

Lottery Stocks in the UK: Evidence, Characteristics and Cause

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August 2021
Revised September 2022

Abstract

Research across international markets identifies lottery-like stocks that contradict the standard positive risk-return trade-off paradigm. This paper, consistent with those results, reports under-performance for lottery-like stocks in the UK market. Moreover, while the under-performance appears stronger in crisis periods, it persists across all periods even when controlling for other return predictors, including size, momentum and downside risk. However, the cause of this under-performance remains a source of debate. Our results show that a left-tail measure subsumes the UK lottery effect. This suggests under-reaction and continuation behaviour to bad news and is combined with limits to arbitrage. In addition, our findings indicate that poor lottery stock performance is partially explained by the anchoring effect and is more prevalent with greater optimism and sentiment. This contrasts with US results where reversion behaviour is reported for lottery-like stocks and supports the need for market specific research.

Keywords: Stock Returns, Lottery Effect, Idiosyncratic Volatility, Max-Effect
JEL: C20, C58, G12

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1. Introduction.

Almost since the inception of CAPM and its prediction of a linear and positive trade-off between risk and expected return (Sharpe, 1964) evidence against has been presented. Early empirical work noted that the relation between beta and asset returns is too flat compared to the model's predictions and that the risk-adjusted performance is negatively related to the estimated beta (see, for example, Douglas, 1968; Black et al., 1972; Blume and Friend, 1973; Fama and MacBeth 1973). Further work argues that variables other than beta are priced by investors. Notable, examples include, the earnings-price ratio (Basu, 1977), book-to-market equity ratio (Statman, 1980), market capitalisation (Banz, 1981) and price momentum (Jagadeesh and Titman, 1993). This led to the development of multi-factor models such as the one introduced by Fama and French (1993).

Perhaps the most striking recent puzzle is presented Ang et al. (2006) who document a negative relation between idiosyncratic volatility and future returns. Stocks with high idiosyncratic volatility (measured relative to, for example, the Fama and French (1993) model) underperform stocks with low idiosyncratic volatility. Subsequent research documents that similar, speculative, features of stocks equally exhibit a negative relation with future returns. Notably, Bali et al. (2011) find that the past maximum daily return inversely predicts subsequent monthly return. This behaviour is attributed to a tendency for investors to prefer stocks with lottery-like features (e.g., large positive daily returns) and a tendency to under-diversify (e.g., Barber and Odean, 2000; Polkovnichenko, 2005; Goetzmann and Kumar, 2008). This lottery-preference behaviour leads investors to overvalue stocks with extreme return observations (see, also, Kumar and Han, 2014; Mitton and Vorkink, 2007).

While the speculative behaviour of investors is one explanation for the inverse risk-return relation, others have been advanced. For example, microstructure biases, such as short-term reversals and bid-ask bounce, are suggested as a cause for the poor performance of high idiosyncratic volatility stocks (Huang et al., 2010; Han and Lesmond, 2011). Stambaugh (2015) suggests that the underperformance of stocks with high idiosyncratic volatility is a result of persistent overpricing of difficult to arbitrage stocks.

Notwithstanding the underlying reason, this anomaly poses a challenge to the CAPM mean-variance model. Notably, Kumar et al. (2016) demonstrate that gambling-motivated investors demand for lottery-like stocks compromises a significant part of overall stock market trade. Therefore, understanding the nature of lottery-like stocks is important and has numerous implications for asset pricing. For instance, ignoring the inverse risk-return relation in lottery-like stocks leads risk-averse investors to misallocate their funds.

Extending the above discussion, this work seeks to contribute to the literature in two ways. First, the existence of this lottery-like behaviour in UK stocks is considered. Second, we examine the characteristics and forces that drive this behaviour. Prior evidence primarily focusses on US stocks, with UK stocks under-researched, despite being a globally important market. Thus, the UK provides a natural base for ‘out-of-sample’ evidence. Moreover, there are distinctive features within the structure and organisational rules of the UK market that present a different context and may provide different results. Generally, UK stocks are smaller, and less liquid compared to the US market (Petrovic et al., 2016). In addition, there are differences in accounting standards and tax law (Papanastasopoulos, 2020).

In regard of specific evidence for the UK,¹ Angelidis and Tessaromatis (2008) consider the pricing of idiosyncratic volatility during the period from 1979 to 2003. Aggregating idiosyncratic volatility across stocks and sorting into small and large stocks, they find that idiosyncratic volatility can only predict returns in small stocks. Moreover, their aggregate measure of idiosyncratic volatility positively predicts the market return (albeit at the 10% significance level). Cotter et al. (2015) examine the UK market during the period 1990-2009. While their results confirm the general negative relation between idiosyncratic volatility and subsequent returns, they show it only to be significant in a down market. Thus, UK evidence is both limited and mixed. Therefore, this paper re-considers UK evidence using an updated sample. Moreover, we use daily data in constructing portfolios, whereas previous evidence uses monthly data. However, more importantly, we seek to explain the existence of the anomaly rather than just identify its presence. US evidence, for example, suggests stock return reversals as an explanation (see, Huang et al., 2009; Bali et al., 2011; Han and Kumar, 2013).

2. Literature Review.

The cross-sectional pricing of idiosyncratic risk received little attention until the results of Ang et al. (2006) who report an inverse relation between idiosyncratic volatility and expected returns. Using the Fama and French (1993) methodology, they sort stocks into deciles according to their idiosyncratic volatility and report that the average cross-sectional return spread between the lowest and highest idiosyncratic volatility portfolios is more than 1% per month. Moreover, this negative idiosyncratic risk and expected returns relation is not explained by commonly used return predictors, including beta, market capitalisation, book-market ratio,

¹ Both Ang et al. (2009) and Cheon and Lee (2017) conduct multi-country analysis that includes the UK for the idiosyncratic and maximum return effect respectively.

momentum, liquidity, bid-ask spread, co-skewness, analyst dispersion and market states.

Fu (2009) questions the measure of idiosyncratic volatility and using a GARCH approach reports a positive relation. Subsequently, Spiegel and Wang (2007), Huang et al. (2010), Brockman et al. (2012), Eiling (2013) and Peterson and Smedema (2011) also support a positive relation. In response, Bali et al. (2010), Fink et al. (2012) and Guo et al. (2014) highlight problematic inferencing in using fitted volatility, notably look-ahead bias. Further, Ang et al. (2009) defend the original measure of idiosyncratic volatility and present additional results in support of the negative relation.

The initial US based finding prompts researchers to consider other markets. Ang et al. (2009) confirm outperformance of the lowest idiosyncratic risk portfolio over the highest for 23 countries from 1980-2003. Supportive single market studies are provided by Gharghori and Veeraraghavan (2011), Zhong and Gray (2016) and Zhong (2018) for Australian, Luis et al. (2012) for Spain, Cotter et al. (2015) for the UK and Nartea et al. (2013) and Wan (2018) for China. Nonetheless, several studies do provide evidence of a positive idiosyncratic volatility and returns relation, including Nartea et al. (2011), Aboulamer and Kryzanowski (2016) and Liu and Iorio (2016).

In related work, Bali et al. (2011) document the tendency of US investors to prefer stocks that experience extreme positive daily returns over the recent past period (e.g., past month). They report a significant negative cross-sectional spread between a portfolio of stocks with extreme high returns over the past month and a portfolio of stocks with the lowest past month returns (and referred to as the max-effect).

Again, the reporting of this effect in US data motivates work for other markets. Cheon and Lee (2018) examine a sample of 47,000 stocks from 42 markets and provide empirical evidence on the universality of the max-effect. Further evidence is provided for European (Annaert et al., 2013), Australian (Zhong and Gray, 2016), South Korean (Nartea et al., 2014), Hong Kong (Chan and Chui, 2016), Chinese (Nartea et al., 2017; Wan, 2018), Taiwanese (Hung and Yang, 2018), and Brazilian (Berggrun et al., 2017) markets.

In considering these effects, Mitton and Vorkink (2007), Kumar (2009) and Han and Kumar (2013) argue that such stocks are preferred by investors because they perceive a greater potential for extreme upside gains. Thus, becoming referred to as lottery-like stocks. The demand for lottery-like stocks pushes up their price, with the consequence that they generate negative future returns. Further support for this effect is provided by Bali et al. (2017), Fong and Toh (2014), Barinov (2018), Kumar et al., (2018) and Lin and Liu (2018).

Moreover, following Miller (1977), where diverse opinion is combined with limits to

arbitrage (such as short-sale constraints), the market will reflect the view of optimists. This leads to a systematic overvaluation and weaker subsequent returns. In an application, Pontiff (2006) employs idiosyncratic volatility as a proxy for limits to arbitrage.²

Alternative arguments include the role of prospect theory (Kahneman and Tversky, 1979) and the associated reference-dependent preferences (see, Bhootra and Hur, 2015; Wang et al., 2017). While others suggest a noise trader role, the level of investor sentiment and the tendency of investors to gamble (lottery-effect) as an explanation for the puzzle (Bali et al., 2011; Fong and Toh, 2014; Hou and Loh, 2016) or that investors prefer positively skewed stocks (Boyer et al., 2010). Notwithstanding the above, some studies argue in favour of risk-based explanations. For instance, investors may prefer assets with high idiosyncratic risk to hedge against aggregate volatility risk and in stocks that have features related to a real growth option (Barinov, 2013, 2018; Chen and Petkova, 2012).

3. Data and Methodology.

3.1. Data:

We use daily stock prices in the construction of monthly portfolios to ensure a sufficient number of observations and combine with monthly accounting data over the period from January 1991 to December 2017. This contrasts with previous UK based work that used monthly data only. The data includes both current trading and delisted stocks to mitigate the well-documented survivorship bias found to affect cross-sectional asset pricing tests (see, for example, Shumway, 1997). To mitigate the further problem of non-synchronous trading, stocks with less than 36 trading days are excluded. The data source is Thomson Reuters DataStream. Following the asset pricing literature, the sample only includes common equities (see, for example, Florackis et al., 2011). In addition to the above daily and monthly data, we obtain data for the Cahart Four-Factor model from Gregory et al. (2013).

Dependent (Lottery-Like) Variables.

Following the literature, we utilise several proxies to represent the lottery effect. The dominant approaches are idiosyncratic volatility (IVOL) and the maximum returns effect (MAX), while the jump in returns (Jump) and price itself (price) are also considered. In our analysis, we focus on IVOL and MAX and create an index based on all four measures. To briefly describe them:

² Further support for the mispricing hypothesis is reported by Conard et al. (2014), Zhong and Gray (2016), Bali et al. (2017), Cheon and Lee (2017), Lin and Liu (2018) and Hung and Yang (2018).

1. *Idiosyncratic Volatility:*

Ang et al. (2006) measure idiosyncratic volatility as the standard deviation of the residual from the Fama-French three factor model. We follow the same approach but use the Carhart four-factor model:

$$R_{i,d} = \alpha_i + \beta^*(R_{m,d}) + \beta_{smb} * SMB_d + \beta_{hml} * HML_d + \beta_{UMD} * UMD_d + \epsilon_{i,d} \quad (1)$$

Where, $R_{i,d}$ is the stock risk premium, $R_{m,d}$ is the market risk premium, SMB is the size spread, HML is the value spread and UMD the momentum effect. From this model and using the past three months data, the idiosyncratic volatility of stock i is defined as the standard deviation of the daily residuals (ϵ_{it}); i.e., $IVOL_{it} = \sqrt{var(\epsilon_{it})}$.

2. *Maximum returns:*

Following Bali et al. (2011), the max-effect is the average of the five maximum daily returns over the previous three months, and denoted by MAX: $MAX_{i,t} = \text{Average}(\max(R_{i,d}))$, $d = 1-5, \dots, D_t$, where $R_{i,d}$ is the return on stock i on day d and D_t is the number of trading days in the past three months. This variable proxies for the upside potential of stocks.

3. *The Residual Jump:*

This variable is measured by summing the absolute value of return residuals extracted from the Carhart four-factor model. The residual is accumulated conditional on its idiosyncratic volatility. To isolate the Jump from regular return fluctuations, two standard deviations are used as a threshold: $\text{Jump} = \sum \text{abs}(\epsilon_{it}) > 2 * \sqrt{var(\epsilon_{it})}$. By construction, this variable detects extreme fluctuations, with longer tail stocks expected to be more attractive for lottery traders.

4. *The Price:*

Many previous studies employ a low price as a proxy for lottery-like stocks (see, for example, Han and Kumar, 2013). The logic is that investors exaggerate the upside potential of low-priced stocks (Birru, 2016). Hence, this is simply the end of month closing price.

5. *Lottery index (Lndx):*

We create a lottery index to represent the joint distribution of the four lottery-like proxies (IVOL, MAX, JUMP and Price). This index is constructed following the method in Han and Kumar (2013). First, stocks are ranked into vigintile according to each lottery-like proxy

separately. Second, the index is created as an average of the vigintile according to the different proxies divided by 20. By construction, the value of the index ranges from 0 to 1. To match the other lottery-like proxies, stocks are ranked according to the inverse price (1/price) where the lowest-priced stocks lie in the 20th rank and so forth.

Control Variables

To examine the existence and nature of the lottery effect for the UK, we control for the presence of other potential return predictors that are documented in the literature. Thus, we include:

1. Market Beta: while this is well-known, to mitigate the impact of nonsynchronous trading, we follow Lewellen and Nagel (2006) and Cederburg and O'Doherty (2016) by adding four lags of the market premium to the regression:

$$R_{i,d} = \alpha_i + \beta_{i,0} * R_{m,d} + \beta_{i,1} * R_{m,d-1} + \beta_{i,2} * \{(R_{m,d-2} + R_{m,d-3} + R_{m,d-4})/3\} + \epsilon_{i,d} \quad (2)$$

$$\beta_{i,t} = \beta_{i,0} + \beta_{i,1} + \beta_{i,2}$$

Where $R_{i,d}$ and R_m are the daily (d) risk premium for stock i and the market portfolio respectively, with $\beta_{i,t}$ the estimated beta.

2. Downside Beta (Dbeta): measured in a similar way to the market beta but the stock return is regressed only on negative market returns rather than the whole market.
3. Co-skewness: This variable measures the association between the stock and variation in the tail of the market portfolio. Following Harvey and Siddique (2000), to measure the co-skewness, the following quadratic form of the market model is fitted:

$$R_{i,d} = \alpha_i + \beta_{i,d} * R_{m,d} + C_{i,d} * R_{m,d}^2 + \epsilon_{i,d} \quad (3)$$

where $C_{i,d}$ represents the co-skewness measure. Positive co-skewness indicates that the stock has lower tail risk and is more likely to generate a positive return.

4. The minimum return (Min5): this variable measures the average five lowest return observations over the past three months. For ease of interpretation, the value is multiplied by -1, thus a higher value indicates a higher level of tail risk.
5. Size (MV): size is measured by a firms market value.
6. Price to 52-week high (PH52): this is the ratio of current price to the highest price over the past 52 weeks: $PH52 = \text{Current } P_i / \text{52-week high price}$. This ratio is employed as a proxy for the anchoring bias (see, George and Hwang, 2004; Hur and Singh, 2019).
7. Mid-term Momentum (Mom): following Jegadeesh and Titman (1993), mid-term momentum is defined as the cumulative return over the past 6 months after skipping a month, i.e., cumulative return over month $t-7$ to month $t-1$.

8. Short-term reversal (Rev): following Jegadeesh (1990), this variable is measured using the stock return at the end of the past month (1-month return).
9. Turnover: the monthly average of daily stock turnover (dollar stock volume divided by the number of shares outstanding).
10. Bid-Ask Spread (Spread): is the monthly average of the daily bid-ask spread. This ratio acts as a proxy for market friction and illiquidity.
11. Amihud (2002) Illiquidity measure (Amih): following Bali et al. (2011) and Amihud (2002), we measure the price impact of illiquidity as the monthly average of the daily absolute stock return to dollar trading volume ratio:

$$Amih_{i,t} = \sum \{ |R_{i,t}| / VOLD_{i,d} \} \quad (4)$$

Where $R_{i,t}$ is the return of stock i in month t , $VOLD_{i,d}$ is the daily trading volume in the dollar for the stock i , in dollars.
12. ROA: is the return on asset and measured by the ratio of earning to total assets.
13. BMV: is the ratio of the book value to the market value.

3.2. Methodology

To examine the presence of the lottery effect in UK stocks, we analyse the performance of lottery portfolios using one-way sorts. To understand the reasons for the lottery effect, we link performance of these lottery portfolios with explanatory variables in both a double-sort analysis and using the Fama and MacBeth cross-sectional regression.

One-way sorts:

Ten equal-sized portfolios are constructed by sorting our stocks into deciles, where stocks are ranked ascendingly according to the level of the lottery proxy. The portfolios are rebalanced monthly. This allows examination of the cross-sectional variation in future performance, as well as other characteristics, of these portfolios. The performance of the lottery-based portfolios is represented by next month's return. To investigate whether high lottery-like stocks over- or under-perform low lottery-like stocks, a zero-cost hedged strategy is created by buying the highest lottery-sorted portfolio and shorting the lowest lottery-sorted portfolio. In addition to the raw value, a Carhart (1997) four-factor model risk-adjusted alpha is obtained.

Double-sorting approach:

In the single-sort analysis, stocks are ranked according to a single characteristic (i.e., the lottery-like features) while ignoring other related features. To further analyse the performance

of lottery-based portfolios, we use a double-sort framework. Nine portfolios are created by sorting stocks into three groups based on any of the established characteristics noted above. Within each portfolio, stocks are then sorted into another three portfolios according to the lottery-like feature. As with one-way sorts, the portfolios are rebalanced monthly. As an example, each month, our stocks are ranked ascendingly by market capitalisation (or any other characteristic), creating three size groups. Then, within each size group, stocks are sorted into another three groups according to the lottery-like proxies. Thus, we can investigate the influence of other stock return factors on the performance of the lottery-like characteristics. If the lottery-like spread in performance varies across different factors, then this is an indication of an association between the two factors. As with the one-way sorts, performance is measured by the risk-adjusted alpha of the zero-cost hedged strategy for each factor.

Fama-MacBeth Regressions

In the double-sort approach, the portfolios control for two characteristics at a time. Therefore, this analysis cannot explicitly control for additional characteristics that may influence returns, while sorting on three or more characteristics is impractical. To control for other factors in a practical multivariate framework, we implement the widely used Fama and MacBeth (1973) two-step cross-sectional analysis. Under the first step, the following cross-sectional regression is estimated monthly:

$$R_{it} = \alpha_{it} + \beta_{\text{lott}} * \text{LOTT}_{it-1} + \sum \beta_x * X_{it-1} + \epsilon_{i,t} \quad (5)$$

Where R_{it} is the stock i risk premium, LOTT is any of the lottery-like proxies and X represents a set of control variables. After estimating this model, the averages of the estimated coefficients are tested against the null hypothesis of no effect using Newey and West (1987) t -statistics.

4. Identifying the Lottery Effect.

Summary Statistics

Table 1 presents summary statistics for the full sample. The average equal-weighted (EW) return is -0.37%, compared to 0.34% for the value-weighted (VW) index (i.e., the all-share index). This suggests that the negative EW performance is mainly generated by small stocks. Nonetheless, the negative return is not unexpected for a period that contains two big market crashes, i.e., the dot-com crash (from March 2000 to October 2002) and the 2008 global financial crisis (December 2007 to June 2009). The averages of IVOL and MAX are comparable to those reported by Walkshäusl (2014) for European markets, Byun and Kim

(2016) for the US and Zhong and Gray (2016) for Australia.

Table 2 reports the correlation coefficient between our variables. These figures reveal some noteworthy relations. All proxies of the lottery effect have the expected significant relation with next month's return. For example, the correlation coefficient between IVOL and the expected return is approximately -11%. This inverse relation serves as preliminary evidence for the lottery effect in the UK and is consistent with previous evidence (e.g., Ang et al., 2009; Bali et al., 2011). Other interesting relations are seen between different proxies of the lottery effect. This includes the high and significant positive relations between IVOL, MAX, Jump and the inverse price, consistent with existing evidence (e.g., Bali et al., 2011; Zhong and Gray, 2016). To illustrate, the correlation between IVOL and MAX is 92% and statistically significant. This high and significant relation indicates commonality among the lottery proxies.

We can also highlight the relation between the lottery proxies and other return predictors. The lottery-like stocks exhibit a statistically and economically significant positive relation with illiquidity measures with, for example, correlation coefficients between IVOL and the bid-ask spread and Amihud illiquidity measure of 62% and 11% respectively. There is also a significant association between the lottery-like stocks and left tail measures, namely the minimum return (Min5), the down beta (Dbeta) and co-skewness (Coskew). To illustrate, the correlation between the inverse price and Min5 is -41% and statistically significant. The negative correlation between PH52 (ratio of current price to highest price over the past 52 weeks) and the lottery-like proxies confirms that lottery-related stocks are more likely to be 'losers'. The correlation between MAX and the PH52 ratio is almost -49%. The results also display a noticeable relation between size and the lottery-like characteristics, for example, the correlation coefficient between the IVOL and the LogMV is -56% and statistically significant. These relations are consistent with previous evidence (see, e.g., Bali et al., 2011; Han and Kumar, 2013; Annaert et al., 2013).

In summary, stocks with lottery-like features are more likely to be small, illiquid and losers with a longer left tail. Thus, these bivariate relations tend towards the view that an explanation for the lottery effect is that it is difficult to arbitrage the mispricing. If investors face difficulties in shorting small and illiquid stocks, such stocks would take a longer time to reflect information regarding expected losses (see, Stambaugh et al., 2015; Atilgan et al., 2020). Thus, these stocks are prone to overvaluation and persistent losses due to slow price correction.

4.1. Portfolios Analysis: One-Way Sorts

We conduct one-way sort where each month stocks are ordered into ten portfolios based on

their lottery-like features. Table 3 presents the characteristics of the ten lottery-sorted portfolios, where the P1-P10 portfolios listed in the first row are constructed using the Lottery index (Lndx). The figures are based on equally weighted portfolios, where P10 contains the stocks with the highest lottery rank and P1 contains the stocks with the lowest rank i.e., the lottery-like proxies increase from P1 to P10. For example, the maximum return (MAX) decreases from 12.7% to 2% as we move from portfolio P10, with the highest level of lottery-likeness, to portfolio P1, with the lowest. The same pattern found for the idiosyncratic volatility (IVOL), idiosyncratic tails (Jump) and the Price (logP).³

Confirming the results in Table 2, Table 3 shows that stocks with lottery-like features are more likely to exhibit downside risk, be losers, illiquid and small in value. Empirical results in Bali et al. (2011), Han et al. (2015) and others show that stocks with lottery-like features are more likely to have lower returns over the medium horizon. Table 3 demonstrates similar patterns. For example, moving from P1 to P10, the minimum returns (Min5) increase from 2.19% to 10.97%. On average, lottery-like stocks generate losses over the past year and generate negative momentum (return over the past 6-month) and low PH52 ratio (ratio of current price to 52-week high price). In addition to market performance, these stocks are losers in terms of fundamental performance measure and generate a negative return on assets (ROA). Comparing portfolio P10 with P1, the differences in momentum (Mom) and ROA are approximately -16.17% and -0.6 respectively. Besides being losers and risky, previous studies find lottery-like stocks to be illiquid and small in value. Consistent with these studies, Table 3 shows that the bid-ask spread of portfolio P10 is substantially higher than for other portfolios, while market value is lower.

Table 4 presents next month's return across the ten lottery-sorted portfolios. We present the results sorting on the Lottery Index (Lndx), idiosyncratic volatility (IVOL) and maximum returns (MAX) and for both value-weighted and equal-weighted portfolios. Again, P10 represents stocks with the highest lottery proxies. In addition to returns, we present the returns difference, both raw and risk-adjusted.⁴ The results confirm an inverse relation between next month's return and the lottery-like features. Regardless of the lottery proxy, moving from the highest portfolio, P10, to the lowest portfolio, P1, the next month return increases. The difference in equal-weighted returns between the highest and lowest Lndx portfolio is -2.74% per month (t-statistic -4.33). When controlling for established risk factors, using the Carhart

³ A similar analysis is conducted, and available upon request, where the portfolios are constructed using the alternative lottery measures.

⁴ Risk adjusted using the Carhart 4-factor model, with Newey-West *t*-statistics.

four-factor model, the adjusted returns remain both negative and statistically significant. For example, the equal-weighted P10-P1 Lndx constructed portfolio has a four-factor model alpha of -3.09% per month (t-statistic -3.12).

These results provide evidence on the existence of the lottery-effect in the UK market. This is consistent with the results in, for example, Ang et al. (2006, 2009) and Bali et al. (2011). Moreover, our results show the anomaly in both equal and value weighted portfolios. Bali and Cakici (2008) show that weighting returns by market value rather than equal weighting, alters the idiosyncratic volatility effect from insignificant to significant. Here, although the returns difference is smaller for the value-weighted returns, it remains statistically significant.

Taking a closer look at the performance of the lottery-formed portfolios, the decrease in returns across the portfolios is not monotonic. Moving from the lowest lottery portfolio P1 through portfolios P2 to P4, the average returns are approximately the same. For the Lndx, the value-weighted returns for portfolios P1-P4 range from 0.56% to 0.62% per month. The difference in returns is more noticeable from portfolio P6 to the highest lottery portfolio P10. The average value-weighted returns of portfolios P6-10, formed by sorting on the past maximum return (MAX) range from 0.28% to -2.09% per month. To examine the effect of this non-monotonic trend, the difference in returns between the second highest (P9) and the second lowest (P2) lottery-like portfolios is reported. With the sole exception of the value-weighted difference in the MAX-sorted stocks, all cross-sectional spreads in the returns of P9-P2 are significant statistically and economically for both raw and risk-adjusted returns.

This latter set of results also highlights a further interesting point. Table 4 reveals that the average monthly return from the P10-P1 hedged portfolio ranges from 2.28% to 4.24% (ignoring the sign), which suggests a substantial annualised return. The average monthly return from the P9-P2 hedged portfolio is reduced by approximately half, ranging from 0.83% to 2.02% (again, ignoring the sign). Table 3 shows that firms in the P10 portfolio are almost three times smaller than those in portfolio P9 and have a bid-ask spread and an Amihud illiquidity ratio of almost double that of the next nearest value. This suggests that the stocks in P10 are both small and illiquid. Therefore, although a substantial P10-P1 hedged return could be made, it may be difficult to realise due to portfolio restrictions on holding small illiquid stocks and the potential inability to sell such stocks when desired, resulting in arbitrage difficulties.

Having established the lottery effect in Table 4, we can combine this with the patterns observed in Table 3 to consider the reason for such behaviour. One observation is that the next month's returns of lottery-like portfolios can be described as a continuation rather than a reversal. Table 4 shows a negative relation with next month return, while Table 3 does likewise

for current month returns. This continuation behaviour in the performance of lottery-related portfolios contradicts US based evidence, which documents reversals in the performance of lottery-like stocks (see, for example, Huang et al., 2009; Bali et al., 2011; Han and Kumar, 2013). This highlights a uniqueness in the UK. The persistence in the performance of the lottery-like portfolios leads to a behavioural explanation. Notably, under-reaction to information leads to continuation anomalies. For example, the mid-term momentum anomaly is related to delayed investor response to information (see, Antoniou et al, 2013; Chen and Zhao, 2012; Verardo, 2009; Doukas and McKnight, 2005). Atilgan et al. (2020) argue that investor under-reaction to bad news is the reason for the persistence of left-tail performance. Another ingredient required for continuation to exist is limits to arbitrage (see, Hong and Stein, 1999). As noted, lottery-like stocks are more illiquid, small and to have a longer left-tail, which means they are harder to arbitrage. Stambaugh et al. (2015) and Gu et al. (2018) suggest that the idiosyncratic volatility puzzle is a manifestation of constrained arbitrage. Together, Tables 3 and 4 provide evidence that lottery-like stocks in the UK are likely to underperform the market with evidence of limits to arbitrage leading to the mispricing.

5. Explaining the Lottery Effect.

5.1. Portfolio Analysis: Double-Sorts

To undertake a deeper look at the relation between the lottery effect and a selection of factors, we consider double-sorted portfolios. Nine portfolios are created by grouping stocks into three portfolios based on a given anomaly, with each portfolio then sorted into a further three groups according to the lottery-like proxy. Our interest is whether a particular factor renders the alpha of the zero-cost lottery strategy insignificant and thus explains the lottery effect.

Tail Behaviour and the Lottery Effect

Table 3 reveals an association between the lottery-proxies and tail measures (down beta, co-skewness and minimum returns). Therefore, we consider this formally, and sort stocks based on both tail risk and lottery features. Stocks are sorted into high, medium and low levels of tail risk and within each of these levels, a further three groups are created from the lottery proxies. Hedged portfolios are built by going long in the high-lottery portfolio and shorting the low-lottery portfolio with the risk-adjusted alphas reported in Table 5.

The results reveal a strong relation between the left tail and performance of the lottery-like stocks. Using the minimum returns (Min5) measure, the negative relation between the lottery proxies and subsequent performance is most prominent for stocks with the longest left

tail. Taking the lottery index as an example, for the highest Min5 portfolio, the risk-adjusted alpha is significant with a value-weighted (equal-weighted) coefficient of -2.23 (-1.53). Of interest, for the lowest Min5 portfolios the alphas are negative but not significant, at -0.15 (-0.08) for the value-weighted (equal-weighted) portfolio. For the IVOL and MAX portfolios, the risk-adjusted alpha remains significant for all low Min5 portfolios.

Both downside beta and co-skewness measure tail risk using the joint distribution based on the association between an asset and the market, conditioning on extreme observations. Thus, they represent a different aspect of information from the Min5. Table 5 shows different results for down-beta and co-skewness compared to Min5, with the risk-adjusted alpha broadly equal across the low- and high-risk portfolios for all lottery proxies. Using IVOL as an example, the equal-weighted risk-adjusted alpha for the low down-beta portfolio and the high down-beta portfolio are -2.45 and -2.55, respectively. Indeed, the mid-portfolio exhibits the lowest risk-adjusted alpha.

Liquidity and the Lottery Effect

The performance of the lottery-like stocks is examined after controlling for illiquidity, proxied by the Amihud (2002) ratio, the bid-ask spread and the number of zero-return days.⁵

The liquidity and lottery sorted portfolio alphas in Table 6 reveal an increasing effect at lower liquidity levels. Each liquidity proxy measures illiquidity; thus, a higher value relates to lower liquidity. We see that the alpha of the lottery hedged portfolios increases with the level of illiquidity. That is, the lottery-like puzzle is stronger with lower levels of liquidity. For the Amihud measure of liquidity and the Lottery index (Lndx), the value-weighted alpha for the highest and lowest level of illiquidity are -3.12 and -0.84 (t-statistics of -8.38 and -3.49) respectively. This pattern of performance highlights the effect of illiquidity on the underperformance of lottery stocks and the negative relation with the subsequent month return, i.e., illiquidity is associated with a negative return for lottery-like stocks.

The reported pattern in alpha across the different levels of liquidity is consistent with previous studies that note an inverse relation between illiquidity and expected returns (see for example, Lu and Hwang, 2007; Foran et al., 2015). Kelly (2014) states that stocks with low liquidity and high market frictions, e.g., high bid-ask spread and high price impact, are infrequently traded due to high trading cost and information uncertainty. Consequently, these stocks have low association with general market movements and high idiosyncratic volatility.

⁵ Of note, liquidity data is not available for all stocks in the sample, which may affect the results.

Furthermore, Han and Lesmond (2011), Han et al. (2015) and Reza et al. (2015) all demonstrate that the idiosyncratic volatility puzzle is linked to bid-ask bounce and other liquidity biases. Malagon et al. (2018) point out that the idiosyncratic volatility puzzle is time-varying and concentrated within recession periods and explained by a correction for liquidity shocks within high idiosyncratic volatility stocks. Further, Hou and Loh (2016) report an ability for market frictions to explain the idiosyncratic volatility puzzle.

The dependency between the idiosyncratic volatility puzzle and trading frictions could be linked to mispricing. Doukas et al. (2010), Stambaugh et al. (2015), Zhong and Gray (2016), Hung and Yang (2018), Gu et al. (2018) and Kumar et al. (2018) are all examples of studies that link both idiosyncratic volatility and the Max-effect to limits to arbitrage and the associated tendency to overvalue costly-to-trade assets. Cao and Han (2016), Zhong and Gray (2016) and Gu et al. (2018) all employ the bid-ask spread and other trading cost measures as a proxy for limits to arbitrage. Moreover, Millar (1977) and Stambaugh et al. (2015) suggest that high information uncertainty induces disagreement between investors and raises the cost of trading. Higher trading costs constrain a short-seller from arbitraging the most overvalued stocks; ultimately, these stocks experience negative returns in the following period. Au et al. (2009) study the UK market and report an inverse effect between the cost of shorting and returns among high idiosyncratic risk stocks. They also show that short-selling activities in the UK are less likely for stocks with high idiosyncratic risk due to arbitrage costs.

Past Returns and Speculative Behaviour

Jegadeesh (1990) and Jegadeesh and Titman (1993) document two of the most widely studied return anomalies, short-term reversal and mid-term momentum. Consistent with results from the US and other developed markets, those for the UK likewise report evidence in favour of these effects (e.g., Hon and Tonks, 2003; Antoniou et al., 2006). Further, several papers report a significant association between past and future returns of lottery-like stocks. Huang et al. (2009) demonstrate that a stock's return in the previous month can fully account for the underperformance of lottery-like stocks. Aboulamer and Kryzanowski (2016) argue that the short-term trend in a stock's return (reversal vs continuation) is important for the sign and magnitude of the IVOL and MAX effects. Arena et al. (2008) find a significant relation between momentum and idiosyncratic volatility. In addition to momentum, the ratio of current to highest 52-weeks price (PH52) is related to anchoring bias identified in the decision-making literature. The nearness of the current price to the past price high creates psychological barriers that lead to a more conservative reaction by investors. This, in turn, leads to under reaction to

current value-related news (Birru, 2015).

Thus, we consider the relation between these price trend factors and the lottery-like features. Table 7 reports the results of first sorting stocks into three groups according to the monthly cumulative return over the period from $t-2$ to $t-7$ (the mid-term momentum), PH52 or the past month return (the reversal effect) and second into three lottery-like portfolios. The results demonstrate a larger lottery effect in stocks with extreme past losses compared to stocks with extreme past gains. Taking the lottery index as example, for losers over the past 6-months (momentum), the value-weighted risk-adjusted alpha of the lottery hedge portfolio is -2.40 ($t=-3.82$) while for winners it is only -0.84 ($t=-2.54$). This is consistent with the results in Bali et al. (2011), Conrad et al. (2014) and Annaert et al. (2013), who show that stocks with a high probability of extreme payoffs are more likely to be losers over the mid-term horizon.

The results in Table 7 also reconfirm the short-term continuation trend in the returns of lottery-like stocks. If we consider the past month loser group with the winner group, the risk-adjusted alpha of the value-weighted MAX hedge portfolio moves from -2.43 ($t=-3.77$) to -0.65 ($t=-2.04$). This short-term continuation in the performance of the lottery-like portfolios is contrary to the reversal pattern documented in US studies. It thus, seems reasonable to exclude a reversal explanation (Huang et al., 2009) in favour of the under-reaction story.

Previous studies relate return reversals to the level of microstructure noise. Hou and Loh (2016) argue that the level of lagged returns can be used as a proxy for market frictions. They show the ability of lagged returns to attenuate the magnitude of the negative idiosyncratic volatility-return relation. Accordingly, the reported dependency between lottery-like anomalies and short-term performance can be explained by the inability of investors to arbitrage the deficiencies in the value of these stocks due to noise and trading costs. Related, Hong et al. (2000) show that due to frictions, bad news diffuses gradually to the market and this slow diffusion causes the continuation pattern in returns.⁶

The effect of the PH52 anomaly on the behaviour of lottery stocks is notable. The results in Table 7 demonstrate a substantial effect of the nearness from the highest price over the past 52 weeks. Evidently, the lottery effect is concentrated in those stocks with a price far from its highest 52-week value. For example, the equal-weighted alpha of the lottery hedge portfolio for the high PH52 group is only -0.24 and insignificant ($t=-1.39$). Again, this result supports the mispricing story for the lottery effect. George and Huang (2004) document

⁶ There is a further body of work that argues managers will seek to delay the disclosure of bad news to the market in order to stop or slow the impact on the stock price (Dye, 1985; Kothari et al., 2009; Kim et al., 2011).

anomalous returns continuation behaviour when the stock price is near or far from its past 52-week high and argue in favour of a behavioural explanation for this continuation. Specifically, they argue that investors are cognitively biased and anchored by past extreme price observations. Consequently, if they use the past high and low prices as a reference point, they are more likely to inefficiently adjust the price for relevant news, which leads to short-term under-reaction. When information is received by the market, the correction process starts, and a continuation trend appears. Recently, empirical work confirms the existence of PH52 (52-week high) momentum, for example, Liu et al. (2011), George et al. (2018), Li and Yu (2012) and Hur and Singh (2019). As lottery-like stocks are more concentrated on the short side of the PH52 momentum, it is intuitive to observe a persistent loss for these stocks if investors slowly adjust to value-relevant information. That these stocks are difficult to short (small and illiquid) also contributes to this explanation.

Effect of Firm Value and Book to Market Value

It is widely reported that market value can inversely predict subsequent returns. This size anomaly is first documented by Banz (1981). Levis (1989) and Andrikopoulos et al. (2008), among others, provide empirical evidence for the size effect in the UK. Fama and French (2008) show that many of the pricing anomalies documented in the market are associated with the size effect. Therefore, firms with smaller market capitalisation are more susceptible to misvaluation. Further, many empirical studies employ market value as a proxy for information uncertainty and arbitrage frictions (see, for example, Zhang, 2006). Another pervasive market anomaly is the value effect, whereby stocks with a higher market to book value ratio (growth stocks) tend to underperform stocks with a lower value of this ratio (value stocks) (see, Rosenberg et al., 1985). A similar result for the UK market is documented in several empirical studies (see, Miles and Timmermann, 1996; Clubb and Naffi, 2007). It is found that the persistent underperformance of low book to market stocks is a manifestation of the difficult to arbitrage mispricing (see, Ali et al., 2003; Doukas et al., 2010). Conard et al. (2014) relate this mispricing to the speculative component created by lottery-like demand.

Table 8 presents the lottery effect taking account of the size and value anomalies. The results show a higher risk-adjusted alpha for the lottery hedge portfolio in groups of stocks with small market value and low book to market ratio. For example, within small stocks, the value-weighted risk-adjusted alpha of the lottery hedge portfolio is -2.67 (t -statistic = -8.05), while for large stocks the equivalent alpha is only -0.96 (t -statistic = -4.14). The results show a similar pattern for low book to market stocks, with the effect more noticeable for the value-weighted

portfolios using the IVOL and MAX strategies. The value-weighted risk-adjusted alpha of the hedge portfolio for both strategies is not significant for high book to market stocks. These patterns for the UK market are consistent with previous empirical evidence for other markets (see, e.g., Han and Kumar, 2013; Annaert et al., 2013; Kang et al., 2014).

As noted, a small market value is widely employed as a proxy for higher information uncertainty and limits to arbitrage, with small firms prone to mis-valuation. Likewise, low book to market stocks are found to be more associated with mispricing. Therefore, it seems understandable that these stocks are more associated with the lottery effect. Another related explanation is the distress risk anomaly. Contrary to intuition, Campbell et al. (2008) show that firms with higher distress risk gain lower expected returns than stocks with lower distress risk. Firms with a very low size or low book-to-market ratio are more likely to default in the near future (see, Campbell et al., 2008; Gao et al., 2018). Furthermore, examining the size effect in the UK market, Andrikopoulos et al., (2008) show that small stocks are more likely to become bankrupt and de-list from the stock exchange. In addition, Campbell et al. (2008) document an anomalous negative premium for stocks with high distress risk. Conrad et al. (2014) confirm the default risk anomaly and link it to gambling-like behaviour by investors. They demonstrate that investors consider highly distressed stocks with a low book-to-market ratio as a speculative investment and find that the negative premium is concentrated within the group of speculative distress risk with high market-to-book ratio. Gao et al. (2018) investigate the default risk anomaly within a global sample of 38 countries, the results for the UK indicate a significant negative premium for the stocks with high distress risk. In addition, they find a link between the puzzling default risk anomaly and the overconfidence level and argue that financially distressed firms are temporarily overpriced.

5.2. Fama-Macbeth Cross-Section Regression Results

The previous sections present evidence of the lottery-effect in UK stocks i.e., the negative relation between lottery-like features and subsequent month's performance. The double-sort portfolios also reveal a clear association with previously documented predictors, including liquidity, left-tail risk (minimum past returns) and the 52-week high momentum. However, double-sorting only allow for a bivariate relation to be examined. Here, we utilise the Fama and MacBeth (1973) approach to investigate lottery-like behaviour in a multivariate setting. This approach is well-known and involves a two-step regression to estimate the return sensitivity of candidate pricing variables. In the first step, a cross-sectional regression of the return on the explanatory variables is performed on a monthly basis. In the second step, the

coefficients from the first step are averaged and tested against the null hypothesis.

Table 9 presents results for different variable sets and provides several interesting observations. First, they reconfirm negative predictability for returns of the different lottery-like proxies. For each of Models 1-3, we observe a significant and negative coefficient on the lottery-like variable. Second, controlling for 52-week high momentum affects the magnitude of the predictive coefficient of the lottery proxies. For instance, the coefficient of the Lndx (MAX) falls from -3.6 (-0.32) to -1.2 (-0.17). Nonetheless, they all retain statistical significance. Third, the results affirm the ability of the left-tail proxy (Min5) to explain the negative relation between the lottery-like proxies and future performance. Notably, Models 10-12 show that after controlling for the Min5 effect, the coefficients on the lottery-like proxies become statistically and economically insignificant.⁷ This highlights the close link between the lottery effect and left-tail momentum, where investors underreact to left tail information (see, Atilgan et al., 2020). Moreover, this result is contrary to that in Bali et al. (2011), who report the inability of left-tail performance to explain the lottery effect. Fourth, other controlling variables such as liquidity proxies and accounting fundamentals (e.g., ROA) only partly explain the lottery-like anomaly (reduced coefficient size), which remains statistically significant.

5.3. Explaining the UK Lottery Effect

We can put the above evidence together with previous work in order to understand the underperformance of lottery-like stocks in the UK. The above results support the existence of the lottery effect in the UK stock market, as seen by the significantly negative coefficient for Lndx, IVOL and MAX in the multivariate regressions. The only exception is with the inclusion of the left-tail proxy Min5 variable that can fully explain the negative relation between future performance and the lottery-like features.

Explaining the ability of the left-tail proxy to account for the UK lottery-like effect, we can consider two recent approaches. Atilgan et al. (2020) argue that investors underreact to recent bad news as proxied by past negative returns. Therefore, they overprice stocks with high left-tail risk, which leads to poor performance in subsequent months. Similarly, poor performance associated with lottery-like features could be a result of investor underreaction to the long left-tail associated with these attributes. In addition, some authors find that ‘hazard’ stocks, stocks with minimum daily returns, exhibit a lottery-like feature (see, Delisle et al. 2021). Accordingly, the left-tail observation can simply be another proxy for the lottery-like

⁷ This equally applies to other models that include Min5 (Models 13-15 and 23-24, except for Model 22)

features of stocks. Therefore, hoping for large returns, investors, especially small individual investors, irrationally overestimate the likelihood of a right tail observation. Hence, the extreme low returns could be considered as another proxy of the lottery-like effect.

Previous work identifies an asymmetry in the response of investors to bad news (see, Easterwood and Nutt, 1999; Hong et al., 2000; Chan et al., 2003). Kothari et al. (2009) argue that firms may delay bad news, which causes an initial underreaction and asymmetric response to information. Tuan et al. (2018) argue that information uncertainty presents a suitable environment for companies to withhold bad news, which in turn leads to higher analyst forecasting errors. Clubb and Wu (2014) analyse UK companies' earnings data and demonstrate that the ability to predict earnings is negatively related to earnings variability. In addition, Artikis and Papanastasopoulos (2019) argue that investors in the UK market are more susceptible to mispricing cash flow components for loss-making firms than profitable ones. Kumsta and Vivian (2019) highlight the underperformance of UK stocks with bad news, arguing that illiquidity of these stocks is the main driver of the mispricing.

Combining this evidence with a limited arbitrage proposition and erroneous expectations triggered by anchoring bias, a sensible explanation is built for the observed underperformance of UK lottery-like stocks. Lottery-like stocks are more likely to represent stocks with bad news (e.g., losers in both market and accounting terms), that trade near to the past 52-week high price and where investors underestimate the left-tail of these stocks. Recalling, that these stocks are small and illiquid, this may deter the short sellers from arbitraging any mispricing.

6. Robustness tests.

In this section we test the stability of the above results against alternatives to the sampling procedures. Han and Lesmond (2011) show that the idiosyncratic volatility puzzle is a manifestation of liquidity bias. Bali and Cakici (2008) demonstrate that the pricing of idiosyncratic risk in the US market is not robust to different samples and weighting schemes. In addition, many market anomalies are found to be attenuated in recent years (Chordia et al., 2014), while others suggest the effect of market state on the lottery effect (Cooper et al., 2004).

Skiping One Month

To investigate whether microstructure issues affect the lottery effect, Table 10 presents the raw returns and associated Carhart four-factor alpha of the lottery-sorted portfolios, after skipping one month and examine predictability of the lottery-like features for the two-month-ahead return. This is thus a robustness check on Table 4. The results here reconfirm the

underperformance of lottery-like stocks. After skipping one month, the raw return of the highest lottery-based portfolio is lower than for those of lowest portfolio, while the hedged portfolio risk-adjusted alpha is significantly negative. For example, using the lottery index, the value-weighted alpha of the lottery-hedge portfolio is -2.9 and significant at the 1% level. This result rules out the potential effect of the microstructure biases on the lottery effect finding.

Table 11 presents the Fama-MacBeth cross-sectional regression results for the two-month-ahead return. Consistent with the previous analysis, these results show a negative and economically and statistically significant coefficient for all lottery proxies (Models 1-3), which become insignificant with the inclusion of the left-tail proxy variables (Models 4-6).

Effect of Different Subsamples

We also consider the robustness of the lottery effect across different samples. First, we consider the effect of low price, small size, and illiquid stocks exclusion on the lottery strategy. The results in Tables 6 and 8 show that the lottery-like stocks exhibit a negative and significant effect even in the most liquid and large firms. Examining this further, Table 12 presents the Fama-MacBeth cross-sectional regression after filtering for stocks with a price less than £10, stocks with a market value lower than the median of the sample, and stocks with Amihud illiquidity ratio higher than the sample median. In Table 12, Models 1, 3, 5, present the regression results that only include the lottery proxy, while Models 2, 4, 6, present the results including all the control variables.

Although weaker in comparison to the full sample results, the lottery effect persists with this filtering, with the coefficients on the lottery effect negative and significant. For example, Model 1 shows that, after filtering low-priced stocks, the coefficient on the lottery index remains significant with a value -3.4, -2.1 and -1.8 across the price, liquidity and size filters. These results apply to the other lottery proxies. Again, the lottery effect weakens when all control variables are included (as before, this relates to the left-tail proxies).

Kumar (2009) shows that the demand for lottery-like stocks is higher in a bear market, where such stocks are more prone to mis-valuation. Walkshausl (2014) demonstrates that the negative return of a lottery-based strategy is higher in crisis periods. Therefore, we consider the performance of the lottery-sorted portfolios over three different sub-periods. The first sub-period spans from 1991 to 2000, the second sub-period from 2001 to 2007 and the third sub-period is from 2008 to 2017. Thus, we can consider the dot-com crash and financial crisis in different sub-samples.

Table 13 provides results comparable to those in Table 4 and shows that the lottery effect

is more prominent in crisis periods. The difference between returns of the highest and lowest decile portfolio is noticeably lower during a period dominated by a bubble rather than a crisis. Although they remain negative, the differential returns and Cahart alpha of the lottery strategy are lower in the period 1991-2000, when financial markets are generally rising (including the dot-com bubble rise) compared to the periods after. Notwithstanding this, the lottery-like stocks do generate a lower return than the non-lottery stocks and the four-factor alpha is significantly negative in most cases. The stronger lottery effect during a crash period is consistent with the evidence in Kumar (2009) and Walkshausl (2014).

7. The Effect of Sentiment and Liquidity

The above evidence reveals a robust lottery effect in the UK, which is explained by left-tail behaviour. Evidence also indicates that the pricing of lottery-like stocks is related to anchoring bias and erroneous expectations by investors. The behavioural literature relates this erroneous valuation to overconfidence (Daniel and Hirshleifer, 2015). Furthermore, work links overconfidence and cognitive biases to excessive trading. Statman et al. (2006), Lou and Shu (2017) and Han et al. (2019) all argue that mispricing is more probable in times of high trading volume and a liquid market. Baker and Stein (2004) develop a model with liquidity as a proxy for sentiment. We thus, consider the effect of excessive trading and investor sentiment on the lottery effect. We use market turnover to represent excessive trading and the Economic Sentiment Indicator (ESI) as a proxy for investor sentiment. Combining both indices as a proxy for the mispricing environment, three activity states are defined, the OPTIMISTIC state in which liquidity and sentiment are above the median value, MILD in which the only one of the two variables are above the median, and the PESSIMISTIC state where both variables are below the median.

Table 14 presents the performance of the lottery portfolios constructed across the three activity levels. Results support an inverse relation between the sentiment measures and lottery performance. Regardless of the lottery proxy employed, the difference in (value-weighted) returns and risk-adjusted alpha is always lower for the pessimistic state. For example, comparing the optimistic and pessimistic states, the difference in returns between the high and low Lndx deciles is -5.2 and -1.1 respectively, with the former statistically significant and the latter not. This suggests that investors in the UK are likely to overvalue lottery-like stocks when trading is driven by optimism. This result is also consistent with the active investing puzzle, which states that investors lose money after excessive trading (Odean, 1999; Daniel and Hirshleifer, 2015).

Table 15 presents the results of the Fama-MacBeth regressions for the lottery-like stocks across different sentiment regimes. Comparing the low sentiment regime to the high sentiment regime, the coefficients of lottery-like proxies are less in magnitude and insignificant in the former. For example, the IVOL coefficient is -1.18 and significant in the high sentiment regime and -0.3 and insignificant in the low regime. A further finding is that the IVOL and MAX variables retain their significant predictive power in the sentiment period with the inclusion of the control (and left-tail) variables. The whole sample results in Table 9 reveal that the lottery-like proxies lost their significance upon the including of the left-tail effect. However, the results here indicate that in the high sentimental regime, both IVOL and MAX are still significant.

8. Summary and Conclusion.

An increasing number of studies report evidence for the tendency of investors to exhibit a preference for lottery-like stocks that have a high potential for extreme returns (see, e.g., Kumar, 2009; Bali et al., 2017). Moreover, evidence from the US, Europe and other markets show a puzzling low performance for a portfolio of stocks with lottery features, such as high idiosyncratic volatility. However, there is an unresolved debate on the drivers of the lottery effect. This study contributes to the debate by investigating the existence of the lottery-like effect in the UK market and, more importantly, its causes.

Our empirical findings support the view that lottery-like stocks underperform other stocks in the UK market. This underperformance appears across all sample periods, although is stronger in crisis periods, and persists after controlling for other returns predictors, including size, momentum and systematic downside risk. This is consistent with the evidence for a range of international markets. However, the key factor behind the poor performance of lottery stocks in the UK differs from that found by studies in the US and other markets. Specifically, the lottery effect in the UK is subsumed by the inclusion of a left-tail measure. This suggests underreaction to news and continuation behaviour in the poor performance of lottery-like stocks. This contrasts with US based evidence that supports reversion behaviour, where poor performance follows previous good performance. In addition, we demonstrate that the poor performance of the lottery stocks is partially explained by the anchoring effect and limited arbitrage proxies.

In sum, the lottery effect exists in the UK market and is a manifestation of investor underreaction to left-tail duration, which is fuelled by limits to arbitrage and investor sentiment trading. These results should be important to both participants in the UK market, whether they

be investors or regulators, and to those engaged in modelling market behaviour. Notably, while the UK is one of the top five largest global markets its behaviour is different to that of the largest (US) and thus, there is a need to understand behaviour across markets and not assume common behaviour throughout.

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Table 1

This table reports the general statistical characteristics of the pooled sample. All stocks are sampled together. EWRet: is the equally-weighted return of all stocks over the whole sampling period, VWRet is the value-weighted return of all stocks over the whole sampling period, IVOL: is the idiosyncratic volatility over the Past 3 months, Max5: is the average of 5 highest daily returns over the past 3 month, Jump: is the sum of the absolute returns over the 2 standard deviation, Price: is the stocks market price at the end of the month, Min5: is the average of 5 lowest daily returns over the past 3 month, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns, Beta: is the market beta measured by using CAPM as a pricing model, ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily spreads between the bid price and the ask price, Turnover: is the monthly average of the daily traded shares to the number of shares outstanding, MV: is the market value of the firm at the end of the month, BMV : is the book to market value ratio, PH52: is the ratio of current price to the 52-week high price. Mom is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return. ROA: if the Return on the asset, ROE: if the Return on Equity, CAPEX: is the ratio of capital expenditure to the total asset. The sample covers January 1991 to December 2017.

Variable	Obs	Mean	Std.Dev		Variable	Obs	Mean	Std.Dev
EWRet	199132	-0.37	13.65		ZDays	199134	0.16	0.14
VWRet	199132	0.34	4.11		Spread	197742	0.02	0.03
IVOL	199132	2.44	1.82		Turnover	182440	8.19	11.25
Max5	199132	5.49	4.02		Amih	192453	1.68	16.97
Jump	199132	22.93	19.35		PH52	199134	0.77	0.22
Price	199132	500.00	1780.64		MOM6	195372	4.21	40.61
Lindx	199132	0.52	0.25		Rev	199134	-0.02	14.16
Beta	199132	0.89	1.15		ROA	193272	-0.01	0.27
MV	199132	1906.53	5618.08		ROE	193395	0.02	0.78
Min5	199132	4.93	3.69		CAPEX	191812	0.05	0.06
Dbeta	199132	0.77	1.15		BMV	188965	0.66	0.76
Coskew	199132	-0.03	0.46					

Table 2: Correlation analysis

This table represents the correlation between the study variables. The correlation coefficients are estimated across the stocks and for the whole sampling period. Ret_{t+1} is the return of stocks over the whole sampling period, IVOL: is the idiosyncratic volatility over the Past 3 months, Max5: is the average of 5 highest daily returns over the past 3 month, Jump: is the sum of the absolute returns over the 2 standard deviation, $1/\log P$: is the reciprocal of the logarithm of the stock price at the end of the month, Min5: is the average of 5 lowest daily returns over the past 3 month, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns, Beta: is the market beta measured by using CAPM as a pricing model, ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily spreads between the bid price and the ask price, Turnover: is the monthly average of the daily traded shares to the number of shares outstanding, MV: is the market value of the firm at the end of the month, BMV: is the book to market value ratio, PH52: is the ratio of current price to the 52-week high price. Mom is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return, ROA: is the Return on the asset. The sample covers January 1991 to December 2017. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

	Ret	IVOL	MAX5	Jump	1/logp	Min5	LogMV	Dbeta	Coskew	Beta	Zdays	Spread	Amih	Rev	Mom	Ph52	ROA	BM
Ret _{t+1}	1																	
MAX5	-0.11*	1																
max5	-0.09*	0.92*	1															
jump	-0.1*	0.92*	0.87*	1														
1/logp	0.03*	0.46*	0.41*	0.45*	1													
Min5	-0.12*	0.91*	0.74*	0.84*	0.41*	1												
LogMV	0.07*	-0.56*	-0.51*	-0.58*	-0.60*	-0.48*	1											
Dbeta	-0.01*	0.063*	0.09*	0.04*	-0.05*	0.12*	0.1*	1										
Coskew	0.00	-0.04*	-0.04*	-0.05*	-0.03*	-0.03*	0.05*	-0.51*	1									
Beta	-0.02*	0.14*	0.18*	0.12*	-0.01*	0.19*	0.03*	0.35*	-0.05*	1								
Zdays	-0.02*	0.18*	0.18*	0.27*	0.35*	0.111*	-0.62*	-0.13*	-0.03*	1	1							
Spread	-0.07*	0.62*	0.58*	0.63*	0.51*	0.57*	-0.70*	-0.04*	-0.03*	0.02*	0.4958*	1						
Amih	-0.01*	0.11*	0.09*	0.114*	0.09*	0.12*	-0.12*	-0.03*	0.00	-0.02*	0.0426*	0.17*	1					
Rev	0.08*	-0.10*	0.06*	-0.09*	-0.11*	-0.26*	0.11*	-0.01*	-0.01*	-0.04*	-0.004	-0.11*	-0.04*	1				
Mom	0.08*	-0.13*	0.11*	-0.12*	-0.14*	-0.42*	0.12*	-0.02*	-0.02*	-0.04*	0.0048*	-0.17*	-0.06*	0.56*	1			
Ph52	0.12*	-0.60*	-0.49*	-0.58*	-0.40*	-0.73*	0.44*	-0.06*	0.00	-0.15*	-0.1430*	-0.48*	-0.11*	0.40*	0.57*	1		
ROA	0.06*	-0.39*	-0.39*	-0.37*	-0.31*	-0.32*	0.35*	-0.02*	0.03*	-0.05*	-0.1641*	-0.39*	-0.04*	0.04*	0.02*	0.25*	1	
BMV	0.02*	0.28*	0.22*	0.27*	0.30*	0.32*	-0.26*	-0.02*	0.00	0.02*	0.0627*	0.24*	0.11*	-0.14*	-0.21*	-0.34*	-0.05*	1

Table 3. Single-Sorts: Characteristics

This table shows the characteristics of the 10 lottery-index portfolios. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the Past 3 months, Max5: is the average of 5 highest daily returns over the past 3 month, Jump: is the sum of the absolute returns over the 2 standard deviation, logP: is the logarithm of the stock price at the end of the month, Min5: is the average of 5 lowest daily returns over the past 3 month multiplied by -1, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns, Beta: is the market beta measured by using CAPM as a pricing model, ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily spreads between the bid price and the ask price, Turnover: is the monthly average of the daily traded shares to the number of shares outstanding, MV: is the market value of the firm at the end of the month, BMV: is the book to market value ratio, PH52: is the ratio of current price to the 52-week high price. Mom is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return, ROA: is the Return on the asset. The sample covers January 1991 to December 2017.

	p10	p9	p8	p7	p6	p5	p4	p3	p2	p1	P10-p1
Lndx	0.94	0.83	0.73	0.64	0.56	0.48	0.40	0.33	0.25	0.15	0.79
IVOL	5.81	3.70	3.05	2.37	2.03	1.77	1.56	1.38	1.19	0.95	4.87
MAX5	12.70	8.21	6.79	5.36	4.61	4.09	3.62	3.23	2.81	2.29	10.41
Jump	59.43	36.38	29.51	22.48	18.73	15.99	13.74	11.73	9.72	7.36	52.07
LogP	3.93	5.91	7.96	7.93	7.71	7.34	7.37	6.59	6.75	7.65	-3.73
Min5	10.97	7.13	6.02	4.83	4.19	3.74	3.38	3.04	2.68	2.19	8.78
DBeta	0.99	0.87	0.84	0.82	0.77	0.76	0.73	0.72	0.70	0.64	0.34
CoSkew	-0.10	-0.05	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.09
Beta	1.17	1.09	1.05	0.97	0.90	0.87	0.81	0.79	0.73	0.66	0.51
MV	92	265	451	754	1110	1517	2038	2737	3859	7559	-7467
Zdays	0.27	0.24	0.21	0.18	0.16	0.15	0.14	0.13	0.12	0.12	0.15
Spread	0.07	0.04	0.03	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.06
Turnover	27.10	18.32	15.31	11.36	10.56	8.24	7.99	7.45	7.23	6.56	20.54
Amih	25.02	7.40	12.69	4.35	5.20	1.71	1.95	2.72	0.73	0.43	24.60
Rev	-1.77	-0.36	-0.19	0.32	0.54	0.69	0.60	0.50	0.51	0.55	-2.33
Mom	-7.68	1.42	3.40	5.53	6.72	6.64	6.72	7.27	7.52	8.49	-16.17
PH52	0.54	0.66	0.70	0.76	0.80	0.82	0.85	0.86	0.88	0.90	-0.36
ROA	-0.54	-0.21	-0.05	-0.03	0.03	0.04	0.03	0.06	0.06	0.06	-0.60
Capex	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.01
BM	1.81	0.94	0.86	0.67	0.62	0.61	0.59	0.56	0.55	0.56	1.25

Table 4. One-Way Sorts: Returns

This table shows the next month's return of the lottery-based portfolios. Each month the stocks are grouped into deciles according to any of the lottery proxies, then each portfolio is held for the subsequent month. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the past 3 months, Max5: is the average of 5 highest daily returns over the past 3 months. P10 is the portfolio of the highest lottery proxy, P9 is the portfolio of second highest lottery proxy, and so on. t-Statistic is the newey and west t-statistic with lag selected automatically. The sample covers January 1991 to December 2017. Alpha is the Carhart four-factor model alpha.

Proxy	Lndx			Ivol			MAX5	
Ret	Ew	Vw		Ew	Vw		Ew	Vw
P10	-2.16	-1.74		-3.45	-2.86		-2.82	-2.09
P9	-1.10	-0.83		-1.28	-0.87		-1.08	-0.48
P8	-0.90	-0.82		-0.75	-0.70		-0.39	0.06
P7	-0.39	-0.14		-0.17	0.04		-0.45	-0.12
P6	0.09	0.44		0.25	0.15		0.19	0.28
P5	0.28	0.27		0.53	0.46		0.37	0.58
P4	0.62	0.58		0.63	0.49		0.49	0.48
P3	0.53	0.52		0.67	0.52		0.50	0.36
P2	0.44	0.38		0.74	0.54		0.55	0.35
P1	0.56	0.54		0.79	0.62		0.59	0.76
P10-P1	-2.72	-2.28		-4.24	-3.49		-3.41	-2.85
t-test	-4.33	-3.12		-5.74	-4.51		-4.58	-3.14
Carh(α)	-3.09	-2.88		-4.66	-3.92		-3.87	-3.36
t	-5.97	-4.28		-9.58	-5.81		-8.26	-5.88
P9-P2	-1.54	-1.21		-2.02	-1.41		-1.63	-0.83
t	-3.58	-1.91		-4.03	-2.17		-3.02	-1.31
Carh(α)	-1.90	-1.46		-2.35	-1.74		-2.02	-1.24
t	-5.24	-2.80		-6.13	-2.84		-5.07	-2.29

Table 5. Double-Sorting: Left-Tail Risk

This table reports a performance analysis of the double-sorted portfolios formed by sorting stocks according to one of the left-tail proxies and one of the lottery proxies. All portfolios are generated through the sorting stocks in the sample into 3 groups by any of the left-tail proxies (i.e., Min5, Dbeta, and Coskew). Then resorting the stocks within each group into 3 portfolios by any of the lottery-related features (Lndx, IVOL, and MAX5), IVOL: is the idiosyncratic volatility, Max: is the maximum daily return over the month. Min5: is the average of 5 lowest daily returns over the past 3 months multiplied by -1, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns. The sample covers January 2000 to December 2017. α : is the Carhart's alpha for the zero-cost strategy that short high lottery stocks and buy long the lowest lottery stocks within each controlling variable. t is the newey t-statistic with lags selected automatically.

		Lndx			lvol			MAX5		
		H	M	L	H	M	L	H	M	L
		Min5								
EW	α	-1.53	-0.42	-0.08	-2.83	-0.78	-0.32	-2.07	-0.63	-0.25
	t	-4.11	-2.88	-0.61	-8.67	-3.90	-2.26	-5.62	-3.49	-1.67
VW	α	-2.23	-0.63	-0.15	-2.68	-0.83	-0.40	-2.50	-0.63	-0.58
	t	-5.37	-2.68	-0.78	-5.46	-3.89	-1.93	-4.32	-2.88	-2.97
		Dbeta								
EW	α	-2.55	-1.70	-2.45	-3.02	-1.97	-2.96	-2.64	-1.69	-2.25
	t	-6.71	-7.34	-7.24	-7.40	-7.47	-8.72	-6.54	-6.99	-6.71
VW	α	-1.75	-1.59	-1.90	-1.97	-1.60	-2.41	-1.54	-1.56	-2.21
	t	-2.82	-5.63	-4.63	-3.32	-6.36	-6.48	-3.03	-4.81	-5.93
		Coskew								
EW	α	-2.53	-1.57	-2.68	-3.01	-1.93	-3.21	-2.18	-1.62	-2.70
	t	-6.68	-7.80	-7.27	-7.77	-8.19	-8.10	-6.00	-6.65	-6.77
VW	α	-1.93	-0.86	-1.65	-2.23	-1.21	-2.28	-1.61	-0.74	-1.34
	t	-3.80	-4.17	-2.82	-4.12	-3.96	-3.88	-3.37	-2.30	-2.45

Table 6. Double-Sorting: Liquidity

This table reports a performance analysis of the double-sorted portfolios formed by sorting stocks according to one of the liquidity proxies and one of the lottery proxies. All portfolios are generated through sorting the stocks in the sample into 3 groups by any of the liquidity proxies (i.e., Spread, Amih, and Zdays). Then resorting the stocks within each group into 3 portfolios by any of the lottery-related features (Lndx, IVOL, and MAX5), IVOL: is the idiosyncratic volatility, Max: is the maximum daily return over the month. ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily spreads between the bid price and the ask price. The sample covers January 1991 to December 2017. α : is the Carhart's alpha for the zero-cost strategy that short high lottery stocks and buy long the lowest lottery stocks within each controlling variable. t is the Newey-West t-statistic with lags selected automatically.

		Lndx			Ivol			MAX5		
		H	M	L	H	M	L	H	M	L
		Spread								
EW	α	-2.42	-1.41	-0.78	-3.84	-1.87	-1.03	-2.97	-1.38	-0.80
	t	-6.24	-4.95	-4.06	-11.52	-7.95	-4.75	-8.63	-4.91	-3.99
VW	α	-2.38	-1.57	-0.80	-3.93	-1.84	-1.03	-3.23	-1.53	-0.78
	t	-6.23	-5.32	-3.40	-8.76	-6.62	-4.21	-7.89	-5.37	-2.91
		Amihud								
EW	α	-3.03	-1.87	-0.98	-3.85	-2.40	-1.33	-3.25	-1.86	-1.07
	t	-8.07	-6.19	-4.32	-10.20	-7.77	-5.11	-8.15	-5.64	-4.22
VW	α	-3.12	-1.79	-0.84	-3.94	-2.28	-1.14	-3.38	-1.78	-0.88
	t	-8.38	-5.13	-3.49	-8.82	-7.64	-5.12	-7.49	-5.68	-2.84
		ZDays								
EW	α	-3.23	-1.18	-1.34	-3.37	-2.76	-1.83	-2.76	-2.27	-1.73
	t	-9.72	-5.94	-5.08	-8.99	-7.40	-5.33	-7.27	-6.70	-5.14
VW	α	-2.76	-0.94	-0.76	-2.69	-2.29	-1.34	-2.13	-1.91	-1.10
	t	-4.28	-4.11	-3.51	-6.43	-5.39	-5.01	-5.02	-5.00	-2.85

Table 7. Double-Sorting: Past Returns

This table reports a performance analysis of the double-sorted portfolios formed by sorting stocks according to one of the past performance proxies and one of the lottery proxies. All portfolios are generated through sorting the stocks in the sample into 3 groups by any of the past performance proxies (i.e., the Momentum, the PH52, and the past month return). Then resorting the stocks within each group into 3 portfolios by any of the lottery-related features (Lndx, IVOL, and MAX5), IVOL: is the idiosyncratic volatility, Max: is the maximum daily return over the month. PH52: is the ratio of current price to the 52-week high price. Mom is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return. The sample covers January 1991 to December 2017. α : is the Carhart's alpha for the zero-cost strategy that short high lottery stocks and buy long the lowest lottery stocks within each controlling variable. t is the newey t-statistic with lags selected automatically

		Lndx			Ivol			MAX5		
		H	M	L	H	M	L	H	M	L
		Mom								
EW	α	-1.10	-1.19	-3.16	-1.53	-1.54	-3.71	-1.30	-1.19	-3.42
	t	-3.88	-5.32	-9.72	-5.91	-6.15	-11.86	-4.48	-5.40	-9.08
VW	α	-0.84	-1.09	-2.40	-1.33	-1.41	-2.22	-1.08	-0.88	-2.76
	t	-2.54	-2.62	-3.82	-3.29	-3.64	-3.75	-4.42	-3.02	-4.17
		PH52								
EW	α	-0.24	-1.05	-2.92	-0.54	-1.24	-3.96	-0.48	-1.11	-3.49
	t	-1.39	-4.96	-8.75	-2.94	-5.26	-12.78	-2.83	-4.92	-8.36
VW	α	-0.61	-1.23	-2.99	-0.88	-1.44	-3.20	-0.71	-1.21	-3.29
	t	-3.60	-3.73	-5.78	-5.32	-4.26	-5.02	-3.08	-3.44	-4.46
		Rev								
EW	α	-1.53	-1.59	-3.07	-1.93	-1.87	-3.59	-1.57	-1.57	-2.98
	t	-4.75	-7.65	-8.46	-6.01	-7.46	-8.53	-4.66	-6.17	-6.74
VW	α	-0.95	-0.85	-2.68	-1.09	-1.21	-2.91	-0.65	-0.73	-2.43
	t	-2.25	-3.80	-4.31	-2.52	-3.96	-5.18	-2.04	-2.45	-3.77

Table 8. Double-Sorting: Size and Value

This table reports performance analysis of the double-sorted portfolios formed by sorting stocks according to market value or book to market ratio in the first step and then by lottery-related features. 9 portfolios generated through sorting stocks in the sample into 3 groups by any of the valuation proxies (market value or book-to-market ratio). Then re-sorting the stocks within each group into 3 portfolios by any of the lottery-related features (Lndx, IVOL, and MAX). Lndx: is the lottery index, IVOL: is the idiosyncratic volatility, Max: is the maximum daily return over the month. MV: is the market value of the firm at the end of the month, BMV : is the book to market value ratio. The sample spans from January 1991 to December 2017. Carh (α): is alpha of the Carhart (1997)'s asset pricing model, $t(\alpha)$ is the newey t-statistic with 3 lag.

		Lndx			Ivol			MAX5		
		MV								
		B	M	S	B	M	S	B	M	S
EW	α	-1.01	-1.80	-2.51	-1.33	-2.16	-3.77	-1.04	-1.83	-2.90
	t	-4.57	-6.52	-7.07	-5.48	-6.85	-10.50	-3.89	-5.90	-8.13
VW	α	-0.96	-1.74	-2.67	-1.27	-2.04	-3.77	-0.90	-1.79	-2.78
	t	-4.14	-6.67	-8.05	-5.68	-7.19	-11.28	-2.88	-5.86	-8.90
		BV								
		H	M	L	H	M	L	H	M	L
EW	α	-1.63	-1.90	-2.77	-1.91	-2.07	-3.26	-1.60	-1.78	-2.65
	t	-4.25	-7.30	-7.72	-4.79	-7.58	-8.50	-4.36	-6.39	-7.18
VW	α	-0.82	-1.58	-2.24	-0.69	-1.67	-2.54	-0.42	-1.07	-2.11
	t	-1.98	-3.90	-5.43	-1.43	-5.01	-7.41	-0.99	-2.60	-5.93

Table 9: Fama and MacBeth Regressions

This table represents average estimated coefficients from monthly Fama-Macbeth cross-sectional regressions. All stocks are sampled together. The left-side of the equation is the stocks' risk premium. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the Past 3 months, Max5: is the average of 5 highest daily returns over the past 3 month, Jump: is the sum of the absolute returns over the 2 standard deviation, logP: is the logarithm of the stock price at the end of the month, Min5: is the average of 5 lowest daily returns over the past 3 month multiplied by -1, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns, Beta: is the market beta measured by using CAPM as a pricing model, ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily spreads between the bid price and the ask price, Turnover: is the monthly average of the daily traded shares to the number of shares outstanding, MV: is the market value of the firm at the end of the month, BMV: is the book to market value ratio, PH52: is the ratio of current price to the 52-week high price. Mom: is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return, ROA: is the Return on asset CAPEX: is the ratio of capital expenditure total asset. R2: is the R square. Obs: is the number of stocks observations. The sample covers January 1991 to December 2017. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Cons	1.45***	1.37***	1.19***	-4.5***	-2.94***	-3.7***	-4.13***	-2**	-2.6***	1.43***	1.5***	1.6***
Lndx	-3.6***			-1.2**			-1.01**			0.40		
IVOL		-0.79***			-0.44***			-0.48***			-0.07	
MAX			-0.32***			-0.17***			-0.18***			-0.045
PH52				5.9***	4.4***	5.22***	5.3***	3.35***	3.9***			
Mom							0.009***	0.011***	0.01***			
Rev							-0.021***	-0.013***	-0.01*			
Min5										-0.47***	-0.40***	-0.40***
Dbeta												
Coskew												
Zdyas												
Amih												
Spread												
LogMV												
Beta												
ROA												
CAPEX												
BM												
Rsq	0.03	0.0357	0.032	0.0523	0.056	0.0561	0.0672	0.0707	0.0702	0.0467	0.0455	0.0469
Obs	199132	199132	199132	199132	199132	199132	195370	195370	195370	199132	199132	199132

Continue

	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
Cons	1.32***	1.4***	1.5***	0.98***	1.22***	1.04***	0.27	0.76*	-0.049	-2.14**	-1.5	-1.33
Lndx	0.45			-1.84***			-2.4***			0.93***		
Ivol		-0.05			-0.60***			-0.68***			-0.11	
MAX			-0.045			-0.20***			-0.22202			-0.05*
PH52										2.74***	2.67***	2.48***
Mom										0.011***	0.012***	0.013***
Rev										-0.029***	-0.023***	-0.02***
Min5	-0.48***	-0.42***	-0.41***							-0.28***	-0.18***	-0.20***
DBeta	0.16**	0.13*	0.17**							0.149***	0.149**	0.17***
Coskew	-0.08	-0.12	0.05							-0.27	-0.22	-0.14
Zdyas				2.7***	1.2***	1.62***				0.31	0.14	0.16
Amih				-0.02	-0.03	-0.02				-0.25	-0.28	-0.30
Spread				-43.4***	-22.1***	-33.3***				-13.7***	-10.7**	-10.5**
LogMV							0.056	0.006	0.09**	-0.012	-0.06	-0.06
Beta							-0.07	-0.003	-0.011	-0.011	0.02	0.03
ROA							2.5***	1.7***	2.02***	1.27***	1.08**	1.1**
CAPEX							-1.54*	-1.4*	-1.67**	-1.42**	-1.44**	-1.46**
BM							0.78***	0.84***	0.78***	1.13***	1.12***	1.12***
Rsq	0.0582	0.0568	0.0582	0.0537	0.0554	0.0527	0.0659	0.071	0.0683	0.1295	0.1301	0.1304
Observations	199132	199132	199132	192404	192404	192404	183815	183815	183815	176128	176128	176128

Table 10. Skipping One-Month

This table show the two-month ahead returns of the lottery-based portfolios. Each month the stocks are grouped into deciles according to any of the lottery proxies, then each portfolio is hold for the subsequent month. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the Past 3 months, Max5: is the average of 5 highest daily returns over the past 3 month. P10 is the portfolio of highest lottery proxy, P9 is the portfolio of second highest lottery proxy, and so on. t-Statistic is the newey and west t-statistic with lag selected automatically. Sample covers January 1991 to December 2017. Alpha is Carhart four factor model alpha.

Decile	Lndx		IVOL		MAX	
	Ew	Vw	Ew	Vw	Ew	Vw
P10	-2.31	-2.27	-3.01	-2.06	-2.62	-2.24
P9	-1.35	-0.90	-1.36	-1.09	-0.93	-0.54
P8	-0.94	-1.00	-0.82	-0.54	-0.65	-0.03
P7	-0.58	-0.26	-0.23	-0.17	-0.30	-0.02
P6	0.02	0.10	0.20	0.34	0.24	0.52
P5	0.43	0.60	0.47	0.57	0.32	0.21
P4	0.62	0.49	0.57	0.58	0.38	0.39
P3	0.47	0.31	0.70	0.58	0.56	0.45
P2	0.64	0.52	0.75	0.70	0.59	0.62
P1	0.57	0.55	0.83	0.57	0.50	0.74
P10-p1	-2.9***	-2.8***	-3.8***	-2.6***	-3.1***	-3.0***
Carh- α	-3.2***	-2.9***	-4.2***	-2.95***	-3.7***	-3.3***
P9-P2	-2.0***	-1.4**	-2.1***	-1.8***	-1.5***	-1.2*
Carh- α	-2.3***	-1.6***	-2.5***	-2.1***	-1.82***	-1.7***

Table 11. Two-Month Ahead Return

This table represents average estimated coefficients from monthly Fama-Macbeth cross-sectional regressions. All stocks are sampled together. The left-side of the equation is the two-month ahead stocks' risk premium. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the Past 3 months, Max5: is the average of 5 highest daily returns over the past 3 month, Jump: is the sum of the absolute returns over the 2 standard deviation, logP: is the logarithm of the stock price at the end of the month, Min5: is the average of 5 lowest daily returns over the past 3 month multiplied by -1, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns, Beta: is the market beta measured by using CAPM as a pricing model, ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily spreads between the bid price and the ask price, Turnover: is the monthly average of the daily traded shares to the number of shares outstanding, MV: is the market value of the firm at the end of the month, BMV: is the book to market value ratio, PH52: is the ratio of current price to the 52-week high price. Mom: is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return, ROA: is the Return on asset CAPEX: is the ratio of capital expenditure total asset. R2: is the R square. Obs: is the number of stocks observations. The sample covers January 1991 to December 2017. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

	Mod1	Mod2	Mod3	Mod4	Mod5	Mod6
Cons	1.4***	1.2***	0.98***	-3.4***	-2.8***	-2.6***
Lndx	-3.4***			0.5*		
Ivol		-0.68***			-0.01	
MAX			-0.26***			-0.07
PH52				3.8***	3.5***	3.4***
Mom				0.008***	0.01***	0.011***
Rev				0.005	0.01*	0.0135**
Min5				-0.13***	-0.06	-0.065*
DBeta				0.15**	0.15**	0.17**
Coskew				0.020765	0.13	0.20
Zdyas				0.6	0.41	0.30
Amih				0.06	0.09	0.06
Spread				-18.0***	-16.5***	-13.9***
LogMV				-0.015	-0.046	-0.046
Beta				-0.007	0.000322	0.012
ROA				1.6***	1.5***	1.37***
CAPEX				-1.6**	-1.6**	-1.56**
BM				1.1***	1.1***	1.07***
Rsq	0.03	0.033	0.03	0.125	0.125	0.125
Obs	199134	199134	199134	176129	176129	176129

Table 12. Exclude Stock Types

This table represents the average estimated coefficients from monthly Fama-Macbeth cross-sectional regressions. All stocks are sampled together. The left-side of the equation is the stocks' risk premium. Lndx: is the lottery-index. IVOL: is the idiosyncratic volatility over the past 3 months, Max5: is the average of 5 highest daily returns over the past 3 months. R2: is the R square. Obs: is the number of stock observations. Panel A shows the stocks with price higher than £10, Panel B shows stocks with lower than the sample-median Amihud's price impact measure, and Panel C shows stocks with market value higher than the sample-median. The full model indicates a model consists of a lottery effect with a set of control variables. The sample covers January 1991 to December 2017. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A	stocks with Price > £10					
Const	1.4	-1.9	1.42	-1.12	1.2***	-0.95
Lndx	-3.4***	0.95**				
Ivol			-0.81***	-0.11		
MAX					-0.32***	-0.051*
Full Model	Yes		yes		yes	
Rsqr	0.028	0.1311	0.034	0.132	0.03	0.132
Obs	191213	169797	191213	169797	191213	169797
Panel B	Liquid stocks					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Const	0.93***	0.42	1.3***	0.71	1.1***	0.76
Lndx	-2.1***	0.78**				
Ivol			-.68***	-0.066		
MAX					-0.24***	0.0
Full Model	Yes		yes		yes	
Rsqr	0.0334	0.1904	0.0377	0.1914	0.038	0.1921
Obs	96225	89401	96225	89401	96225	89401
Panel C:	Big stocks					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Const	0.83	-0.34	1.14***	-0.23	0.91***	-0.21
Lndx	-1.83***	0.85**				
Ivol			-0.59***	0.13		
MAX					-0.20***	0.06
Full Model	Yes		yes		yes	
Rsqr	0.028	0.18	0.032	0.182	0.033	0.182
Obs	99564	91439	99564	91439	99564	91439

Table 13. Different Sample Periods

This table shows the next month's return of the lottery-based portfolios over a different period of time. Each month the stocks are grouped into deciles according to any of the lottery proxies, then each portfolio is held for the subsequent month. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the past 3 months, Max5: is the average of 5 highest daily returns over the past 3 months. P10 is the portfolio of the highest lottery proxy, P9 is the portfolio of second highest lottery proxy, and so on. t-Statistic is the newey and west t-statistic with lag selected automatically. The sample covers January 1991 to December 2017. Alpha is the Carhart four-factor model alpha.

Port	Lndx			IVOL			MAX		
	1991 to 2000	2001 to 2007	2008 to 2017	1991 to 2000	2001 to 2 007	2008 to 2017	1991 to 2000	2001 to 2007	2008 to 2017
P10	-0.28	-4.04	-2.85	-0.71	-4.90	-3.63	-0.14	-4.16	-2.60
P9	0.42	-2.08	-1.65	0.83	-2.08	-1.75	0.65	-1.46	-0.93
P8	0.49	-1.70	-1.26	-0.10	-1.45	-0.78	0.73	-0.42	-0.28
P7	0.53	-1.11	-0.75	0.66	-0.82	0.01	0.43	-0.84	-0.18
P6	0.89	-0.18	0.23	0.87	0.29	-0.68	1.04	-0.16	-0.19
P5	1.00	0.17	-0.46	1.17	0.00	0.05	1.12	0.22	0.29
P4	1.28	0.46	0.14	1.11	0.89	-0.43	0.96	0.15	0.24
P3	0.62	0.28	-0.17	0.81	1.07	-0.16	0.96	0.51	-0.35
P2	1.20	0.33	0.30	1.14	0.08	0.25	0.57	0.47	0.05
P1	0.73	0.24	0.42	1.05	0.19	0.48	0.82	0.79	0.68
P10-P1	-1.01	-4.16***	-3.35***	-1.76*	-4.95***	-4.2***	-0.96	-4.86***	-3.34***
Carh(α)	-1.79***	-3.69***	-3.87***	-2.63***	-4.54***	-4.84***	-2.0**	-4.25***	-4.15***
P9-P1	-0.79	-2.45**	-1.91*	-0.31	-2.18**	-1.98*	0.08	-1.9	-1.0
Carh(α)	-1.37**	-1.98***	-2.25***	-1.1*	-1.7*	-2.46**	-0.87	-1.17	-1.65*

Table 14. Lottery Portfolios and Sentiment

This table shows the next month's return of the lottery-based portfolios through different period emotional trading. Optem: is a period of high sentiment and high liquidity, Pessem: is the periods of low sentiment and low liquidity. Mild: consists of all other periods that don't belong to either Optem or Pessem. Each month the stocks are grouped into deciles according to any of the lottery proxies, then each portfolio is held for the subsequent month. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the past 3 months, Max5: is the average of 5 highest daily returns over the past 3 months. P10 is the portfolio of the highest lottery proxy, P9 is the portfolio of second highest lottery proxy, and so on. t-Statistic is the newey and west t-statistic with lag selected automatically. The sample covers January 1991 to December 2017. Alpha is the Carhart four-factor model alpha.

Lottery	Lndx			IVOL			MAX		
	Optem	Mild	Pessem	Optem	Mild	Pessem	Optem	Mild	Pessem
P10	-5.22	-2.10	0.15	-6.56	-2.73	0.09	-4.75	-2.31	1.06
P9	-3.41	-1.02	1.20	-2.80	-0.78	0.55	-2.26	-0.44	0.78
P8	-2.90	-0.56	0.48	-1.84	-0.76	0.77	0.49	-0.35	1.02
P7	-1.71	-0.59	1.58	-0.96	-0.12	1.18	-1.41	-0.34	1.89
P6	-0.63	0.15	1.92	-0.43	-0.10	1.48	-0.55	0.15	1.35
P5	-0.35	0.11	1.38	-0.39	0.32	1.66	-0.51	0.58	1.64
P4	0.20	0.54	1.29	0.13	0.24	1.33	0.30	0.34	1.13
P3	-0.21	0.02	1.31	0.35	0.33	1.19	-0.18	0.18	0.99
P2	0.43	0.38	1.36	-0.30	0.43	1.49	0.13	0.19	0.81
P1	-0.05	0.41	1.05	-0.11	0.59	0.99	0.31	0.74	1.08
P10-P1	-5.2***	-2.5***	-1.1	-6.5***	-3.3***	-1.1	-5.1***	-3.0***	-0.23
Carh(α)	-3.8***	-3.1***	-2.1**	-5.2***	-3.97***	-2.1*	-3.7**	-3.7***	-1.5
Obs	53	196	53	53	196	53	53	196	53

Table 15. Fama-MacBeth and Sentiment

This table represents the average estimated coefficients from monthly Fama-Macbeth cross-sectional regressions for each level of sentimental activity. All stocks are sampled together. The left-side of the equation is the stocks' risk premium. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the past 3 months, Max5: is the average of 5 highest daily returns over the past 3 month R²: is the R square. Obs: is the number of stock observations. No control indicates regressions with only the lottery proxies as independent, while under the Control column the models add the set of the controlling variables. The sample covers January 1991 to December 2017. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

	No control			Control		
Panel A:	High Sentiment					
Cons	1.4**	1.1*	0.6	-4.8*	-4.0	-3.8
Lndx	-6***			0.59		
Ivol		-1.18***			-0.41**	
Max			-0.41***			-0.16***
Rsq	0.03	0.041	0.035	0.11	0.11	0.114
Obs	35503	35503	35503	32173	32173	32173
Panel B:	Mild Sentiment					
Cons	1.44***	1.43***	1.3***	-1.33	-0.66	-0.42
Lndx	-3.52***			1.1**		
Ivol		-0.75***			-0.09	
Max			-0.31***			-0.05
Rsq	0.031	0.035	0.032	0.13	0.13	0.13
Obs	122007	122007	122007	108095	108095	108095
Panel C:	Low Sentiment					
Cons	1.57***	1.43***	1.25**	0.27	0.51	0.4
Lndx	-1.6			0.68		
Ivol		-0.3			0.03	
Max			-0.1			0.02
Rsq	0.021	0.025	0.024	0.12	0.12	0.122
Obs	34337	34337	34337	30429	30429	30429