based on whether the Baker and Wurgler (2007) sentiment index is above or below the median of the full sample. We then rerun the baseline regression with each subsample. For the brevity of the table, we display only the results related to ZSCORE. Note that all the regression, dataset and table specifications align with the baseline Table 2.

Table 7
Different holding periods.

	(1) CAR[7,11]	(2) CAR[12,16]	(3) CAR[17,21]	(4) CAR[22,26]	(5) CAR[27,31]
ZSCORE × MNews	**−0.00**	**−1.61**	**5.49**	**1.25**	**2.90**
	(−0.00)	**(−0.41)**	**(1.40)**	**(0.24)**	**(0.78)**
ZSCORE	−0.16***	−0.06	−0.08	−0.03	−0.10*
	(−2.72)	(−1.02)	(−1.36)	(−0.45)	(−1.79)
MNews	−7.11	−14.16	7.40	−10.55	−1.36
	(−0.49)	(−1.26)	(0.69)	(−0.85)	(−0.12)
Control X	YES	YES	YES	YES	YES
Adj. R^2 (%)	1.32	1.74	1.63	1.89	1.95
Observations	3,201,352	3,197,001	3,194,567	3,192,100	3,191,494

This table provides a long-run performance analysis based on several 5-day windows in the post-event periods. In detail, we replace the dependent variable of the baseline regression model (2) with the 5-day CAR in different post-event periods. For the brevity of the table, we report only results related to ZSCORE, the average z-score on the other lottery proxies, see Appendix A for construction details. Note that all the other regression, dataset and table specifications are consistent with the baseline table.

Table 8
Retail and institutional attention.

Cycle (j)	−5	−4	−3	−2	−1	0	1	2	3	4	5
Panel A: Retail investor clientele's abnormal attention on stocks (DASVI)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ZSCORE × Macroday	0.59**	0.42*	0.36*	−0.21	−0.10	0.15	0.23	0.04	0.13	0.10	0.63**
	(2.50)	(1.83)	(1.71)	(−0.91)	(−0.46)	(0.65)	(1.04)	(0.18)	(0.54)	(0.46)	(2.50)
ZSCORE	−1.73***	−1.80***	−1.86***	−1.84***	−1.92***	−2.38***	−2.08***	−2.06***	−2.10***	−2.09***	−2.18***
	(−3.79)	(−3.97)	(−4.12)	(−4.13)	(−4.25)	(−5.33)	(−4.56)	(−4.51)	(−4.64)	(−4.61)	(−4.71)
Macroday	−1.63***	−1.48***	−0.60***	0.81***	0.85***	−1.17***	−1.64***	−0.50**	1.00***	1.56***	−1.24***
	(−6.35)	(−6.23)	(−2.70)	(3.36)	(3.68)	(−4.53)	(−6.97)	(−2.26)	(4.28)	(6.77)	(−4.41)
Observations	2,800,729	2,812,044	2,823,840	2,836,705	2,852,190	3,012,996	2,852,068	2,836,550	2,823,542	2,811,614	2,800,102
Pseudo R^2 (%)	0.0144	0.0154	0.0152	0.0167	0.0177	0.0266	0.0209	0.0194	0.0204	0.0212	0.0211
Panel B: Institution clientele's abnormal attention on stocks (DAIA)											
	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
ZSCORE × Macroday	0.37	0.16	0.67*	1.03**	0.68	−0.53	0.65*	1.38***	1.52***	3.15***	2.81***
	(0.95)	(0.42)	(1.79)	(2.53)	(1.62)	(−1.34)	(1.75)	(3.61)	(3.76)	(7.66)	(7.40)
ZSCORE	−13.45***	−13.65***	−13.90***	−14.19***	−14.32***	−14.09***	−13.96***	−13.71***	−13.39***	−13.33***	−12.90***
	(−13.20)	(−13.37)	(−13.60)	(−13.81)	(−13.80)	(−13.71)	(−13.64)	(−13.34)	(−13.06)	(−12.99)	(−12.62)
Macroday	−5.83***	−0.35	1.89***	7.01***	5.89***	−2.55***	4.98***	2.17***	5.18***	2.70***	−3.98***
	(−14.05)	(−0.85)	(4.76)	(17.52)	(14.44)	(−6.34)	(14.06)	(5.66)	(12.53)	(6.64)	(−9.39)
Observations	3,215,099	3,216,401	3,224,742	3,235,798	3,247,957	3,305,185	3,248,036	3,235,954	3,224,976	3,216,697	3,215,463
Pseudo R^2 (%)	0.66	0.66	0.67	0.72	0.73	0.71	0.69	0.65	0.62	0.59	0.58

This table reports the retail and institutional clientele's abnormal attention changes on lottery-like stocks during a window [t−5, t+5], centring on macronews days, by running probit panel regressions:

$$ATTN_{i,t+j} = \beta_0 + \beta_1 ZSCORE_{i,m-1} Macroday_t + \beta_2 ZSCORE_{i,m-1} + \beta_3 Macroday_t + \epsilon_{i,t+j}$$

where the dependent variable of $ATTN_{i,t+j}$ is the retail or institutional abnormal attention paid to stock i on day t, with a gap j ranging −5 to +5. $DASVI$ ($DAIA$) is a dummy variable of one if retail (institutional) investors' attention to the stock is abnormally high, and zero otherwise. $ZSCORE$ is the lottery-like level measured at the most recent month's end (See Appendix A for details). $Macroday_t$ determines whether day t is a macronews day. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample periods for retail investors' attention and institutional investors' attention are from 2004 to 2023 and from 2010 to 2023, respectively, due to the data availability. Coefficients are reported in percentages. Both observation number and Pseudo R^2 in percentage are also reported.

given asset, this "cross-learning" behaviour will be less likely to occur. Therefore, the *information-driven comovement* will disappear.

How persistent can the comovement be after the macro-news day? While the previous exercise demonstrates that the demand for lottery-type stocks appears persistent and can be influenced over the [+2,+6] window, understanding whether the impact could last even longer would be helpful to validate the theory. To explore this, we repeat the baseline exercise but utilise the five-day window of CAR in subsequent periods, namely CAR[7,11], CAR[12,16], CAR[17,21], CAR[22,26], and CAR[27,31], respectively. If investors' demand for lottery-type stocks can be persistently and positively affected by macro-news content, it is expected that the interaction term between $ZSCORE$ and $MNews$ will become positive and statistically significant, and vice versa.

Interestingly, Table 7 reports that the coefficients of $ZSCORE \times MNews$ are consistently insignificant in the long run. Collectively, the results suggest that investors' demand for lottery-type stocks is hardly affected by the information content more than five days after macro-news announcements, which further supports the *information-driven comovement* explanation.

5. Alternative explanations: Attention-induced spillover?

Prior literature documents attention-induced lead–lag effects across different stocks (see. e.g., Hoberg & Phillips, 2018; Huang et al., 2022, 2021). Investors react slowly to news transferred across economically-linked firms, which can drive asset price comovement. In our setting, it is also possible that investors underreact to macronews content and slowly incorporate information into the price of lottery-type stocks, an explanation we refer to as *attention-induced spillover* theory.

We test this theory by examining the volume of investor attention around macro news days. Since prior research indicates that attention-driven lead–lag effects are more likely associated with retail investor behaviours, we distinguish between retail and institutional investors to determine which group is more active among lottery-type stocks around macronews days. If the comovement between lottery-type stocks and the market index is due to attention-induced spillover, we should observe an increasing trend in retail attention volume following the macro news day. To empirically proxy for retail investor's attention, we follow Da et al. (2011) to obtain Google Search Volume Index (SVI) data from Google Trends for each firm on a daily basis. We then construct an abnormal SVI (ASVI) measure using a one-month rolling window and define the daily ASVI (DASVI) as a dummy variable of 1 if the attention is abnormally high. Abnormal Institutional Attention (AIA) is constructed following Ben-Rephael et al. (2017) as a proxy for institutional attention based on Bloomberg readership data. Daily AIA (DAIA) is a dummy variable set to one if institutional attention is abnormally high.

With two attention indicators, we perform probit panel regressions using abnormal investor attention indicators (i.e., DASVI or DAIA) against the interaction term between $ZSCORE$ and $MNews$, separated by each individual trading day from t−5 to t+6. If retail investors are attentive to lottery-type stocks after macronews days, we would expect a positive and statistically significant coefficient in the post-event period. The regression equation is detailed as follows:

$$ATTN_{i,t+j} = \beta_0 + \beta_1 ZSCORE_{i,t} Macroday_t + \beta_2 ZSCORE_{i,t} + \beta_3 Macroday_t + \epsilon_{i,t+j} \quad (3)$$

where $ATTN_{i,t+j}$ represents investor attention (DASVI or DAIA) for firm i on day t with a j day gap. A positive j indicates the post-event period, whereas a negative j indicates the pre-event period. All the independent variables are consistent with the previous research design.

In Panel A of Table 8, where we examine changes in retail attention, the coefficient of $ZSCORE \times MNews$ is, in most cases, insignificantly different from zero. However, there are considerable increases in attention volume 5 days before and after the event, which is difficult to reconcile with the comovement pattern previously documented.

In contrast, we observe a high volume of institutional attention ahead of the event in Panel B of Table 8, where AIA is used as the dependent variable, suggesting that institutional investors are aware of scheduled events. There is also a consistently high volume of attention in the post-event period from t+1 to t+5, aligning more closely with previous findings. Altogether, the two sets of regression results do not support the *attention-induced spillover* theory.

6. Conclusion

Previous literature has documented that the investors' demand for lottery-type stocks is conditional and has various dependencies. We show that this demand is also affected by the content of information on days when significant news (macronews) is released. When the market index indicates positive macronews content, the demand for lottery-type stocks significantly increases, leading to a price run-up, while conversely, a decreasing market index, suggesting negative news content, results in a drop in the price of lottery-type stocks. This impact sometimes persists when these lottery-type stocks have no overlapping earnings announcements, or on the FOMC announcement days when the information content is more intensive and attentive, and during the early years, when the overall information environment is less efficient.

We document that the comovement between the market index and lottery-type stocks aligns more closely with the information-based theory proposed by Veldkamp (2006). On days with information spillovers, investors tend to price one asset based on a common subset of information relevant to many other assets. Since these lottery-type stocks are more likely to experience information asymmetries, their price comovement with the market asset is thus more pronounced. We further test alternative explanations, including retail attention-induced spillover theory or the mechanical effects of these lottery-type stocks, which are also high-beta assets. However, empirical results do not support these theories.

Our findings have broad implications for both retail and institutional investors, as well as policymakers. We show that retail investors appear to price individual stocks using common information components extracted from macronews. This behaviour increases demand for lottery-like stocks when macronews signals are positive, which in turn generates predictable returns. Institutional investors can use this pattern to design trading strategies or provide liquidity to retail investors. Meanwhile, such increasing trading activity by retail investors following macronews can amplify noise and reduce market efficiency. Policymakers may utilise this pattern to assess whether the timing and format of their disclosures are appropriate for financial markets, and to introduce measures that better protect retail investors.

Further implications include the potential to develop more methodologies for detecting information spillover. This paper indicates that the conditional demand for lottery-type stocks is not limited to days with major news events, but also extends to other days with information spillovers, even though the information content is less intensive and difficult to observe. Our study downplays the significance of the presence or absence of pre-scheduled events, but instead underscores the importance of the content of information events for lottery-type stocks in the post-event period.

Appendix A. Variables definitions

Variable	Description
Panel A: Macroeconomic events	
FOMC	The Federal Open Market Committee (FOMC) serves as the policy-setting branch of the Federal Reserve, tasked with establishing short-term interest rates within the United States. At the conclusion of each FOMC gathering, which occurs eight times annually, the Fed publicly shares its policy decisions. These announcements are typically made at 14:00 Eastern Time.
EM	The employment status report encompasses data on (1) Non-farm Payroll, (2) Unemployment Rate, (3) Average Weekly Hours for All Employees, and (4) Average Hourly Earnings. This information is disclosed on a monthly basis, with the release typically occurring at 8:30 Eastern Time.
ISM PMI	The Institute of Supply Management Manufacturing Purchasing Managers Index monitors the overall economic condition in relation to the business sector. This index is derived from a monthly survey conducted among purchasing managers from approximately 300 manufacturing companies across the nation. The findings are disclosed monthly, typically at 10:00 Eastern Time.
PC	Personal consumption expenditures represent the monthly counterparts to the quarterly spending figures reported in the GDP data, presented in both nominal and inflation-adjusted (real) terms. These figures are released on a monthly basis, typically at 8:30 Eastern Time.
Panel B: Lottery measures	
MAX	Bali et al. (2011) document that a stock with a large maximum daily return in the previous month is more likely to be overvalued and therefore exhibits low return in the following month. This is known as "the max effects". We follow this study and take each stock's maximum daily return (MAX) in the previous month as the first measure of the lottery feature.

Variable	Description
EXPSKEW	We use the expected idiosyncratic skewness estimated from Boyer et al. (2010)'s model as our second measure. The construction of SKEWEXP is as follows: we regress each stock's daily excess returns against (Fama & French, 1993) three factors to obtain residuals. We calculate the standard deviation and skewness of these residuals every month. Next, the estimated coefficients are obtained in the cross-sectional regressions by taking the idiosyncratic skewness against the 60-month-lagged idiosyncratic volatility, idiosyncratic skewness, small and medium size firm dummy variables, Fama–French-17-industry dummies and NASDAQ dummy. Finally, we estimate the SKEWEXP for the next 60-month period as the multiplication between the obtained coefficients and the same variables employed in the last step but without lags. Stocks with high expected idiosyncratic skewness negatively predict their future returns.
IVOL	Following Ang et al. (2006), we regress each stock's daily excess return against (Fama & French, 1993) three factors every month, with at least ten observations required. The IVOL is constructed by taking the standard deviation of residuals within each month. High IVOL stocks tend to yield low future returns, as Aabo et al. (2017) document that the number of noise traders tends to be associated with high IVOL stocks.
PRC	The natural logarithm of one plus stock price, multiplied by −1. As low-price stocks tend to generate relatively high pay-offs (Kumar, 2009; Liu et al., 2020), we employ the price as one of the lottery measures.
ZSCORE	We take the average of the individual z-scores of the above lottery measures for each stock in a month, with at least three lottery measures available. The individual score of these stocks is obtained by ranking stocks in an ascending order based on each lottery measure (Liu et al., 2020).
Panel C: Stock characteristic	
ME	The market capitalisation is the multiplication between share adjusted close prices and adjusted total shares outstanding, where the adjusted close price is the close price divided by the 'cumulative factor to adjust price', and the adjusted shares outstanding is the number of shares outstanding times the 'cumulative factor to adjust shares'. A company could have several securities with different market values. We, therefore, take the sum of the market value of these securities as their market capitalisation. Known as size effects, investors are believed to require a higher premium on holding stocks with smaller market cap (Fama & French, 1993; Van Dijk, 2011; Zakamulin, 2013).
BM	The book-to-market ratio (BM) is book equity divided by the market capitalisation, where book equity is the sum of stockholders' equity, deferred taxes and investment tax credit, but minus preferred stock (Daniel & Titman, 1997). Literature finds that high BM firms generally outperform low BM firms, reflecting the value effects in the stock market (Caglayan et al., 2018; Fama & French, 1993, 1995; Pontiff & Schall, 1998).
MOM	The momentum signal is calculated as the cumulative returns of the past 12 months, skipping the most recent month's return to exclude the reversal effect. Stocks with past up-trends are believed to outperform stocks with past downtrends (Jegadeesh & Titman, 1993).
TURN	Turnover ratio, the monthly trading volume divided by the monthly total shares outstanding. Kumar (2009) document that stocks with high monthly turnover are more likely to be attention-grabbing.
ILLIQ	The illiquidity is measured as the absolute monthly returns on a stock divided by the respective monthly trading volume in dollars (the monthly price multiplied by the monthly trading volume). It is well documented that investors require a higher premium on holding stocks with less liquidity to compensate for the illiquidity risk (Amihud, 2002; Amihud & Noh, 2021; Cakici & Zaremba, 2021).
BETA	To obtain the daily market beta for a stock, we regress the stock's excess returns on market excess returns within a rolling window of 252 trading days. The data is calculated with the BETA suite provided by WRDS.
Panel D: Attention measures	
AIA	Ben-Rephael et al. (2017) proxy for abnormal institutional attention (AIA) with reading activity data from the Bloomberg terminal. Bloomberg assigns a score ranging between 0 and 4 to measure how strongly a company receives attention from institutions on a date. Inspired by them, we obtain the AIA score from Bloomberg and construct a dummy variable, termed DAIA, indicating whether the institutional attention is abnormal. DAIA is set to one if the AIA score is 3 or 4, and zero otherwise.
ASVI	We follow Da et al. (2011), but at a daily level, to obtain search volume index (SVI) data from Google Trends to proxy for retail investor attention. The SVI captures the search trend for keywords associated with tickers for listed companies within a particular period. The sample is filtered to exclude tickers with synonymous meanings, such as GPS and BABE. To obtain the Abnormal Search Volume Index (ASVI), we compute the logarithmic change between the SVI and the median SVI of the most recent month. Inspired by Ben-Rephael et al. (2017), we assign a score of 1, 2, 3 and 4 if the ASVI is between 80% and 90%, 90% and 94%, 94% and 96%, or greater than 96% of the previous 30 days' ASVI, respectively. Then, we define a dummy variable, DASVI, as one if the score is 3 or 4, and zero if the score is below 3.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.irfa.2026.105145.

Data availability

The authors do not have permission to share data.

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