Are Stocks with Extreme Daily Returns Really Lottery? A Tale of Intraday and Overnight Returns[*]

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Abstract
This study aims to relate the tug of war between intraday and overnight returns to investors' lottery preference in explaining stock returns. Motivated by the notion that intraday returns are more salient to investors than overnight returns, we propose that more salient intraday returns contribute more to the overpricing of lottery stocks. To verify this conjecture, we propose two lottery proxies, namely maximum intraday return (IMAX) and maximum overnight return (OMAX). We empirically show that stocks with higher IMAX significantly underperform those with lower IMAX, and that the return predictability associated with OMAX is relatively weak. We further confirm the role of the salience theory in characterizing IMAX as a better proxy of lottery preference to explain stock returns.

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1. Introduction

Recent research has extensively established that investors exhibit preference toward stocks with lottery-like payoffs (Harvey and Siddique, 2000; Smith, 2007; Kumar, 2009), which in turn leads such stocks to be overpriced and to exhibit subsequent underperformance. Among the vast literature, Bali et al. (2011) propose the maximum daily return (denoted as MAX) over the previous month as the proxy of lottery preference, and this measure is extensively examined in follow-up studies. This line of research has attracted substantial attention from researchers to explore possible explanations for the lottery-related anomalies. For example, Barinov (2018) hypothesizes that lottery-like stocks are hedges against unexpected increases in market volatility, hence this anomaly is attributed to the aggregate volatility risk. An et al. (2020) instead suggest that reference-dependent preference explains the lottery anomaly, while Chen et al. (2021) propose an explanation based on the local bias. The salience theory of Bordalo et al. (2012, 2013) also provides an alternative theoretical framework to characterize that investors' attention is drawn to assets that are salient relative to a benchmark, resulting in the overpricing of assets with lottery-like payoffs.

The main purpose of this study is to provide further understanding of the lottery-related anomalies by taking the roles of intraday and overnight returns into account. We are motivated by the considerable literature on the patterns of intraday and overnight returns, among which a tendency of positive overnight returns followed by negative returns during daytime trading hours is well documented.[1] Berkman et al. (2012) show that this negative overnight-intraday return pattern is driven by retail investors' buying pressure at the open, causing the stock's opening price to be high relative to its fundamental price. This is also consistent with the argument of Lou

[1] See, for example, Miller (1989), Cliff et al. (2008), Branch and Ma (2012), Aboody et al. (2018), and Bogousslavsky (2021).

et al. (2021) and Akbas et al. (2022) that the tug of war between opposing investor clienteles causes the return predictability between intraday and overnight returns.

The negative overnight-intraday return pattern provides us the main motivation to establish the possible linkage between the intraday component of extreme daily returns and investors' lottery preference. We propose that if investors pay attention to the salient overnight news and trade the stock at the open, they are less incline to overweight the probability of this salient state if a negative reversal during the trading hours occurs. As a result, stocks with extreme overnight returns are less prone to overvaluation and low future returns. Hence, excluding overnight returns from the MAX measure of Bali et al. (2011), i.e., considering the intraday component only, might be an effective way to identify lottery-like payoffs.

Existing studies have established that investors' speculative trading due to their lottery or gambling preference is closely related to trading volume (Boyer and Vorkink, 2014; Blauet al., 2016; Byun and Kim, 2016). While the open-to-close return is accompanied by trading volumes and the close-to-open return is accompanied by zero or very little volume due to thin trading (Barardehi et al., 2021), speculative trading induced by investors' lottery preference is more prevalent during daytime trading hours. In addition, extreme returns occurring during daytime trading hours should be more salient to investors than extreme returns occurring overnight because the former attracts more investors' attention through trading activities. Thus, Bordalo et al.'s (2012, 2013) salience theory provides a plausible support for our argument of using the intraday returns to measure lottery-like payoffs.

To explore our conjecture, we rely on Bali et al.'s (2011) maximum daily return (denoted as MAX) over the previous month to conceptualize investors' lottery preference, with a particular focus on the roles of intraday and overnight returns. By decomposing the intraday and overnight fractions of MAX, we find that the intraday and overnight components on average account for 73.75% and 25.77% of a stock's MAX value, respectively, confirming that the intraday return at least plays a critical role to account for a stock's MAX.

The preliminary decomposition results motivate us to propose two measures, namely maximum intraday return (denoted as IMAX) and maximum overnight return (denoted as OMAX), that are defined as the maximum daily open-to-close and close-to-open returns within a month. It should be noted that the occurrences of IMAX and OMAX are unnecessarily to be consistent with the occurrence of MAX, hence they can be treated as potential determinants of stock returns that are distinct to MAX. We hypothesize that investors' attention during daytime trading hours causes stocks with higher values of IMAX to be overpriced and thus have lower subsequent returns than those with lower values of IMAX. We also expect that the negative relation between OMAX and future stock returns is weaker due to investors' relatively limited attention.

Over the sample period from July 1992 to December 2022, we obtain average return premia of 1.500% and 1.161% under equal and value weights for the IMAX strategy, which involves buying the lowest IMAX decile of stocks and short selling the highest IMAX decile of stocks. The corresponding equally- and value-weighted return premia for the OMAX strategy are 0.799% and 0.447%, respectively. This finding is consistent with our conjecture that IMAX better accounts for future stock returns than OMAX. As a comparison, the MAX strategy generates average premia of 1.418% and 0.903% with equal and value weights, which are close to but lower than the IMAX premia.

While IMAX and MAX both negatively relate to future stock returns when they are considered alone, it is important to examine whether their explanatory ability is subsumed by each other. Applying an approach of the Fama-MacBeth (1974) cross-sectional regressions, we show that MAX, IMAX, and OMAX all significantly and negatively correlate with future stock returns when considered alone, consistent with the evidence from the portfolio analyses. Nevertheless, only IMAX retains its significance when it is contrasted with MAX or OMAX, or both. The significance of MAX coefficient disappears once IMAX is included in the regressions. Our evidence indicates that IMAX dominates MAX and OMAX in explaining future stock returns, highlighting the importance of IMAX as a more effective proxy to capture lottery-like payoffs of stocks.

While the IMAX measure is motivated by Bordalo et al.'s (2012, 2013) salience theory, it is important to examine the explanation based on the salience theory for the return predictability generated by IMAX. The salience theory posits that assets with more salient upsides (downsides) are more likely to be overvalued (undervalued) and hence have lower (higher) subsequent return performance. We hypothesize that if the return predictability of IMAX is induced because investors' attention is drawn to the extreme returns occurring during daytime trading hours, a stock's salient payoffs in an upward trend would further enhance the overvaluation, leading to severer subsequent underperformance. Hence, we expect the IMAX premium to be stronger among stocks with higher magnitude of salient upsides.

We follow Cosemans and Frehen (2021) to construct the empirical measure of the salience theory (denoted as ST) to concretize Bordalo et al.'s (2012, 2013) theoretical framework. We allocate individual stocks into three groups according to their values of the ST measure, and we perform the Fama-MacBeth (1974) cross-sectional regressions separately for the three ST groups. We show that the coefficient of IMAX is insignificant for the low ST group, and that the significance of the negative IMAX coefficient increases with the ST measure. This finding confirms our hypothesis that the negative relation between IMAX and stock returns is strengthened when a stock experienced more salient and upside payoffs in the past. We also show that the coefficients of MAX and OMAX do not significantly vary across the ST groups, thus confirming that the salience theory accounts for the IMAX premium but not the MAX and OMAX premia.

Our main argument that IMAX better characterizes lottery-like payoffs is built on Bordalo et al.'s (2012, 2013) assumption that investors' attention is drawn to the most salient attributes that investors tend to overweight in their decision making. A recent study by Lou et al. (2019) instead claims that two distinct clienteles tend to dominate the overnight and daytime trading sessions, in turn leading to a daily "tug of war" and hence inducing return predictability. Motivated by this notion, Akbas et al. (2022) propose an intensity of daily tug of war to describe daytime arbitrageurs' overcorrection to the overnight information. They show that a more intense daily tug of war between opposing investor clienteles could result in return reversals. To rule out the possibility that our results are induced by this overcorrection explanation, we follow Akbas et al. (2022) to construct two measures, namely abnormal positive daytime reversal (ABPR) and abnormal negative daytime reversal (ABNR). We apply the Fama-MacBeth (1974) regressions to show that neither ABPR nor ABNR could account for the return predictability of IMAX. Thus our findings are unlikely to be the result of daytime arbitrageurs' overcorrection.

The next research question of our study is to understand why Bali et al.'s (2011) MAX measure accounts for the cross-sectional variations of stock returns. Motivated by our hypothesis that lottery-like payoffs occurring during daytime trading hours are more salient to investors, we propose that stocks whose occurrence of MAX is accompanied by a higher fraction of intraday return are prone to severer overvaluation, in turn causing lower future returns. As a result, the

MAX premium should be more pronounced among stocks whose MAX consists of a higher fraction of intraday return. We apply the Fama-MacBeth (1974) regressions to confirm that the negative relation between MAX and stock return is stronger among stocks with higher fractions of intraday returns to constitute their MAX values. Furthermore, the significantly negative coefficient of IMAX remains unchanged when the interaction effect between the intraday fraction and MAX is considered. This finding confirms that IMAX and MAX are two distinct phenomena to account for future stock returns, hence highlighting the uniqueness of IMAX to proxy for investors' lottery preference.

Our study contributes to the literature on lottery-related anomalies by highlighting the unique role of salient intraday returns in measuring lottery-like payoffs of stocks. The proposed measure of IMAX is motivated and supported by the salience theory, thus providing a theoretical support for the advantage of IMAX over MAX. We also contribute to the literature on the tug of war between intraday and overnight returns by discriminating investors' perception of salient intraday returns from arbitrageurs' overcorrection due to investor heterogeneity. We show that isolating overnight returns from intraday returns could be an effective way to understand how investors form their evaluation of lottery-like payoffs. This finding is unrelated to Akbas et al.'s (2022) evidence of the relation between intense tug of war and future stock returns, suggesting that investors' lottery preference and the heterogeneity between distinct clienteles seem to be independent phenomena.

The remaining of this study proceeds as follows. Section 2 provides the literature review and hypothesis development. In Section 3, we describe the variable constructions and data used in this study. Section 4 presents the empirical evidence of the IMAX premium and tests of potential explanations, as well as the impact of the intraday fraction of return on the MAX premium. The last section concludes.

2. Literature review and hypotheses development

The literature uncovers substantial evidence that investors prefer lottery-like assets that are featured by the relatively small probability of large payoffs. Garrett and Sobel (1999) show that lottery players are risk averse but favor positive skewness of returns. Harvey and Siddique (2000) and Smith (2007) both provide supportive evidence for the pricing ability of skewness. Mitton and Vorkink (2007) develop a theoretical model with heterogeneous skewness preferences to obtain an equilibrium in which idiosyncratic skewness is priced. Kumar (2009) characterizes lottery-type stocks as those having low price, high idiosyncratic volatility, and high idiosyncratic skewness. Bali et al. (2011) further propose MAX as a strong predictor of future stock returns, and they further show that the negative relation between MAX and stock returns is not explained by skewness measures.

Follow-up studies provide several explanations for the lottery-related anomalies, with particular focuses on the role of investors' behavior. Barinov (2018) shows that investors prefer stocks with lottery-like payoffs because such stocks are hedges against unexpected increases in market volatility. An et al. (2020) propose that the return of lottery-related anomalies dependents on investors' embedded capital gains. They obtain significantly stronger underperformance for lottery-like stocks with large capital losses in the past. Chen et al. (2021) instead focus on the internet search to develop the gambling sentiment, and they show that this sentiment index is positively related to investors' demand for lottery-like stocks.

Our study is motivated by Bordalo et al. (2012, 2013), who develop the salience theory to characterize the overvaluation of assets with lottery-like payoffs. Their model indicates that investors' attention is drawn to assets that are salient relative to a benchmark, thus resulting in overvaluation that is followed by lower returns. While the open-to-close return is accompanied by trading volumes and the close-to-open return is accompanied by zero or very little volume due to thin trading (Barardehi et al., 2021), it is intuitive that extreme returns occurring during daytime trading hours are more salient and draw more attention from investors than extreme returns occurring overnight.

Our study is also related to the vast literature on the patterns of intraday and overnight returns. Miller (1989), Cliff et al. (2008), Branch and Ma (2012), Aboody et al. (2018), and Bogousslavsky (2021) all show that the positive overnight returns of individual stocks tend to be followed by negative returns during trading hours of the subsequent trading day. Berkman et al. (2012) show that this negative relation between overnight and intraday returns is concentrated among stocks that retail investors pay more attention at the open. The buying pressure of retail investors at the open causes the opening prices to be high relative to its fundamental prices. As a result, stocks with extremely high overnight returns are more prone to subsequent price corrections during daytime trading hours, making them less likely be become a lottery target to retail investors.

Our study further links to the ongoing debate on the tug of war between intraday and overnight returns. Lou et al. (2021) initiate this line of research by linking investor heterogeneity to the continuation and reversal patterns of the intraday and overnight components of monthly returns. They obtain strong continuation patterns in intraday and overnight returns and a cross-period reversal effect between overnight and daytime periods. Hendershott et al. (2020)

show that overnight returns are positively related to beta while intraday returns are negatively related to beta, causing the overall poor performance of the capital asset pricing model (CAPM). Akbas et al. (2022) propose a measure of daytime reversals based on the intensity of daily tug of war between opposing investor clienteles, and they obtain significant return predictability for this measure. The aforementioned studies all highlight and verify the differences in the nature of intraday and overnight returns and their impacts on future stock returns.

Bogousslavsky (2021) proposes that holding positions overnight is riskier to institutional investors because lending fees are typically charged only on positions held overnight and margin requirements are higher overnight. The overnight risk thus incentivizes arbitrageurs to trade on mispricing to reduce their positions before the end of the day. Confirming this conjecture, he shows that mispricing anomalies perform well during trading hours but perform poorly at the end of the day and overnight. This finding indicates that mispricing exists primarily in intraday returns but not overnight returns, implying the possibility that investors' lottery preference is formed based on intraday returns rather than on overnight returns.

The above discussions lead us to propose that lottery-like payoffs occurring during trading hours should be more salient than lottery-like payoffs occurring overnight. Our central prediction is that the lottery premium should be more pronounced when it is constructed using lottery-like intraday returns and is less significant when lottery-like overnight returns is considered.

We propose two measures, namely maximum intraday return (denoted as IMAX) and maximum overnight return (denoted as OMAX). The former is defined as the maximum open-to-close return within a month and the latter is defined as the maximum close-to-open return within a month. We hypothesize that stocks with higher values of IMAX are more prone to overpricing and thus have lower subsequent returns than those with lower values of IMAX.

For OMAX, we expect its relation with future stock returns is weaker. Thus, a strategy of a long position on low OMAX stocks and a short position on high OMAX stocks is expected to generate insignificant premium. Accordingly, we propose the following hypotheses:

Hypothesis 1: Stocks with higher IMAX generate significantly lower returns than those with lower IMAX.

Hypothesis 2: The relation between OMAX and stock returns is relatively weak.

It should be noted that lottery stocks identified by IMAX or OMAX could be distinct from those identified by MAX. Thus, the return predictability associated with IMAX and OMAX might be independent to the MAX anomaly. The second purpose of this study is to examine whether the intraday component of MAX accounts for the MAX premium. To this end, we calculate the fraction of intraday return to daily return on the day of MAX occurrence. We expect that the overpricing of high MAX stocks is concentrated among stocks with the highest fractions of intraday return at the occurrence of MAX, leading to the existence of the MAX effect. We thus propose the following hypothesis:

Hypothesis 3: The MAX effect is stronger among stocks whose MAX values comprises higher fractions of intraday returns.

3. Construction of variables and data

3.1. Variable definitions

Following most studies in the literature (Bali et al., 2017; Barinov, 2018; Cheon and Lee, 2018), our main variables are initiated by the concept of Bali et al.'s (2011) MAX measure. For a given month t, MAX is defined as MAX$\{R_{i,d}\}$, where $R_{i,d}$ is stock i's return on day d within month t. To consider the lottery measures based on intraday and overnight returns, we follow

Lou et al. (2019) by defining the intraday return of stock *i* on day *d* as $R_{i,d}^{I} = P_{i,d}^{C} / P_{i,d}^{O} - 1$, where $P_{i,d}^{C}$ is the closing price of stock *i* on day *d* and $P_{i,d}^{O}$ is the open price of stock *i* on day *d*. We next define the overnight return of stock *i* on day *d* as $R_{i,d}^{O} = (1 + R_{i,d}) / (1 + R_{i,d}^{I}) - 1$, where $R_{i,d}$ is stock *i*'s daily return calculated using closing prices between days *d* and *d*–1, i.e., $R_{i,d} = P_{i,d}^{C} / P_{i,d-1}^{C} - 1$. The maximum intraday return (IMAX) and maximum overnight return (OMAX), are defined as $\mathrm{MAX}\{R_{i,d}^{I}\}$ and $\mathrm{MAX}\{R_{i,d}^{O}\}$, respectively. In this study, IMAX and OMAX are the main variables associated with the tests of **Hypotheses 4.1** and **4.2**.

To test **Hypothesis 4.3**, we propose the fraction of intraday return to daily return on the day of MAX occurrence, denoted as FRAC, to capture the impact of intraday return on the relation between MAX and stock returns. In particular, FRAC is computed as $R_{i,d \in \mathrm{MAX}}^{I} / \mathrm{MAX}\{R_{i,d}\}$, in which $R_{i,d \in \mathrm{MAX}}^{I}$ is stock *i*'s intraday return on the day of the MAX occurrence. A higher value of FRAC signifies that the stock's MAX is largely dominated by its intraday return. A lower value of FRAC, instead, signifies that the stock's MAX is largely dominated by its overnight return.

We also follow the literature to consider several pervasive firm characteristics as the control variables, including firm size (SIZE) and book-to-market (BM) ratio of Fama and French (1992), gross profitability (GP) of Novy-Marx (2013), asset growth (AG) of Cooper et al. (2008), intermediate-term past return (PR12) of Jegadeesh and Titman (1993), short-term past return (REV) of Jegadeesh (1990) and Lo and MacKinlay (1990), illiquidity (ILLIQ) of Amihud (2002), and idiosyncratic volatility (IVOL) of Ang et al. (2006).

From each July of year *y* to June of year *y*+1, SIZE is defined as a stock's market capitalization at the end of June year *y*. BM is a stock's book value of equity at the end of fiscal year end *y*–1 divided by its market value of equity at the end of December in year *y*–1. GP is defined as revenues minus cost of goods sold, scaled by total assets at the end of fiscal year end y–1. AG is the growth rate in total assets from year $y-2$ to year $y-1$. PR12 is the cumulative return from month t–12 to month t–2, while REV is a stock's monthly return in month t–1. ILLIQ is the daily absolute return divided by daily dollar trading volume, averaged across all trading days in month t–1. Finally, IVOL is estimated as the standard deviation of residuals from the following regression:

$$R_{i,d} = \alpha_i + \beta_i^{MKT} \times MKT_d + \beta_i^{SMB} \times SMB_d + \beta_i^{HML} \times HML_d + \varepsilon_{i,d}, \quad (1)$$

where MKT_d, SMB_d, and HML_d are factor realizations of Fama and French's (1993) three-factor model on day d. IVOL is calculated as $\sqrt{Var(\varepsilon_{i,d})}$, in which $\varepsilon_{i,d}$s are obtained from Equation (1). We follow Ang et al. (2006, 2009) and most follow-up studies such as Fu (2009), Bali et al. (2011), Stambaugh et al. (2015), Hou and Loh (2016), and Bogousslavsky (2021) by using daily return data within month t–1 for the estimation.

3.2. Data description

Our sample consists of all U.S. common stocks with share codes of 10 and 11 that are listed on NYSE, AMEX, and Nasdaq. The sample period spans from July 1992 to December 2022. Our sample starts in July 1992 because daily opening prices are available from the Center for Research in Security Prices (CRSP) database since then. We obtain return data from the CRSP database, while the accounting data are retrieved from the Compustat database. We exclude financial and utility firms from the sample, and we require firms with stock prices above \$5 at the end of the previous month to mitigate the illiquidity and thin-traded problems.

We consider several risk-based factor models to obtain abnormal returns. We obtain the data on Fama and French's (1993, 2015) three and five factors from Kenneth French's website.[2] We also adopt two sets of six-factor models by augmenting the momentum factor and the aggregate liquidity factor of Pastor and Stambaugh (2003) into Fama and French's (2015) five-factor model. The momentum factor is also obtained from Kenneth French's website, while the aggregate liquidity factor is obtained from Robert F. Stambaugh's website.[3] Finally, we adopt two sets of q-factor models of Hou et al. (2015) and Hou et al. (2021), namely the Q4 and Q5 models. We obtain the data on Q4 and Q5 models from Lu Zhang's website.[4]

Panel A of Table 1 provides summary statistics of the three lottery proxies, MAX, IMAX, and OMAX. For each firm-month observation, we first identify each stock's MAX in month $t-1$. We compute the daily, intraday, and overnight returns on the trading day of MAX occurrence, and we obtain the means, medians, and standard deviations of the three variables for each month. We next calculate the time-series averages of these cross-sectional statistics. Over our sample period, the average MAX value is 6.582%, with a median of 4.987% and a standard deviation of 6.985%. The average (median) MAX comprises an intraday component of 4.854% (3.755%) and an overnight component of 1.696% (0.743%), indicating that MAX is mainly attributed to the intraday component.

[Insert Table 1 here]

We next observe each stock's IMAX in month $t-1$, and we obtain summary statistics in the same way. On the trading day of the IMAX occurrence, the average and median values of IMAX values (i.e., intraday returns) are 5.711% and 4.500%, respectively. The average and median daily returns on the trading day of IMAX occurrence are 5.360% and 4.110%, resulting in the

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[2] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[3] See http://finance.wharton.upenn.edu/~stambaug/.
[4] See http://global-q.org/index.html#/.

average and median values of -0.370% and -0.037% for the overnight component. This observation suggests that IMAX usually occurs following a negative overnight return that is close to zero. It should also be noted that the average and median daily returns at the IMAX occurrence are slightly lower than the average and median daily returns at the MAX occurrence, indicating that MAX and IMAX might occur on different trading days.

We next turn our focus to the occurrence of OMAX in month $t-1$. We observe average and median OMAX values (i.e., overnight returns) of 3.490% and 2.275%, remarkably lower than the corresponding values of MAX and IMAX. This finding partially confirms our conjecture that the magnitude of OMAX is less salient to investors than the magnitude of IMAX. In addition, on the day of OMAX occurrence, the average and median intraday returns are -0.487% and -0.210%, respectively. Overall, the lack of continuation between overnight and intraday returns not only confirms that IMAX and OMAX are unrelated, but is also consistent with the extent evidence on the tug of war between opposing investor clienteles as documented by Lou et al. (2021) and Akbas et al. (2022).

We also report the time-series averages of cross-sectional correlations between the three lottery proxies in Panel B. The highest correlation exists between MAX and IMAX, which is 0.767 on average. The average correlation between MAX and OMAX is 0.645, and the lowest average correlation of 0.354 exists between IMAX and OMAX. These observations indicate that the three lottery proxies are positively correlated, but that the relation between IMAX and OMAX is relatively weak.

Next, we focus on the summary statistics of deciles formed on MAX, as presented in Panel C. For each month t, we allocate individual stocks into deciles according to their values of MAX in month $t-1$. The average MAX values ranges from 1.614% to 19.885% from the lowest to highest MAX deciles. We also notice that the intraday and overnight components of MAX also increase monotonically from the lowest to highest MAX deciles. For the highest MAX decile, the intraday and overnight components on average account for 69% and 30% of MAX, with corresponding average values of 13.229% and 6.375%, respectively. We also calculate the fraction of the occurrence of MAX that overlaps the occurrence of IMAX (OMAX), i.e., a stock's MAX and IMAX (OMAX) occur on the same trading day. We show that 71% of stocks allocated in the highest MAX decile belong to highest IMAX decile on the same day. For the lowest MAX decile, only 41% of MAX stocks overlap IMAX stocks. The overlapping fraction between MAX and OMAX is remarkably lower, with 38% and 20% of MAX stocks overlapping OMAX stocks for the lowest and highest MAX deciles, respectively.

4. Empirical analyses

4.1. Portfolio analyses

We first examine whether the three lottery proxies are effective in explaining future stock returns. For each month t, we sort individual stocks into deciles according to their values of MAX, IMAX, or OMAX identified in month $t-1$. For each decile portfolio, we calculate equally- and value-weighted returns in month t. We define the premium of the lottery anomaly as the difference in returns between the lowest and highest deciles. If the proposed measure captures investors' lottery preference, the return premium associated with this proxy should be significantly positive.

In Table 2, we report the average returns of decile portfolios and the premia for the three lottery proxies. The MAX strategy generates average premia of 1.418% and 0.903% per month under equal and value weights, respectively. The average premia of the IMAX strategy are higher than those of the MAX strategy, with equally- and value-weighted returns of 1.500% and 1.161%, respectively. The raw returns of MAX and IMAX strategies are all significant at the 5% significance level, regardless of adoption of the weighting scheme. Among the three strategies, the OMAX strategy has the worst performance of 0.799% and 0.447% under equal and value weights, and the value-weighted return premium is insignificant with a *t*-statistic of 1.26.

[Insert Table 2 here]

We also obtain abnormal returns for the three lottery strategies by regressing the raw return premia between long and short positions on each factor model, and we obtain the intercept as the abnormal return. We find that the abnormal premia of the IMAX are consistently positive and significant regardless of adoption of the factor model and the weighting scheme. For the MAX strategy, the abnormal premia are all significantly positive for the equally-weighted portfolios. They are mostly significant and positive for the value-weighted portfolios, with one exception when the Q5 model is used as the risk adjustment. Finally, we find that the OMAX strategy constructed using either equal or value weights fails to generate significantly positive abnormal premia when Q4 and Q5 models are used as risk adjustments. For value-weighted portfolios, the OMAX strategy has marginally significant and positive abnormal premium only when Fama and French's (2015) five-factor model or the liquidity-augmented six-factor model is used to adjust for risk exposure.

Overall, the results from Table 2 are in support of **Hypothesis 1** that stocks with higher IMAX generate significantly lower returns than those with lower IMAX, thus confirming the return predictability of IMAX. This finding implies the possibility that investors emphasize on intraday returns when searching for possible targets exhibiting lottery features. Out results also confirm **Hypothesis 2** that the relation between OMAX and future stock returns is relatively weak, suggesting a lower possibility that investors rely on overnight returns to form their lottery preference.

4.2. Cross-sectional regressions

In addition to portfolio-based analyses, we also adopt an approach of the Fama-MacBeth (1973) cross-sectional regressions, which enables us to simultaneously test **Hypotheses 1** and **2**, expressing in the following form:

$$R_{i,t} = \alpha_t + \beta_{1,t} \times MAX_{i,t-1} + \beta_{2,t} \times IMAX_{i,t-1} + \beta_{3,t} \times OMAX_{i,t-1} + \sum_{j=1}^{J} \gamma_{j,t} \times CV_{i,j,t-1} + \varepsilon_{i,t}, \qquad (2)$$

where $R_{i,t}$ is stock i's return in month t; $MAX_{i,t-1}$, $IMAX_{i,t-1}$, and $OMAX_{i,t-1}$ are defined as in Section 3.1; $CV_{i,j,t}$ is the jth control variable as defined as in Section 3.1. Once we obtain the coefficient estimates from Equation (2) for each month t, we calculate and test the time-series averages of the coefficients from the regressions based on t-statistics adjusted by Newey and West's (1987) robust standard errors. According to **Hypotheses 1**, the average coefficient of $\beta_{2,t}$ is expected to be significantly negative, while the prediction of **Hypotheses 2** suggests that the average coefficient of $\beta_{3,t}$ is insignificant.

In Panel A of Table 3, we present the estimation results of Equation (2) without the inclusion of control variables. In Models (1) to (3), we perform univariate regressions by including each of the three lottery proxies in the regressions. The results indicate that when considered alone, the average coefficients on MAX, IMAX, and OMAX are all significantly negative. We also note that the t-statistics of the average coefficients on MAX, IMAX, and OMAX are -4.28, -4.97, and -2.81, respectively, indicating that MAX and IMAX has stronger return predictability than OMAX. Overall, the estimation results of univariate regressions are consistent with the findings obtained from the portfolio-based analyses shown in Table 2.

[Insert Table 3 here]

In Models (4) to (7), we provide several combinations to include part or all of the three proxies in Equation (2). When MAX and IMAX are included simultaneously in Model (4), we find that the average coefficient on IMAX remains significantly negative with a *t*-statistic of -5.31, while the average coefficient on MAX becomes insignificant (*t*-statistic = -0.94). This evidence indicates that the MAX effect seems to be subsumed by the IMAX effect. We also show in Model (5) that the MAX effect is stronger than the OMAX effect, as the average coefficient on MAX is significantly negative while the that on OMAX is significantly positive. Hence, the MAX effect subsumes the OMAX effect. Next, unsurprisingly, we show in Model (6) that the IMAX effect subsumes the OMAX effect as only the coefficient on IMAX is negative and significant (*t*-statistic = -5.34). Finally, we include all lottery proxies in Mode (7), and we show that the coefficient on IMAX is significantly negative, while those on MAX and OMAX are negative but insignificant. Overall, the results from Panel A of Table 3 suggest that IMAX plays a dominant role in explaining future stock returns among the three potential proxies of lottery preference.

We next include the control variables in Equation (2), and we present the estimation results in Panel B of Table 3. Consistent with the results in Panel A, we find that IMAX is the only variable that consistently and significantly explain future stock returns with a negative sign. The coefficients on MAX and OMAX, however, become positive when the control variables are included. Among the control variables, the average coefficients on BM and GP are significantly positive, suggesting that the value and profitability effects are robust when the lottery effect is explored. The coefficients on AG, REV, and IVOL are all significantly negative in all model specifications, suggesting the presence of investment, short-term reversal, and idiosyncratic risk effects in our analyses. More importantly, the negative relation between IMAX and future stock returns are not eliminated by these effects, again confirming our prediction that intraday returns play an important role in capturing investors' lottery preference.

4.3. The explanation based on the salience theory

In this study, the idea of proposing IMAX to capture lottery-like payoffs is motivated by Bordalo et al.'s (2012, 2013) salience theory, thus it is important to examine whether test the salience explanation for the IMAX premium. We hypothesize that the dominating role of IMAX in characterizing lottery-like payoffs is built on Bordalo et al.'s (2012, 2013) assumption that investors' attention is drawn to the most salient attributes that investors tend to overweight in their decision making. Hence, the IMAX effect is expected to be stronger among stocks whose payoffs are more salient to investors.

The salience theory is initiated by Bordalo et al. (2012, 2013), who develop a theoretical framework to characterize investors' attention that is drawn to stocks having salient upsides (downsides) relative to their benchmarks. Cosemans and Frehen (2021) further develop the empirical construction of salience payoffs, denoted as ST, and they show that ST exhibits stronger explanatory power with a negative sign for future stock returns. In this study, we mainly follow Cosemans and Frehen's (2021) approach to construct ST and apply this measure to explain the IMAX premium.

The construction of the ST measure proceeds in the following way. First, because the salience of a stock's payoff on day d (denoted as $r_{i,d}$) depends on its distance from the benchmark, the salience function of the daily payoff is given as:

$$\sigma\left(R_{i,d}-\bar{R}_d\right)=\frac{\left|R_{i,d}-\bar{R}_d\right|}{\left|R_{i,d}\right|+\left|\bar{R}_d\right|+\theta}, \tag{3}$$

where $\bar{R}_d$ is the average return of the market on day *d*. We follow Cosemans and Frehen (2021) by using equal weights across all common stocks to calculate the average market return as the benchmark. We also follow Cosemans and Frehen (2021) by setting $\theta = 0.1$ based on Bordalo et al.'s (2012) calibration to match the experimental evidence on the long-shot lotteries.

Next, we sort each stock's daily payoff $R_{i,d}$ within the previous month, and then assign ranks $k_{i,d}$, ranging from 1 for the most salient to *D* for the least salient, in which *D* is the number of trading days in the previous month. Each payoff $R_{i,d}$ may occur with an equal probability π_d, i.e., $\pi_d = 1/d$. We next define the salience weight as:

$$\omega_{i,d}=\frac{\delta^{k_{i,d}}}{\sum_{d'}\delta^{k_{i,d'}}\times\pi_{d'}}, \tag{4}$$

where the parameter δ captures the degree to which salience distorts decision weights and proxies for the decision-maker's cognitive ability. We again follow Cosemans and Frehen (2021) by setting $\delta = 0.7$ based on Bordalo et al.'s (2012) calibration.

Once we obtain $\omega_{i,d}$, we define the ST measure as $ST_{i,t-1}=Cov\left[\omega_{i,d},R_{i,d}\right]$ for each individual stock *i*, which is estimated using daily observations in month *t*–1. By its construction, a higher value of the ST measure signifies more salient upsides in the stock's past returns distributions, while a lower value of the ST measure signifies more salient downsides in its past returns distributions.

To examine whether the salience theory explains the IMAX effect, for each moth *t* we partition the sample into three subgroups according to each stock's value of ST computed using daily return data in month *t*−1. Within each ST subgroup, we perform the cross-sectional regression of Equation (2) for each month *t*, and we obtain the average coefficients in the time series separately for each ST subgroup. If the salience theory explains the IMAX effect, the coefficient on IMAX should be significantly negative in the high ST subgroup and should be insignificant in the low ST subgroup.

We confirm our prediction based on the results from Table 4, which presents the average coefficients from Equation (2) for each ST subgroup. The average coefficients on IMAX are -0.040, -0.072, and -0.069 with corresponding *t*-statistics of -1.43, -3.14, and -3.39 for low, medium, and high ST subgroups, respectively. The lack of significance for the IMAX coefficient in the low ST subgroup indicates that past salient downsides mitigates the overpricing of stocks with higher IMAX values. The higher significance in the *t*-statistic of the IMAX coefficient for the high ST subgroup signifies a higher tendency of overpricing for stocks with higher past salient upsides and higher IMAX values. Thus, we confirm that the salience theory well differentiates the IMAX effect in the cross-section.

[Insert Table 4 here]

We also show in Table 4 that the MAX and OMAX effects do not appear in any ST subgroup, suggesting that the salience theory does not induce MAX or OMAX effects when the IMAX effect is controlled. This finding also highlights the unique role of IMAX in predicting future stock returns that is related to the salience theory.

4.4. The explanation based on the daytime reversals

Lou et al. (2019) initiate a daily tug of war between intraday and overnight returns by claiming that two distinct clienteles tend to dominate the overnight and daytime trading sessions. As a result, return predictability is induced for intraday and overnight returns. The daily tug of war motivates Akbas et al. (2022) to propose a measure to capture the intensity of daily tug of war, which describes daytime arbitrageurs' overcorrection to the overnight information. They show that a more intense daily tug of war between opposing investor clienteles results in return reversals. To rule out the possibility that our results are induced by this overcorrection explanation, we follow Akbas et al. (2022) to construct two measures, namely abnormal positive daytime reversal (ABPR) and abnormal negative daytime reversal (ABNR). Based on the two measures, we examine whether the overcorrection explanation is useful to account for the return predictability of IMAX.

We first follow Akbas et al. (2022) by defining a trading day as positive daytime reversal if a negative $R_{i,d}^{O}$ is followed by a positive $R_{i,d}^{I}$. Analogously, a trading day is defined as negative daytime reversal if a positive $R_{i,d}^{O}$ is followed by a negative $R_{i,d}^{I}$. For each month *t*, we calculate the ratio of trading days with positive (negative) daytime reversals to the number of trading days in the month, which Akbas et al. (2022) denote as $PR_{i,t}$ ($NR_{i,t}$). Conceptually, a higher value of $PR_{i,t}$ or $NR_{i,t}$ signifies a higher level of intensity in a daily tug of war for stock *i* during month *t*. Akbas et al. (2022) next define the abnormal frequency of positive daytime reversals, $ABPR_{i,t}$, as the ratio of $PR_{i,t}$ to the average $PR_{i,t}$ over the past 12 months. A similar procedure is applied for the abnormal frequency of negative daytime reversals, $ABNR_{i,t}$.

We propose that if the underperformance of high IMAX stocks is due to daytime arbitrageurs' overcorrection to the negative overnight information, the IMAX premium should be higher among stocks with higher values of $ABPR_{i,t}$ than those with lower values of $ABPR_{i,t}$. Although $ABPR_{i,t}$ is more straightforward to account for the negative relation between IMAX and stock returns, we also apply $ABNR_{i,t}$, which is shown to better account for future stock returns by Akbas et al. (2022), as a further examination to provide a robustness check. While we propose IMAX as a better proxy of lottery-like payoffs, we expect that the IMAX premium cannot be explained by daytime arbitrageurs' overcorrection. That is, both $ABPR_{i,t}$ and $ABNR_{i,t}$, should not explain our results.

To verify our conjecture, we again apply the approach used in Section 4.3. In particular, for each moth t we partition the sample into three subgroups according to each stock's value of ABPR (or ABNR) computed using daily return data in month $t-1$. Within each ABPR (or ABNR) subgroup, we perform the cross-sectional regression of Equation (2) for each month t, and we obtain the average coefficients in the time series separately for each ABPR (or ABNR) subgroup. Table 5 provides the estimation results.

[Insert Table 5 here]

We find that the average coefficients on IMAX are significantly negative for all ABPR subgroups, with average IMAX coefficients of -0.107, -0.048, and -0.094 with *t*-statistics of -3.63, -1.88, and -4.47 for low to high ABPR subgroups. The same evidence is obtained when ABNR is used for the analyses. Specifically, the average IMAX coefficients are -0.066, -0.081, and -0.095 with *t*-statistics of -2.83, -3.80, and -3.57 for low to high ABNR subgroups. Thus, we confirm that the negative relation between IMAX and future stock returns is not induced by daytime arbitrageurs' overcorrection.

4.5. Robustness checks based on multiple-length of MAX

So far, our analyses are implemented based on the proxies constructed using single-day extreme returns. Bali et al. (2011) show that averaging the 5 highest daily returns within the precious month can generate a higher lottery premium than using the single-day MAX. Hence, it is worthwhile to extend our analyses to the multiple-day measures. To this end, we construct three measures, namely MAX(5), IMAX(5), and OMAX(5), by averaging the 5 highest daily, intraday, and overnight returns within month $t-1$. We compare their relative explanatory power for future stock returns by replacing the single-day proxies with the 5-day proxies in Equation (2).

We report the estimation results in Table 6, with control variables excluded in Panel A and control variables included in Panel B. Again, we show that the average coefficients on MAX(5), IMAX(5), and OMAX(5) are all significantly negative when considered alone. In a horse race of comparing the explanatory power of the three proxies, we show that MAX(5) and IMAX(5) both exhibit strong predictability for future stock returns in various combinations of explanatory variables without including control variables. The explanatory power of MAX(5), however, becomes weaker or insignificant when control variables are included. Nevertheless, the explanatory power of IMAX(5) remains strong and robust when control variables are included. Overall, the results from Table 6 confirms that the superior return predictability of IMAX over MAX and OMAX is robust to the multiple-day measures.

[Insert Table 6 here]

We next examine the explanations based on salience theory and daytime arbitrageurs' overcorrection for the return predictability of the multiple-day measures. In Panel A of Table 7, we report the average coefficients on MAX(5), IMAX(5), and OMAX(5) separately for low, medium, and high ST subgroups. Consistent with the results from Table 4, we obtain an insignificant average coefficient on IMAX(5) for the low ST subgroup and significantly negative IMAX(5) coefficients for medium and high ST subgroups. Among the three ST subgroups, the high ST subgroup has the largest *t*-statistic in absolute value for the IMAX(5) coefficient than the remaining two ST subgroups. Thus, the support for the salience theory in explaining the IMAX effect is robust to the multiple-day measures.

[Insert Table 7 here]

We next sort individual stocks into three subgroups by the values of ABPR and ABNR, with the estimation results for the three subgroups reported in Panels B and C of Table 7, respectively. Again, we show that the IMAX(5) coefficients are pervasively negative with significance for all ABPR and ABNR subgroups, confirming our expectation that the lack of support for daytime arbitrageurs' overcorrection in explaining the IMAX effect is unaffected by the length of days to compute the lottery proxies.

4.6. The impact of intraday returns on the MAX effect

The final task of this study is to test **Hypothesis 3**, which predicts that the MAX effect is stronger among stocks whose MAX values comprises higher fractions of intraday returns. To explore this possibility, we adopt the approach of cross-sectional regressions, expressed in the following form:

$$R_{i,t} = \alpha_t + \beta_{1,t} \times MAX_{i,t-1} + \beta_{2,t} \times IMAX_{i,t-1} + \beta_{3,t} \times OMAX_{i,t-1} + \beta_{4,t} \times FRAC_{i,t-1}$$
$$+\beta_{5,t} \times MAX_{i,t-1} \times FRAC_{i,t-1} + \sum_{j=1}^{J} \gamma_{j,t} \times CV_{i,j,t-1} + \varepsilon_{i,t}, \qquad (5)$$

where $FRAC_{i,t-1}$ is the fraction of stock *i*'s intraday return to daily return on the day of MAX occurrence in month t–1, as defined in Section 3.1. According to **Hypothesis 3**, we predict that the negative return predictability of MAX is stronger among stocks having higher values of FRAC. That is, we expect that the average coefficient of $\beta_{5,t}$ from Equation (5) is significantly negative.

We examine several model specifications of Equation (5) to examine our prediction, with the estimation results provided in Table 8. In Model (1), we include $MAX_{i,t-1}$, $FRAC_{i,t-1}$, and their interaction term. We show that the average coefficient on the interaction term is -0.081 with a *t*-statistic of -4.64, thus confirming our prediction. We next include two more independent variables, $IMAX_{i,t-1}$ and $OMAX_{i,t-1}$, as presented in Model (2). We again obtain a significantly negative coefficient on $MAX_{i,t-1} \times FRAC_{i,t-1}$, which is -0.088 with a *t*-statistic of -3.26. It is noteworthy that the average coefficient on $IMAX_{i,t-1}$ is significantly negative at -0.060 with a *t*-statistic of -2.84, indicating that the IMAX effect and intraday return's enhancing effect on the MAX premium seem to coexist.

We further include control variables in the regressions, as presented in Models (3) and (4), and we still obtain significantly negative coefficient on $MAX_{i,t-1} \times FRAC_{i,t-1}$. That is, the impact of intraday returns on the MAX effect is robust to the inclusion of control variables. In Model (4), we again demonstrate the coexistence of significantly negative coefficients on $IMAX_{i,t-1}$ and $MAX_{i,t-1} \times FRAC_{i,t-1}$, confirming that the inclusion of control variables does not subsume the IMAX effect and intraday return's enhancing effect on the MAX premium.

[Insert Table 8 here]

We next test the explanation based on the salience theory for intraday return's enhancing effect on the MAX premium. We again sort individual stocks into three subgroups based on the ST values and perform the cross-sectional regressions of Equation (5) separately for the three subgroups. As presented in Panel A of Table 9, we obtain significantly negative coefficient β_5 only for the high ST subgroup. In particular, the average coefficients on $MAX_{i,t-1} \times FRAC_{i,t-1}$ are -0.064 (*t*-statistic = -1.52), -0.060 (*t*-statistic = -1.33), and -0.051 (*t*-statistic = -2.80) for low, medium, and high ST subgroups. Hence, the salience theory is also applied to explain the phenomenon of higher MAX effect among stocks whose MAX values comprise higher fractions of intraday returns.

[Insert Table 9 here]

Finally, we explore the explanation based on daytime arbitrageurs' overcorrection for the findings obtained in Table 8. We form three subgroups based on the ABPR or ABNR values, and we report the estimation results of Equation (5) separately for the three ABPR and ABNR subgroups in Panels B and C, respectively. We show that the average coefficients on $MAX_{i,t-1} \times FRAC_{i,t-1}$ are consistently negative and significant for all ABPR subgroups. For ABNR subgroups, we obtain significantly negative coefficients on $MAX_{i,t-1} \times FRAC_{i,t-1}$ for low and high ABNR subgroups. That is, either ABPR or ABNR effect fails to effectively differentiate the enhancing effect of intraday return on the MAX premium.

5. Conclusions

In this study, we aim to provide further understanding of the lottery-related anomalies by taking the roles of intraday and overnight returns into account. We are motivated by the negative overnight-intraday return pattern to establish the possible linkage between the intraday component of extreme daily returns and investors' lottery preference. We propose that if investors pay attention to the salient overnight news and trade the stock at the open, they are less incline to overweight the probability of this salient state if a negative reversal during the trading hours occurs. As a result, stocks with extreme overnight returns are less prone to overvaluation and low future returns. In addition, while the open-to-close return is accompanied by trading volumes and the close-to-open return is accompanied by zero or very little volume due to thin trading as suggested by Barardehi et al. (2021), speculative trading induced by investors' lottery preference is more prevalent during daytime trading hours. These arguments motivate us to propose an alternative proxy of investors' lottery preference based on extreme intraday returns.

Accordingly, we propose two measures, IMAX and OMAX, that are defined as the maximum daily open-to-close and close-to-open returns within a month. We hypothesize that IMAX better characterizes lottery-like payoffs and hence exhibits stronger explanatory power for future stock returns than MAX and OMAX. We apply empirical methodologies based on portfolio analyses and cross-sectional regressions, and we obtain consistent evidence in support of our hypothesis. We also confirm the unique role of the salience theory in explain the IMAX effect and the failure of the explanation based on daytime arbitrageurs' overcorrection. These findings are helpful to understand the channel behind the negative relation between IMAX and future stock returns.

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Table 1: Summary statistics of lottery measures

This table presents the summary statistics of main variables associated with lottery proxies for the sample period from July 1992 to December 2022. For each month t, MAX is defined as MAX$\{R_{i,d}\}$, where $R_{i,d}$ is stock i's return on day d within month t. IMAX and OMAX are defined as MAX$\{R^I_{i,d}\}$ and MAX$\{R^O_{i,d}\}$, where $R^I_{i,d}$ and $R^O_{i,d}$ are stock i's intraday and overnight returns on day d within month t. We first report the statistics of the three proxies in Panel A. For each firm-month observation, we first obtain each stock's MAX (IMAX or OMAX) in month $t-1$. We compute the daily, intraday, and overnight returns on the trading day of MAX (IMAX or OMAX) occurrence, and we obtain the means, medians, and standard deviations of the three variables for each month. We next calculate the time-series averages of the cross-sectional statistics. In Panel B, we report the time-series averages of the cross-sectional correlations between the three lottery proxies. In Panel C, we report the summary statistics of deciles formed on MAX. For each month t, we allocate individual stocks into deciles according to their values of MAX in month $t-1$. We next report the time-series averages of cross-sectional means for various variables within each MAX decile, including MAX, the intraday and overnight components of MAX, the percentages of intraday and overnight components to MAX, and two dummy variables indicating whether the day of MAX occurrence coincides the day of IMAX or OMAX in the same month.

	MAX			IMAX			OMAX		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Panel A: Statistics of daily, intraday, and overnight returns on days identifying MAX measures									
Daily return	6.582	4.987	6.985	5.360	4.110	6.399	2.945	1.896	6.006
Intraday return	4.854	3.755	5.465	5.771	4.500	5.489	-0.487	-0.210	4.178
Overnight return	1.696	0.743	4.587	-0.370	-0.037	3.225	3.490	2.275	4.858

	MAX	IMAX	OMAX
Panel B: Correlations between MAX measures			
MAX	1	0.767	0.645
IMAX		1	0.354
OMAX			1

	Low	2	3	4	5	6	7	8	9	High
Panel C: Statistics of variables for MAX deciles										
MAX	1.614	2.627	3.292	3.935	4.629	5.439	6.453	7.858	10.183	19.885
Intraday return	1.189	2.019	2.542	3.038	3.583	4.208	4.978	6.035	7.725	13.229
Overnight return	0.426	0.607	0.747	0.892	1.039	1.219	1.458	1.795	2.405	6.375
% of intraday return	72%	77%	78%	78%	78%	78%	77%	77%	76%	69%
% of overnight return	28%	23%	22%	22%	22%	22%	22%	23%	24%	30%
IMAX dummy	41%	49%	53%	56%	58%	60%	62%	65%	68%	71%
OMAX dummy	20%	18%	20%	20%	21%	22%	23%	25%	28%	38%

Table 2: Returns of decile portfolios formed on different lottery proxies

This table presents the average returns of decile portfolios and the return premia formed on each of the three lottery proxies of MAX, IMAX, and OMAX. For each month *t*, we sort individual stocks into deciles according to their values of MAX, IMAX, or OMAX identified in month *t*−1. For each decile portfolio, we calculate equally- and value-weighted returns in month *t*. We define the premium of the lottery anomaly as the difference in returns between the lowest and highest deciles. In addition to raw returns, we also obtain abnormal returns by regressing the raw return premia between long and short positions on each factor model, and we obtain the intercept as the abnormal return. We consider Fama and French's (2015) five-factor model, a momentum-augmented six-factor model, a liquidity-augmented six-factor model, Hou et al.'s (2015) Q4 model, and Hou et al.'s (2021) Q5 model. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	MAX		IMAX		OMAX	
	EW	VW	EW	VW	EW	VW
Low	1.139 ***	1.073 ***	1.103 ***	1.104 ***	0.874 ***	0.926 ***
	(6.63)	(5.97)	(6.29)	(6.14)	(4.67)	(5.26)
2	1.171 ***	0.974 ***	1.191 ***	1.032 ***	0.974 ***	0.936 ***
	(5.23)	(5.19)	(5.41)	(5.25)	(4.20)	(4.83)
3	1.144 ***	0.976 ***	1.128 ***	0.903 ***	1.005 ***	1.067 ***
	(4.72)	(4.63)	(4.69)	(4.19)	(3.87)	(5.25)
4	1.102 ***	0.797 ***	1.094 ***	0.879 ***	1.009 ***	0.911 ***
	(4.19)	(3.33)	(4.14)	(3.57)	(3.75)	(3.81)
5	1.017 ***	0.914 ***	1.062 ***	0.877 ***	0.871 ***	0.760 ***
	(3.57)	(3.35)	(3.77)	(3.33)	(2.95)	(3.05)
6	0.853 ***	0.798 ***	0.884 ***	0.786 **	0.906 ***	0.769 **
	(2.80)	(2.72)	(2.90)	(2.56)	(2.85)	(2.58)
7	0.759 **	0.652 *	0.754 **	0.718 **	0.809 **	0.818 **
	(2.25)	(1.96)	(2.28)	(2.07)	(2.34)	(2.55)
8	0.511	0.587	0.656 *	0.743 *	0.740 **	0.683 *
	(1.36)	(1.47)	(1.76)	(1.86)	(2.07)	(1.89)
9	0.302	0.436	0.252	0.419	0.433	0.498
	(0.72)	(1.00)	(0.60)	(0.95)	(1.11)	(1.31)
High	-0.279	0.170	-0.397	-0.057	0.095	0.479
	(-0.56)	(0.35)	(-0.78)	(-0.11)	(0.22)	(1.15)
Low–High	1.418 ***	0.903 **	1.500 ***	1.161 **	0.779 **	0.447
	(3.34)	(2.14)	(3.45)	(2.46)	(2.22)	(1.26)
FF5 alpha	1.334 ***	0.791 ***	1.428 ***	1.070 ***	0.593 ***	0.326 *
	(6.76)	(3.63)	(6.83)	(4.25)	(2.87)	(1.66)
FF5+MOM alpha	1.210 ***	0.679 ***	1.313 ***	0.939 ***	0.442 **	0.267
	(5.90)	(2.81)	(6.23)	(3.38)	(2.02)	(1.28)
FF5+LIW alpha	1.351 ***	0.772 ***	1.449 ***	1.071 ***	0.651 ***	0.491 **
	(6.69)	(3.29)	(6.79)	(4.13)	(3.16)	(2.31)
Q4 alpha	1.032 ***	0.565 *	1.135 ***	0.688 **	0.252	0.195
	(3.93)	(1.88)	(4.14)	(2.14)	(1.05)	(0.74)
Q5 alpha	0.922 ***	0.415	0.992 ***	0.557 *	0.162	0.117
	(3.68)	(1.42)	(3.93)	(1.87)	(0.66)	(0.47)

Table 3: Cross-sectional regressions

This table presents the estimation results of the Fama-MacBeth (1973) cross-sectional regressions. For each month t, we perform the following cross-sectional regression:

$$R_{i,t} = \alpha_t + \beta_{1,t} \times MAX_{i,t-1} + \beta_{2,t} \times IMAX_{i,t-1} + \beta_{3,t} \times OMAX_{i,t-1} + \sum_{j=1}^{J} \gamma_{j,t} \times CV_{i,j,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock i's return in month t; $MAX_{i,t-1}$, $IMAX_{i,t-1}$, and $OMAX_{i,t-1}$ are the maximum daily, intraday, and overnight returns in month $t-1$; $CV_{i,j,t}$ is the jth control variable. The control variables include firm size (SIZE), book-to-market (BM) ratio, gross profitability (GP), asset growth (AG), intermediate-term past return (PR12), short-term past return (REV), illiquidity (ILLIQ), and idiosyncratic volatility (IVOL). Once we obtain the coefficient estimates from the regression for each month t, we calculate the time-series averages of the coefficients from the regressions. In Panel A, we include lottery proxies only while in Panel B, we include lottery proxies and control variables simultaneously. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
Panel A: Cross-sectional regressions without controls							
MAX	-0.063 ***			-0.008	-0.079 ***		-0.002
	(-4.28)			(-0.94)	(-5.03)		(-0.14)
IMAX		-0.099 ***		-0.092 ***		-0.098 ***	-0.099 ***
		(-4.97)		(-5.31)		(-5.34)	(-4.80)
OMAX			-0.043 ***		0.032 ***	-0.002	-0.003
			(-2.81)		(3.08)	(-0.18)	(-0.20)
Panel B: Cross-sectional regressions with controls							
MAX	0.035 **			0.067 ***	0.027		0.067 ***
	(2.13)			(4.08)	(1.52)		(3.46)
IMAX		-0.060 ***		-0.076 ***		-0.043 ***	-0.073 ***
		(-4.26)		(-5.38)		(-2.76)	(-4.27)
OMAX			0.044 ***		0.036 ***	0.033 ***	0.008
			(3.94)		(3.06)	(2.78)	(0.55)
SIZE	-0.009	-0.009	-0.004	-0.023	-0.006	-0.008	-0.021
	(-0.32)	(-0.30)	(-0.14)	(-0.79)	(-0.20)	(-0.28)	(-0.73)
BM	0.150 **	0.146 **	0.153 **	0.138 *	0.151 **	0.145 *	0.139 *
	(2.01)	(1.97)	(2.03)	(1.88)	(2.02)	(1.96)	(1.91)
GP	0.684 ***	0.663 ***	0.701 ***	0.667 ***	0.697 ***	0.682 ***	0.680 ***
	(4.26)	(4.15)	(4.36)	(4.17)	(4.34)	(4.26)	(4.23)
AG	-0.363 **	-0.385 **	-0.385 **	-0.366 **	-0.372 **	-0.375 **	-0.365 **
	(-2.32)	(-2.48)	(-2.46)	(-2.37)	(-2.40)	(-2.43)	(-2.37)
PR12	0.004 *	0.004	0.004	0.004	0.004	0.004	0.004
	(1.65)	(1.46)	(1.58)	(1.56)	(1.62)	(1.50)	(1.54)
REV	-0.019 ***	-0.011 **	-0.017 ***	-0.018 ***	-0.020 ***	-0.014 ***	-0.019 ***
	(-3.72)	(-2.34)	(-3.74)	(-3.44)	(-3.87)	(-2.79)	(-3.55)
ILLIQ	0.123	0.102	0.065	0.117	0.075	0.070	0.099
	(0.74)	(0.63)	(0.41)	(0.69)	(0.45)	(0.43)	(0.57)
IVOL	-0.335 ***	-0.110 **	-0.293 ***	-0.276 ***	-0.354 ***	-0.192 ***	-0.287 ***
	(-4.26)	(-2.18)	(-4.59)	(-3.62)	(-4.55)	(-3.35)	(-3.93)

Table 4: Cross-sectional regressions by groups of the salience theory

This table presents the estimation results of the Fama-MacBeth (1973) cross-sectional regressions separately for different groups sorted by the salience theory values. For each month *t*, we partition the sample into three subgroups according to each stock's value of ST computed using daily return data in month $t-1$. Within each ST subgroup for each month *t*, we perform the following cross-sectional regression:

$$R_{i,t} = \alpha_t + \beta_{1,t} \times MAX_{i,t-1} + \beta_{2,t} \times IMAX_{i,t-1} + \beta_{3,t} \times OMAX_{i,t-1} + \sum_{j=1}^{J} \gamma_{j,t} \times CV_{i,j,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock *i*'s return in month *t*; $MAX_{i,t-1}$, $IMAX_{i,t-1}$, and $OMAX_{i,t-1}$ are the maximum daily, intraday, and overnight returns in month $t-1$; $CV_{i,j,t}$ is the *j*th control variable. The control variables include firm size (SIZE), book-to-market (BM) ratio, gross profitability (GP), asset growth (AG), intermediate-term past return (PR12), short-term past return (REV), illiquidity (ILLIQ), and idiosyncratic volatility (IVOL). Once we obtain the coefficient estimates from the regression for each month *t*, we calculate the time-series averages of the coefficients from the regressions for each ST subgroup. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	ST subgroup		
	Low	Medium	High
MAX	-0.037	0.005	0.087 ***
	(-0.94)	(0.11)	(3.25)
IMAX	-0.040	-0.072 ***	-0.069 ***
	(-1.43)	(-3.14)	(-3.39)
OMAX	0.032	0.058 **	-0.004
	(1.20)	(2.22)	(-0.27)
SIZE	-0.042	-0.044	0.014
	(-1.19)	(-1.44)	(0.40)
BM	0.108	0.058	0.188 **
	(1.30)	(0.80)	(2.31)
GP	0.573 ***	0.418 **	0.882 ***
	(2.69)	(2.20)	(4.47)
AG	-0.767 ***	-0.034	-0.126
	(-3.18)	(-0.16)	(-0.56)
PR12	0.001	0.005 *	0.007 **
	(0.33)	(1.70)	(2.58)
REV	-0.033 ***	-0.035 ***	-0.009 *
	(-3.77)	(-4.61)	(-1.70)
ILLIQ	-0.061	-0.546	0.132
	(-0.17)	(-1.27)	(0.55)
IVOL	-0.325 ***	-0.167	-0.332 **
	(-4.39)	(-1.43)	(-2.47)

Table 5: Cross-sectional regressions by groups of abnormal daytime reversals

This table presents the estimation results of the Fama-MacBeth (1973) cross-sectional regressions separately for different groups sorted by the values of abnormal daytime reversals. We consider abnormal positive daytime reversal (ABPR) and abnormal negative daytime reversal (ABNR). For each month *t*, we partition the sample into three subgroups according to each stock's value of ABPR or ABNR computed using daily return data in month $t-1$. Within each ABPR or ABNR subgroup for each month *t*, we perform the following cross-sectional regression:

$$R_{i,t} = \alpha_t + \beta_{1,t} \times MAX_{i,t-1} + \beta_{2,t} \times IMAX_{i,t-1} + \beta_{3,t} \times OMAX_{i,t-1} + \sum_{j=1}^{J} \gamma_{j,t} \times CV_{i,j,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock *i*'s return in month *t*; $MAX_{i,t-1}$, $IMAX_{i,t-1}$, and $OMAX_{i,t-1}$ are the maximum daily, intraday, and overnight returns in month $t-1$; $CV_{i,j,t}$ is the *j*th control variable. The control variables include firm size (SIZE), book-to-market (BM) ratio, gross profitability (GP), asset growth (AG), intermediate-term past return (PR12), short-term past return (REV), illiquidity (ILLIQ), and idiosyncratic volatility (IVOL). Once we obtain the coefficient estimates from the regression for each month *t*, we calculate the time-series averages of the coefficients from the regressions for each ABPR or ABNR subgroup. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	ABPR subgroup			ABNR subgroup		
	Low	Medium	High	Low	Medium	High
MAX	0.082 ***	0.069 **	0.059 **	0.076 ***	0.043	0.095 ***
	(2.76)	(2.52)	(2.28)	(3.04)	(1.55)	(3.37)
IMAX	-0.107 ***	-0.048 *	-0.094 ***	-0.066 ***	-0.081 ***	-0.095 ***
	(-3.63)	(-1.88)	(-4.47)	(-2.83)	(-3.80)	(-3.57)
OMAX	-0.019	0.025	0.012	0.001	0.022	-0.016
	(-0.78)	(1.23)	(0.62)	(0.03)	(1.16)	(-0.62)
SIZE	-0.036	-0.060 *	0.005	0.009	-0.037	-0.044
	(-1.02)	(-1.87)	(0.17)	(0.26)	(-1.12)	(-1.37)
BM	0.158 *	0.095	0.135 *	0.132 *	0.167 **	0.099
	(1.81)	(1.23)	(1.68)	(1.66)	(2.04)	(1.16)
GP	0.790 ***	0.549 ***	0.588 ***	0.784 ***	0.732 ***	0.453 **
	(3.71)	(3.04)	(3.03)	(3.50)	(3.95)	(2.43)
AG	-0.440 **	-0.318	-0.149	-0.453 *	-0.472 *	-0.215
	(-2.11)	(-1.34)	(-0.59)	(-1.90)	(-1.88)	(-1.00)
PR12	0.005 *	0.003	0.005 *	0.005 *	0.005 *	0.002
	(1.67)	(1.03)	(1.81)	(1.95)	(1.79)	(0.78)
REV	-0.018 ***	-0.025 ***	-0.013 **	-0.020 ***	-0.014 **	-0.025 ***
	(-2.87)	(-3.90)	(-2.18)	(-3.16)	(-2.30)	(-4.01)
ILLIQ	0.511	-0.545	0.478	0.448	-0.082	-0.097
	(1.27)	(-1.58)	(0.91)	(1.31)	(-0.26)	(-0.25)
IVOL	-0.249 **	-0.357 ***	-0.221 **	-0.290 ***	-0.267 ***	-0.262 **
	(-2.48)	(-4.35)	(-2.46)	(-3.52)	(-3.03)	(-2.40)

Table 6: Cross-sectional regressions of five-day MAX measures

This table presents the estimation results of the Fama-MacBeth (1973) cross-sectional regressions by using the 5-day averaged lottery proxies as the main independent variables. For each month *t*, we perform the following cross-sectional regression:

$$R_{i,t} = \alpha_t + \beta_{1,t} \times MAX(5)_{i,t-1} + \beta_{2,t} \times IMAX(5)_{i,t-1} + \beta_{3,t} \times OMAX(5)_{i,t-1} + \sum_{j=1}^{J} \gamma_{j,t} \times CV_{i,j,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock *i*'s return in month *t*; $MAX(5)_{i,t-1}$, $IMAX(5)_{i,t-1}$, and $OMAX(5)_{i,t-1}$ are the5-day average values of $MAX_{i,t-1}$, $IMAX_{i,t-1}$, and $OMAX_{i,t-1}$; $CV_{i,j,t}$ is the *j*th control variable. The control variables include firm size (SIZE), book-to-market (BM) ratio, gross profitability (GP), asset growth (AG), intermediate-term past return (PR12), short-term past return (REV), illiquidity (ILLIQ), and idiosyncratic volatility (IVOL). Once we obtain the coefficient estimates from the regression for each month *t*, we calculate the time-series averages of the coefficients from the regressions. In Panel A, we include lottery proxies only while in Panel B, we include lottery proxies and control variables simultaneously. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
Panel A: Cross-sectional regressions without controls							
MAX(5)	-0.188 ***			-0.058 *	-0.230 ***		-0.075 **
	(-4.53)			(-1.92)	(-5.74)		(-2.23)
IMAX(5)		-0.232 ***		-0.177 ***		-0.235 ***	-0.180 ***
		(-4.79)		(-4.55)		(-5.59)	(-3.81)
OMAX(5)			-0.148 ***		0.092 ***	0.002	0.038
			(-2.75)		(2.74)	(0.05)	(0.95)
Panel B: Cross-sectional regressions with controls							
MAX(5)	-0.186 **			-0.008	-0.218 **		-0.040
	(-2.04)			(-0.08)	(-2.47)		(-0.46)
IMAX(5)		-0.207 ***		-0.199 ***		-0.197 ***	-0.183 ***
		(-4.48)		(-5.32)		(-3.70)	(-4.08)
OMAX(5)			0.103 **		0.139 ***	0.046	0.060
			(2.40)		(3.56)	(0.90)	(1.28)
SIZE	0.003	-0.019	0.006	-0.017	0.014	-0.012	-0.007
	(0.09)	(-0.65)	(0.20)	(-0.57)	(0.47)	(-0.43)	(-0.26)
BM	0.134 *	0.128 *	0.158 **	0.123 *	0.138 *	0.128 *	0.127 *
	(1.88)	(1.77)	(2.11)	(1.75)	(1.95)	(1.81)	(1.83)
GP	0.653 ***	0.667 ***	0.712 ***	0.662 ***	0.685 ***	0.682 ***	0.677 ***
	(4.09)	(4.18)	(4.43)	(4.15)	(4.28)	(4.26)	(4.22)
AG	-0.340 **	-0.360 **	-0.371 **	-0.340 **	-0.330 **	-0.333 **	-0.326 **
	(-2.27)	(-2.37)	(-2.35)	(-2.27)	(-2.20)	(-2.18)	(-2.17)
PR12	0.004	0.004	0.004	0.004	0.004	0.003	0.004
	(1.51)	(1.42)	(1.57)	(1.51)	(1.52)	(1.40)	(1.48)
REV	-0.004	-0.006	-0.016 ***	-0.006	-0.004	-0.007	-0.006
	(-0.52)	(-1.22)	(-3.47)	(-0.78)	(-0.49)	(-1.28)	(-0.76)
ILLIQ	0.100	0.083	0.031	0.061	0.012	0.039	0.012
	(0.60)	(0.52)	(0.18)	(0.36)	(0.07)	(0.22)	(0.07)
IVOL	0.011	-0.043	-0.280 ***	-0.023	-0.022	-0.072	-0.028
	(0.14)	(-1.05)	(-5.11)	(-0.30)	(-0.29)	(-1.62)	(-0.38)

Table 7: Cross-sectional regressions of five-day MAX measures by different groups

This table presents the estimation results of the Fama-MacBeth (1973) cross-sectional regressions by using the 5-day averaged lottery proxies as the main independent variables separately for different groups sorted by the values of the salience theory or abnormal daytime reversals. For each month *t*, we partition the sample into three subgroups according to each stock's value of ST, ABPR, or ABNR computed using daily return data in month $t-1$. Within each ST, ABPR, or ABNR subgroup for each month *t*, we perform the following cross-sectional regression:

$$R_{i,t} = \alpha_t + \beta_{1,t} \times MAX(5)_{i,t-1} + \beta_{2,t} \times IMAX(5)_{i,t-1} + \beta_{3,t} \times OMAX(5)_{i,t-1} + \sum_{j=1}^{J} \gamma_{j,t} \times CV_{i,j,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock *i*'s return in month *t*; $MAX(5)_{i,t-1}$, $IMAX(5)_{i,t-1}$, and $OMAX(5)_{i,t-1}$ are the5-day average values of $MAX_{i,t-1}$, $IMAX_{i,t-1}$, and $OMAX_{i,t-1}$; $CV_{i,j,t}$ is the *j*th control variable. The control variables include firm size (SIZE), book-to-market (BM) ratio, gross profitability (GP), asset growth (AG), intermediate-term past return (PR12), short-term past return (REV), illiquidity (ILLIQ), and idiosyncratic volatility (IVOL). Once we obtain the coefficient estimates from the regression for each month *t*, we calculate the time-series averages of the coefficients from the regressions for each ST, ABPR, or ABNR subgroup. Panels A to C present the estimation results for groups formed by ST, ABPR, and ABNR, respectively. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Groups formed by salience theory/abnormal daytime reversals		
	Low	Medium	High
Panel A: Stocks grouped by ST			
MAX(5)	-0.140	-0.181	-0.020
	(-1.22)	(-1.25)	(-0.17)
IMAX(5)	-0.085	-0.123 **	-0.221 ***
	(-1.14)	(-2.30)	(-3.50)
OMAX(5)	0.103	0.153 **	-0.012
	(1.35)	(2.24)	(-0.21)
Panel B: Stocks grouped by ABPR			
MAX(5)	-0.089	0.020	-0.020
	(-0.83)	(0.20)	(-0.17)
IMAX(5)	-0.159 **	-0.171 ***	-0.234 ***
	(-2.06)	(-2.99)	(-3.80)
OMAX(5)	0.056	0.076	0.088
	(0.71)	(1.22)	(1.45)
Panel C: Stocks grouped by ABNR			
MAX(5)	-0.059	-0.124	0.101
	(-0.55)	(-0.99)	(0.73)
IMAX(5)	-0.190 ***	-0.171 ***	-0.196 ***
	(-2.78)	(-2.59)	(-3.49)
OMAX(5)	0.024	0.107	0.040
	(0.31)	(1.61)	(0.60)

Table 8: Cross-sectional regressions of MAX considering the fraction of intraday returns

This table presents the estimation results of the Fama-MacBeth (1973) cross-sectional regressions considering the impact of the fraction of intraday returns on MAX. For each month t, we perform the following cross-sectional regression:

$$R_{i,t} = \alpha_t + \beta_{1,t} \times MAX_{i,t-1} + \beta_{2,t} \times IMAX_{i,t-1} + \beta_{3,t} \times OMAX_{i,t-1} + \beta_{4,t} \times FRAC_{i,t-1} + \beta_{5,t} \times MAX_{i,t-1} \times FRAC_{i,t-1} + \sum_{j=1}^{J} \gamma_{j,t} \times CV_{i,j,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock i's return in month t; $MAX_{i,t-1}$, $IMAX_{i,t-1}$, and $OMAX_{i,t-1}$ are the maximum daily, intraday, and overnight returns in month $t-1$; $FRAC_{i,t-1}$ is the fraction of stock i's intraday return to daily return on the day of MAX occurrence in month t–1; $CV_{i,j,t}$ is the jth control variable. The control variables include firm size (SIZE), book-to-market (BM) ratio, gross profitability (GP), asset growth (AG), intermediate-term past return (PR12), short-term past return (REV), illiquidity (ILLIQ), and idiosyncratic volatility (IVOL). Once we obtain the coefficient estimates from the regression for each month t, we calculate the time-series averages of the coefficients from the regressions. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model (1)	Model (2)	Model (3)	Model (4)
MAX	-0.018	0.049 **	0.068 ***	0.085 ***
	(-1.52)	(2.56)	(3.98)	(3.44)
IMAX		-0.060 ***		-0.039 **
		(-2.84)		(-2.13)
OMAX		-0.050 **		-0.016
		(-2.47)		(-0.87)
FRAC	0.055	0.055	0.031	-0.028
	(0.57)	(0.53)	(0.29)	(-0.25)
FRAC×MAX	-0.081 ***	-0.088 ***	-0.062 ***	-0.049 *
	(-4.64)	(-3.26)	(-3.66)	(-1.91)
SIZE			-0.015	-0.018
			(-0.52)	(-0.63)
BM			0.142 *	0.139 *
			(1.92)	(1.93)
GP			0.663 ***	0.673 ***
			(4.16)	(4.22)
AG			-0.368 **	-0.364 **
			(-2.38)	(-2.35)
PR12			0.004	0.004
			(1.59)	(1.53)
REV			-0.019 ***	-0.019 ***
			(-3.68)	(-3.56)
ILLIQ			0.141	0.174
			(0.83)	(0.99)
IVOL			-0.323 ***	-0.291 ***
			(-4.16)	(-3.98)

Table 9: Cross-sectional regressions of MAX considering the fraction of intraday returns by different groups

This table presents the estimation results of the Fama-MacBeth (1973) cross-sectional regressions considering the impact of the salience theory and the fraction of intraday returns on MAX separately for different groups sorted by the values of the salience theory or abnormal daytime reversals. For each month *t*, we partition the sample into three subgroups according to each stock's value of ST, ABPR, or ABNR computed using daily return data in month *t*−1. Within each ST, ABPR, or ABNR subgroup for each month *t*, we perform the following cross-sectional regression:

$$R_{i,t} = \alpha_t + \beta_{1,t} \times MAX_{i,t-1} + \beta_{2,t} \times IMAX_{i,t-1} + \beta_{3,t} \times OMAX_{i,t-1} + \beta_{4,t} \times FRAC_{i,t-1} + \beta_{5,t} \times MAX_{i,t-1} \times FRAC_{i,t-1} + \sum_{j=1}^{J} \gamma_{j,t} \times CV_{i,j,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock *i*'s return in month *t*; $MAX_{i,t-1}$, $IMAX_{i,t-1}$, and $OMAX_{i,t-1}$ are the maximum daily, intraday, and overnight returns in month *t*−1; $FRAC_{i,t-1}$ is the fraction of stock *i*'s intraday return to daily return on the day of MAX occurrence in month *t*–1; $CV_{i,j,t}$ is the *j*th control variable. The control variables include firm size (SIZE), book-to-market (BM) ratio, gross profitability (GP), asset growth (AG), intermediate-term past return (PR12), short-term past return (REV), illiquidity (ILLIQ), and idiosyncratic volatility (IVOL). Once we obtain the coefficient estimates from the regression for each month *t*, we calculate the time-series averages of the coefficients from the regressions for each ST, ABPR, or ABNR subgroup. Panels A to C present the estimation results for groups formed by ST, ABPR, and ABNR, respectively. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Groups formed by salience theory/abnormal daytime reversals		
	Low	Medium	High
Panel A: Stocks grouped by ST			
MAX	-0.012	0.013	0.087 ***
	(-0.25)	(0.24)	(3.26)
FRAC	0.083	0.001	0.002
	(0.49)	(0.00)	(0.01)
FRAC×MAX	-0.064	-0.060	-0.051 ***
	(-1.52)	(-1.33)	(-2.80)
Panel B: Stocks grouped by ABPR			
MAX	0.068 ***	0.050 **	0.078 ***
	(2.80)	(1.99)	(3.29)
FRAC	-0.007	0.123	0.025
	(-0.05)	(0.92)	(0.19)
FRAC×MAX	-0.057 **	-0.073 ***	-0.062 ***
	(-2.34)	(-3.00)	(-2.78)
Panel C: Stocks grouped by ABNR			
MAX	0.077 ***	0.064 ***	0.056 **
	(2.83)	(2.77)	(2.41)
FRAC	0.258	-0.120	0.016
	(1.58)	(-0.87)	(0.12)
FRAC×MAX	-0.094 ***	-0.024	-0.069 ***
	(-3.91)	(-1.00)	(-2.93)