The Inflation Gamble*

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March 17, 2025

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that have greater sensitivity to inflation and are harder to arbitrage. Further, lottery-type

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in high inflationary environments generates predictable patterns in stock returns.

Keywords: Inflation, skewness preference, lottery stocks, gambling, mispricing, idiosyn-

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JEL classification: G12, G14, G41.

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And in a cost of living crisis where inflation is at a 40-year high, young people are being increasingly drawn to desperate measures, gambling for a lucky win that might change their fate.

- Adele Walton, Vice Magazine.

1. Introduction

High inflationary episodes in the United States are uncommon. Except for a short period of high annualized inflation over 5% in July and August of 2008, the U.S. has not experienced such an episode since 1990. How do investors and various other market participants react to inflation-induced shocks that significantly reduce their purchasing power? And what is the impact of those behavioral shifts on the prices of financial assets that exhibit greater sensitivity to changes in inflation?¹

Traditional economic theory posits that investors should reduce their exposure to risky assets during high inflationary periods as the equity premium declines (e.g., Carroll et al. (1992), Carroll (1997)). Similarly, investors and experts such as Paul Volcker and Warren Buffett liken inflation to a tax, and the common recommendation for dealing with this tax is to increase investments in treasury bonds and commodities like gold and other precious metals. In contrast to these predictions, Bonaparte et al. (2024) find that investors increase their allocations to risky assets when inflation rises, as certain financial assets may be an effective hedge against inflation.

In this paper, we examine whether an alternative economic channel affects investor behavior and asset prices during high inflationary periods. Outside of the financial markets setting, a small chance of winning a large prize is more tempting to individuals during economic downturns, especially since gambling instruments are priced low (e.g., Mikesell (1994),

¹Although episodes of extreme inflationary environments are infrequent and the most recent extreme episode has generated considerable attention, which motivated our study, our evidence suggests that inflation varies considerably over time and would affect investor behavior and stock prices in a meaningful manner even when changes in inflation levels are moderate.

Capacci et al. (2017)).² In a similar manner, certain types of speculative investments can be attractive to inflation-sensitive investors as they feel "poorer." Higher equity returns can partially mitigate the perceived loss in purchasing power induced by higher inflation.

In particular, if those investors have prospect-theoretic preferences, their risk-taking propensity will increase as they move into the "loss" domain of the value function (Kahneman and Tversky (1979)).³ In addition, if investors assign larger probability weights to extreme returns, they will find lottery-type investments more attractive (Kahneman and Tversky (1992)). Overall, during periods of high inflation, investments in the speculative, lottery-like segments of the market will increase due to an increased investor appetite for risk and skewness.

If these inflation-induced demand shifts are systematic, they can also affect asset prices. We use the theoretical framework of Barberis and Huang (2008) to examine the potential asset pricing implications of inflation-induced trading activities. If the demand for lottery-like investments is systematic and arbitrage costs are high, the Barberis and Huang (2008) asset pricing model predicts that lottery-type stocks will be overpriced during periods of high inflation. If arbitrage forces are not infinitely powerful during high inflationary periods when economic uncertainty rises, this mispricing may not get corrected immediately, resulting in lower average returns in the future.

We test this key asset pricing prediction in this paper. In related studies, Green and Hwang (2011) examine the asset pricing predictions of the Barberis and Huang (2008) model using IPOs as lotteries, and Barberis et al. (2016) examine those theoretical predictions more directly using distributions of past return to capture the gambling behavior of investors. Our

²Media articles also report evidence of increased short-term borrowing and gambling during recessions when people are not able to make their ends meet. See, for example, Gambling and the Cost of Living Crisis: A Perfect Storm in the Making, by Adele Walton, August 18, 2022. Available at https://www.vice.com/en/article/gambling-and-the-cost-of-living-crisis-a-perfect-storm-in-the-making/. Also, see the following article by the Council on Compulsive Gambling of NJ: Are People Turning Towards Gambling to Beat Rising Inflation?. The article is available at https://800gambler.org/are-people-turning-towards-gambling-to-beat-rising-inflation/.

³Investors in high inflationary environments are likely to feel that they have experienced a loss due to a decline in their purchasing power even when they do not actually lose money.

study extends this literature and examines the predictions of the Barberis and Huang (2008) model in a novel economic setting where inflation is high and the risk-taking and gambling propensity of investors increase.

We begin our empirical analysis by examining whether risk-taking and gambling propensity are higher during periods of high inflation. Using the aggregate monthly risk aversion estimates from Bekaert et al. (2022), we find a strong negative relation between inflation and risk aversion. We also demonstrate that per-capita state-level lottery revenue is higher in U.S. states with higher inflation levels. Further, we find that interest in gambling activities such as sports betting, as revealed through Google Trends search intensity, is higher during periods of high inflation. Together, these findings using multiple data sources portray a consistent picture and provide direct support for our conjecture that higher levels of inflation encourage more risk-taking and gambling among individuals.

If a large number of stock market investors exhibit a similar behavior when they perceive or experience higher levels of inflation, they may systematically increase their exposure to lottery-type investments. Consequently, their correlated trading activities may influence stock prices in market segments that contain lottery-type stocks with high inflation sensitivity. We use a variety of tests to examine this key conjecture.

Specifically, we follow Barberis et al. (2016) and use past return distributions to characterize the gambling behavior of prospect-theoretic investors. To identify speculative, lottery-type investments, we focus on the following two measures used in the related empirical asset pricing literature: idiosyncratic volatility (IVOL) and maximum daily return (MAXRET) of Bali et al. (2011).⁴ Of course, not all lottery stocks will attract investor attention to the same degree during high inflationary periods. Firms that are more responsive to small fluctuations in inflation—whether increases or decreases—will attract greater investor attention

⁴In our main analysis, we focus on IVOL and MAXRET measures as both measures are known to exhibit a strong and robust negative relation with average future returns. For robustness, we consider other related return-based measures to identify speculative, lottery-type stocks, including the lottery index measure of Kumar (2009), expected skewness measure of Boyer et al. (2010), and idiosyncratic skewness. These related measures yield similar results.

tion. Consequently, the absolute value of return sensitivity to inflation can reveal firms that attract greater investor attention when inflation rises.

To identify firms with high inflation-induced gambling demand, we obtain a firm-level inflation sensitivity measure by regressing each firm's past sixty months of returns on inflation innovations and the three Fama-French factors. This inflation sensitivity beta (*iBeta*) captures the sensitivity of a stock's returns to inflation innovations and is likely to be correlated with unobserved inflation-induced gambling demand. Returns of firms with high sensitivity to positive or negative inflation innovations are likely to react more strongly to inflation-induced gambling demand, and consequently, these firms are more likely to be overpriced.

We begin our main empirical analysis by forming monthly portfolios double sorted on iBeta and one of the lottery characteristics and measuring portfolio returns in the following month. We find that the high IVOL portfolio underperforms the low IVOL portfolio within each iBeta quintile, but the gap is the largest for the highest iBeta quintile. These magnitudes are larger when we consider the MAXRET measure to identify lottery-type investments. During the 1963-2022 sample period, the monthly MAXRET premium is -0.151% (t-statistic = -0.97) for the lowest iBeta quintile, and this magnitude jumps to -0.696% (t-statistic = -4.51) for the highest iBeta quintile. The average difference of -0.894% per month is statistically significant with a t-statistic of -3.90. This evidence is consistent with our key conjecture and suggests that inflation-sensitive lottery stocks are likely to be more overpriced.

We gather additional support for the gambling channel by investigating whether the pricing effects are more pronounced among firms with higher retail trading intensity. Existing evidence suggests that the degree of speculation in investment decisions differs between retail and institutional investors. Specifically, Kumar (2009) finds that retail investors are more likely to overweight stocks that have lottery-like characteristics, relative to institutional investors. If our findings reflect the effects of gambling demand, the underperformance of the long-short strategy would be more pronounced for stocks with higher retail trading

intensity. Consistent with this conjecture, we find that the underperformance of lottery-type stocks with high inflation beta is more pronounced among firms with higher retail trading.

We also use a measure of Catholic-to-Protestant religious adherence to capture a firm's sensitivity to gambling behavior. Kumar et al. (2011) finds that religion-induced gambling attitudes influence investor behavior. Specifically, investors who reside in areas with a high Catholic-to-Protestant ratio (CPRATIO) are more likely to hold lottery-type stocks. In light of this evidence, we expect inflation-induced lottery demand to be even greater among firms headquartered in high CPRATIO regions. Consistent with this conjecture, we find that our Long—Short strategies that attempt to exploit the overpricing of lottery stocks yield significantly more negative returns when we restrict our attention to firms headquartered in high CPRATIO counties.

To further ensure that these pricing effects are generated by the trading activities of gambling-inclined investor clientele, we use the Lou et al. (2019) return decomposition method to examine whether the abnormal returns are driven by the intraday or the overnight component of the close-to-close return. The Lou et al. (2019) study finds that there is a significant difference between the intraday and overnight investor clienteles. Specifically, retail investors are more likely to impact price movements during overnight trading hours, while sophisticated investors trade throughout the trading day to correct any mispricing. Further, Chhaochharia et al. (2024) demonstrate that overnight returns are likely to reflect the gambling tendencies of retail investors.

In light of these findings, we expect to find that overnight returns will reflect mispricing among lottery stocks and potential mispricing generated by inflation-induced gambling demand will get corrected during the intraday period. Consistent with this conjecture, we find that the average overnight return for lottery-type stocks with high inflation sensitivity is more positive, indicating larger mispricing. In contrast, the average intraday return for lottery-type stocks with high inflation sensitivity is more negative, suggesting a stronger intraday correction.

To test more directly whether gambling propensity drives mispricing, we follow Stambaugh et al. (2015) and Kumar et al. (2024) and create a composite measure of mispricing based on 11 previously established anomalies. The composite mispricing measure is created such that higher values of mispricing measure (MIS) indicate greater mispricing. We expect mispricing to be largest (smallest) for stocks that are sorted into the top (bottom) lottery stock and inflation sensitivity portfolios.

Consistent with our conjecture, we find that the average mispricing among inflation sensitive lottery stocks is significantly higher compared to stocks that rank lower in lottery characteristics. Further, the mispricing spread is larger following periods of higher abnormal realized inflation. We also find that the mispricing gap between the two extreme portfolios becomes smaller in the twelve months following the portfolio formation month. Examining the returns of a the Long—Short portfolio of IVOL or MAXRET within the top *iBeta* quintile, we find a similar pattern. The overpricing of inflation-sensitive lottery stocks gets corrected within 4-6 months, as the four-factor alpha becomes insignificant. Together, these empirical findings are consistent with our key conjecture that increased gambling demand in high inflationary environments affects the returns of lottery-type stocks.

We perform several additional tests to ensure the robustness of our findings. In particular, our results are not driven by an increase in hedging activities. Further, the greater mispricing of lottery stocks do not reflect the impact of broader market sentiment, economic factors, policy uncertainty, or broader market anxiety. We also confirm that our results are not driven by the abnormal market conditions during the COVID-19 pandemic.

These results contribute to an emerging finance literature that examines the link between macroeconomic conditions, portfolio decisions, and asset prices. The existing literature demonstrates that risk attitudes vary with changes in wealth, background risk, and past experiences.⁵ Previous studies also identify a negative relation between inflation and equity returns and attribute this link to the correlation between inflation and real activity, money

⁵See Campbell and Cochrane (1999); Barberis et al. (2001); Heaton and Lucas (2000); Guiso and Paiella (2008); Guiso et al. (2018).

demand, and changes in the investment opportunity set (e.g., Fama and Schwert (1977); Kaul (1987); Stulz (1986)). Further, Bekaert et al. (2013) finds that lax monetary policy lowers risk aversion, while Bonaparte et al. (2024) demonstrate that individuals are more likely to allocate wealth to risky assets during periods of high inflation. Extending these results, we focus on gambling behavior in financial markets and show that the negative inflation-return relation may reflect overpricing of lottery-type stocks with high inflation sensitivity.

Beyond this emerging macro-finance literature, our results provide empirical support to the behavioral asset pricing literature that examines the impact of prospect-theoretic preferences on asset prices. In particular, Barberis and Huang (2008) show that lottery-type stocks with high skewness are overpriced when prospect-theoretic investors overweight small probabilities. Consistent with their theoretical predictions, we find that gambling propensity increases during high inflationary periods, perhaps because investors assign larger weights to small probabilities as they perceive to be in the "loss" domain when their purchasing power declines. Consequently, lottery-type stocks become more overpriced and generate lower average returns in the future.

2. Data and Methods

2.1. Main Data Sources

We use data from several sources. To identify time-variation in aggregate risk aversion, we obtain aggregate monthly risk aversion estimates from Bekaert et al. (2022). This aggregate measure of risk aversion is estimated using observed financial variables and a no-arbitrage framework. Risk aversion coefficients are deduced based on a utility-maximization function reflecting time-varying relative risk aversion of a representative agent in a generalized habit-like model with preference shocks. The risk aversion measure is available for the 1986 to 2024 period.

Specifically, the risk aversion index of Bekaert et al. (2022) is a model-implied market-level

time-varying measure of risk aversion, consistent with the movements of financial markets and the macroeconomy. The asset pricing model used is an extension of the habit formation models of Campbell and Cochrane (1999); Menzly et al. (2004); Wachter (2006). The model-implied risk aversion measure has two components based on fundamental and nonfundamental news. The second component is likely to reflect mood changes or shifts in consumer/investor sentiment. Bekaert et al. (2022) suggest that their index is a complement to other sentiment indices like the Baker and Wurgler (2006) sentiment index. They show that their risk aversion measure is highly correlated with various consumer sentiment indices that are not part of the estimation. The estimation of the model is based on financial data (e.g., prices of equities and corporate bonds, equity earnings, and corporate bond loss rates) and macroeconomic data like industrial production.

To capture potential time variation in interest in gambling, we obtain data on internet search intensity for four gambling-related terms using Google Trends. We obtain search intensities for "gambling," "lottery," "Powerball," and "sports betting" to gauge people's interest in gambling. We download the monthly search intensity for each of the four terms and then create an overall gambling search intensity score, which is the sum of the search intensities across all four terms. The sample period is from January 2004 to October 2024

We also obtain data on state-level lottery revenues from the U.S. Census Bureau's Annual Survey of State and Local Government Finances. We adjust annual lottery revenues to 2010 dollars to account for the impact of inflation. This dataset is available from 1977 to 2021. To capture geographic variation in inflation, we obtain state-level inflation estimates from Hazell et al. (2022). We then compute abnormal state inflation by subtracting national annual inflation rate from the state-level inflation measures. We scale state lottery revenues by state population from the US Census Bureau.

We use data on stock-level portfolio holdings from a large discount brokerage to examine whether inflation influences individuals' investment decisions. The data contains information on the portfolio holdings of 77,995 retail investors from 1991 to 1996. The data also includes

demographic information of the individuals such as income and residential location (ZIP code). After restricting the data to include only observations with available demographic information, we are left with 44,281 unique households.

Our main empirical analyses rely on stock returns data from the Center for Research in Security Prices (CRSP). Firm-level financial information is from Compustat. The sample period covers the period from January 1963 to December 2022. We include all common stocks (share codes 10 and 11) that have an end-of-month share price of at least \$1 and exclude firms with negative book equity and those that belong to the financial sector $(6,000 \le \text{Standard Industrial Classification} \le 6,999)$. Factor returns and risk-free rates are from Professor Kenneth French's data library.

We complement the financial data with data on consumer prices and inflation expectations over the next year from Federal Reserve Economic Data (FRED), along with three additional datasets that allow us to measure return sensitivity to gambling behavior. Specifically, we construct a measure of retail trading intensity using trade information from the Trades and Quotes (TAQ) and the Institute for the Study of Security Markets (ISSM) databases (Kumar (2009)). Additionally, we use the TAQ data to decompose daily stock returns into intraday and overnight return components following Lou et al. (2019). This data is available from 2010 to 2018.⁶

We estimate arbitrage cost using shorting fee scores from Markit Data Explorers. While we consider multiple arbitrage cost measures, our main variable is $BO_Inventory_Value$, defined as the lendable supply of shares of a firm scaled by its market capitalization. Lower values of $BO_Inventory_Value$ imply higher arbitrage costs since it measures the availability of shares for shorting.

To examine whether lottery demand is greater in more gambling prone regions, we obtain information on religious adherence using the "Churches and Church Membership" files from

⁶The sample period begins in 2010 because the reliability of subpenny price movements for capturing retail trades is obfuscated by brokerages adopting the practice of providing fractional cents of price improvement to retail investors via internalization or wholesalers. These trends stabilized around 2010, making subpenny price movements a more reliable measure of retail trading activity (Boehmer et al. (2021)).

the American Religion Data Archive (ARDA). The Glenmary Research Center provides a dataset that contains county-level statistics for 133 Judeo-Christian denominations. This dataset includes detailed information on the number of churches and their adherents. The religion data at the county level is available for 1980, 1990, 2000, and 2010. Following related studies, we obtain annual data for other years through linear interpolation across these decennial observations.

Finally, to control for the effects of investor sentiment and general economic conditions, we use a monthly measure of investor sentiment from Baker and Wurgler (2006). We also obtain a monthly index that captures economic policy uncertainty from Baker et al. (2016). To account for the effects of business cycles, we collect monthly recession indicators from the NBER. The monthly data for the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) for the 1990 to 2024 period is obtained from the CBOE.

2.2. Measuring Inflation Sensitivity

To identify lottery stocks that are more likely to be affected by inflation-induced gambling demand, we quantify each firm's inflation sensitivity by computing a time-varying conditional inflation beta. Specifically, at the end of each month t, we regress a stock's excess returns on monthly inflation innovations and the three Fama-French factors. Inflation innovations are filtered using an ARMA(1,1) model to account for the autogregressive nature of monthly inflation. This model allows us to isolate the signal component of inflation from noise.⁷ We then take the absolute value of the coefficient estimates on inflation as the measure of inflation sensitivity, and denote this sensitivity measure as iBeta.⁸

We use the absolute value of inflation sensitivity since we want to identify stocks that attract greater investor attention when there is either a positive or negative change in in-

⁷Our model choice follows prior studies, including Fama and Gibbons (1984), Vassalou (2000), and Boons et al. (2020).

 $^{^8}$ For robustness, we compute iBeta using expected inflation instead of realized inflation innovations. The expected inflation measure, obtained from the Federal Reserve, is an estimate of the expected rate of inflation over the next year.

flation.⁹ Andrei et al. (2023) show that heightened investor attention is associated with an increase in market betas. Such steepening in the CAPM relation suggests that investor attention is likely associated with both increases in positive and negative return covariances, which is captured by the absolute value of the *iBeta* measure.

Panel C of Table I presents average values of several key stock characteristics for high and low *iBeta* firms. High *iBeta* category contains stocks in the top *iBeta* quintile, while the Low *iBeta* category contains stocks that fall into the bottom *iBeta* quintile. Stocks in the second through fourth quintiles of *iBeta* are characterized as "Others."

We find that high *iBeta* stocks are more volatile and have higher levels of skewness, compared to low *iBeta* stocks. High *iBeta* stocks have an average monthly volatility of 3.858% versus 2.501% for low *iBeta* stocks. Similarly, high *iBeta* stocks have an average skewness of 0.543, as compared to 0.419 for low *iBeta* stocks. They also have smaller average market capitalization (\$501 million versus \$3,845 million) and lower average stock price (\$12.45 versus \$28.11).

We report measures of retail trading intensity and arbitrage costs for the three iBeta categories. Consistent with our assumption, we find that high iBeta firms are traded more actively by retail investors and they also have higher arbitrage costs. In addition, using the Stambaugh et al. (2015) measure, we find that high iBeta firms have higher mispricing.

To validate our assumption that high sensitivity to both positive and negative inflation innovations would be associated with inflation-induced gambling demand, we report the mean firm attributes separately for large positive and large negative inflation sensitivity (see the last two columns in Table I, Panel C). Consistent with our assumption, we find that retail trading intensity is high for both extreme categories. Arbitrage cost and mispricing measures reveal a similar pattern. These findings suggest that our choice of absolute inflation sensitivity as a proxy for unobserved inflation-induced gambling demand is reasonable.

 $^{^{9}}$ We also examine the effects of positive and negative iBeta estimates separately and find similar results.

2.3. Defining Lottery-Type Stocks

Motivated by the finance literature on gambling, we use two stock characteristics to identify lottery-type investments: idiosyncratic volatility (IVOL) and maximum daily return (MAXRET). Stocks with high values for these two measures are likely to be perceived as gambles with a small probability of a large payout. IVOL is computed as the standard deviation of residuals from the regression of daily excess returns on the Carhart (1997) four factors in month t-1. We select IVOL as one of our lottery proxies because investors may conflate large unpredictable stock price movements with the possibility of extreme positive returns. Additionally, investors may assign a higher probability to upside price swings and ignore the risk of the downside, thereby increasing their perception of skewness.

The use of IVOL as a lottery proxy is supported by the existing literature. In particular, Kumar (2009) demonstrates that individual investors are more likely to hold stocks with high idiosyncratic volatility, especially during economic downturns. Hou and Loh (2016) posit that lottery preferences help explain the negative IVOL return relation.

Maximum daily return (MAXRET) is the maximum return using daily prices in month t-1, as defined in Bali et al. (2011). We select MAXRET as a measure of skewness because it is a salient stock attribute that investors are likely to anchor upon. If investors infer future performance from past performance, they are likely to believe that stocks with extremely high returns in the past month may have extremely high returns in the following month.

These two lottery measures are designed to capture perceived lottery-like behavior of individual stocks. We also consider other stock attributes that may capture the lottery-like behavior of stocks, such as expected skewness (ESKEW), idiosyncratic skewness (ISKEW), and total skewness (SKEW) that may be used to increase portfolio skewness. While it is possible that more sophisticated investors consider these measures, IVOL and MAXRET are characteristics that are more easily perceived. Nevertheless, in our robustness tests, we show that our results are similar when we consider alternative measures of return skewness.

3. Main Empirical Results

3.1. Inflation, Risk Aversion, and Gambling

Our asset pricing tests are based on the conjecture that gambling tendencies strengthen during high inflationary periods because investors may be tempted to gamble using lottery-type stocks to at least partially compensate for inflation-induced loss in purchasing power. This prediction is based on the assumption that such inflation-induced increased risk-taking and gambling tendencies are likely to be prevalent more broadly, which could also spillover into financial markets. In our first set of tests, we provide several pieces of evidence using multiple data sources to provide support for this assumption.

3.1.1 Graphical Evidence

To set the stage, we use search intensity data from Google Trends to determine whether individuals show more interest in gambling when inflation is high. Specifically, we use the following four terms to gauge overall interest in gambling activities: "gambling," "lottery" "Powerball," and "sports betting." We combine the search intensity data with the monthly Consumer Price Index (CPI) to test whether gambling-related search intensity increases when inflation increases. The monthly inflation rate is the percentage change in the CPI from one month to the next, and the annual inflation rate is the percentage change over a 12-month period.

During the 2004-2024 period, we find a positive relation between inflation and gambling. The correlation between annual inflation rate and overall gambling search intensity measure is 0.476 (see Figure 1, Panel A). This relation is slightly stronger (= 0.507) when we consider sports betting alone (see Figure 1, Panel B). These results suggest that periods of rising inflation may prompt households to engage more in high-risk, high-reward financial decisions, such as gambling, perhaps as a reaction to economic uncertainty or a search for alternative forms of financial relief.

3.1.2 Inflation and Aggregate Risk Aversion

If the increase in gambling attitudes is due to an increase in the demand for risky bets, we expect to find a decline in risk aversion when inflation is high. To test this conjecture, we examine the relation between an aggregate monthly risk aversion index and changes in monthly CPI. We obtain the aggregate monthly risk aversion index from Bekaert et al. (2022). This index is an aggregate measure of risk aversion based on observable financial variables and a no-arbitrage framework. The sample period is from 1986 to 2024.

Using this risk aversion index and monthly inflation data from FRED, we estimate the following regression model:

$$Risk\ Aversion_t = c + \theta Inflation_t + \varepsilon_t \tag{1}$$

where $Risk\ Aversion_t$ is the dependent variable and captures aggregate risk aversion in month t. $Inflation_t$ is the rate of inflation in month t measured as the monthly percentage change in CPI. For robustness, we consider different measures of inflation, including expected and realized inflation estimates. The coefficient θ represents the sensitivity of risk aversion to inflation. A positive (negative) value of θ indicates that inflation is associated with greater (less) aversion to risk. We also include year and month fixed effects to control for year and month specific variation in risk aversion and inflation.

The regression estimates are presented in Table II. We find that risk aversion is significantly negatively related to monthly inflation. Specifically, a one standard deviation change in monthly CPI is associated with a 15.7 to 18.4% decrease in the monthly risk aversion index, relative to its mean. These estimates suggest that, during inflationary periods, the risk-taking propensity of financial market participants is likely to increase. Given that this risk aversion index is based on observable asset prices and risk measures, our findings imply that inflation is likely to have a meaningful impact on the risk preferences of investors.

 $[\]overline{^{10}}$ We compute the economic magnitude of the impact as $100 \times \frac{-2.015 \times 0.269}{3.455} = 15.7\%$.

3.1.3 Inflation and State Lottery Demand

Next, we examine more directly whether reduction in risk aversion coincides with an increase in gambling-related activities. While the Google search intensity measures suggest an increase in gambling interest during high inflationary periods, we use lottery revenue data to strengthen this link. Specifically, we test whether increase in inflation correspond to an increase in demand for state lotteries. We use the annual state lottery revenues and excess state-level inflation to estimate the following regression model:

State Lottery_{s,t} =
$$c + \lambda State\ Inflation_{s,t} + \varepsilon_{s,t}$$
 (2)

where $State\ Lottery$ is the lottery revenue per capita (in 2010 dollars) in state s in year t. $State\ Inflation_{s,t}$ is the excess inflation in state s relative to the national inflation rate in year t. We consider the effect of excess state inflation to isolate the local perception of inflation, which may differ from national level changes in the CPI. This local measure allows us to identify whether state-specific differences in inflation impact local lottery demand.

Our main focus is on the coefficient on excess state inflation, λ , which captures the impact of local inflation on the demand for lotteries in the state. A positive (negative) value of λ indicates that higher local inflation is associated with a greater (lower) demand for state lotteries. We include state fixed effects to account for time invariant characteristics at the state-level that may be correlated with lottery revenues. Further, we cluster standard errors at the state-level to account for potential correlation in error terms across observations within the same state.

The regression estimates are presented in columns (5) and (6) of Table II. We find that a one standard deviation increase in excess state inflation is associated with a 11.04 to 11.30% increase in real per capita state lottery revenue, relative to its mean value. ¹¹ This evidence suggests that shifts in local inflation can have an economically meaningful impact

¹¹We compute the economic magnitude of the impact as $100 \times \frac{6.067 \times 1.068}{58.7} = 11.04\%$.

on state-level lottery expenditures.

3.1.4 Inflation and Individual Investor Portfolios

To strengthen the link between inflation and gambling, we directly examine the portfolio holdings of individual investors and test whether individuals who have a higher sensitivity to inflation allocate a larger portion of their holdings to stocks with lottery characteristics. We use data on the portfolio holdings of investors from a large discount brokerage between 1991 and 1996.

We use the excess portfolio weights relative to the market portfolio to capture the allocation choices of investors. We define excess portfolio weight for each investor as the weight of stock i in the investor portfolio in month t minus the weight of stock i in the market portfolio in month t divided by the weight of stock i in the market portfolio in month t (Kumar (2009); Bonaparte et al. (2024)).

We measure an individual's sensitivity to inflation by constructing an experienced inflation (EI) measure, which accounts for the local inflation experiences of each individual investor. Following Malmendier and Nagel (2011), for each household i in year t, we calculate the experienced inflation measure as the weighted average of past realized inflation levels,

$$EI_{it}(\lambda) = \sum_{k=1}^{age_{it}-1} w_{it}(k,\lambda)I_{t-k}^{R},$$
(3)

where,

$$w_{it}(k,\lambda) = \frac{(age_{it} - k)}{\sum_{k=1}^{age_{it} - 1} (age_{it} - k)^{\lambda}}.$$

 I_{t-k}^R is the realized annual regional inflation rate in year t-k. We compute regional inflation using regional CPI estimates from the Bureau of Labor Statistics (BLS). The weights (w_{it}) are a function of the number of years between an individual's current age and the realized rate of inflation in a given year. The shape of the weighting function is determined by λ , which is set to 1.25 in our analysis so that there is a higher weight on more recent years.

We analyze the extent to which investors with higher inflation sensitivity overweight lottery stocks. In particular, we regress excess portfolio weights on EI, lottery stock characteristics (IVOL and MAXRET), and the interaction between EI and the lottery stock characteristics. The coefficient on the interaction term indicates whether inflation-sensitive investors allocate more of their portfolios to lottery stocks.

Table III presents the results. For ease of economic interpretation, we define EI, IVOL, and MAXRET using indicator variables based on above and below median cutoffs. Columns (1) and (2) present the results for the full sample of investors. We find that investors with above-median inflation sensitivity assign significantly larger weights to stocks that have high IVOL and MAXRET. The weight of high IVOL (MAXRET) stocks among inflation-sensitive investor portfolios is 1.136% greater (0.915% greater) relative to the market portfolio.

We also examine whether there is heterogeneity in the tendency to allocate higher weights to lottery stocks based on household income. We hypothesize that inflation increases investors' propensity to gamble because they are hoping for a large payoff to help compensate for losses in purchasing power. We posit that investors with lower income will be more sensitive to these losses in purchasing power as they are more likely to feel that "pain" caused by inflation.

To examine this possibility, we perform a subsample analysis to test whether low-income households with higher inflation sensitivity have a greater tendency to overweight lottery stocks relative to those with higher income. We define low-income households as those with income codes less than 5, corresponding to an income of \$62,500. We define high-income households as those with income codes equal to or greater than 5, where the income codes range from 0 to 9.

Columns (3) through (6) of table III present the subsample results. We find that low-income households with high inflation sensitivity assign a significantly larger weight to lottery stocks relative to those with higher incomes. Specifically, inflation-sensitive low-income households hold an excess of 1.739% (1.391%) in high IVOL (MAXRET) stocks. In contrast,

inflation sensitive high-income households hold an excess of only 0.622% and 0.548% in high IVOL and high MAXRET firms, respectively. The statistical significance of this relation is also weaker for the high income subsample.

These results provide further evidence that gambling tendencies are sensitive to inflation. In particular, this evidence using household portfolios demonstrates that inflation-induced gambling tendencies are not isolated solely in activities like sports betting and lotteries, but also impact investment decisions of U.S. households.

3.2. Sorting Results

In this section, we begin the test of our main conjecture, which posits a link between inflation and performance of lottery-type investments. Specifically, we analyze the performance of portfolios sorted on *iBeta* and one of the two main lottery proxies (IVOL and MAXRET). We begin by independently sorting stocks into quintiles based on the absolute value of their inflation betas and on each of the two lottery characteristics. Information used to form portfolios is available at the end of each month. We compute the value-weighted returns of each of the twenty five portfolios during the following month. These portfolio returns are then used to obtain the four-factor alpha estimates.¹²

Table IV presents the monthly alpha estimates for single-sorted as well as the double-sorted portfolios. We also report the alpha estimates for various Long-Short portfolios. The single sort results indicate that high iBeta, high IVOL, and high MAXRET portfolios are overpriced. The average portfolio returns decline across all three measures. The monthly alpha difference between high and low iBeta portfolios is -0.258 (t-statistic = -2.71), which translates into an annual risk-adjusted performance difference of 3.10%. Similarly, consistent with the evidence in prior studies, the monthly alpha difference between high and low IVOL and MAXRET portfolios are -0.885 (t-statistic = -5.35) and -0.579 (t-statistic = -4.23), respectively.

¹²Our results are robust to using the Fama-French 5-factor risk adjustment. See Appendix Table A.2.

Further, consistent with our main conjecture, we find that the degree of overpricing of high IVOL portfolio varies with inflation sensitivity. The alpha estimate of the high IVOL portfolio in the low iBeta quintile is -0.482 (t-statistic = -2.78), while this alpha in the high iBeta quintile is -1.003 (t-statistic = -5.75). Similarly, the alpha estimates of the high MAXRET portfolio in the low and high iBeta quintiles are -0.151 (t-statistic = -0.97) and -0.696 (t-statistic = -4.51), respectively.

Examining the relation between average returns and lottery characteristic for firms with high inflation sensitivity, we find that the performance spread between low and high IVOL portfolios is largest for the highest iBeta quintile (alpha difference = -1.408, t-statistic = -5.75). The pattern is similar when we examine portfolios sorted on MAXRET. The performance spread across low and high MAXRET portfolios in the highest iBeta quintile is = -1.131 with a t-statistic of -5.16.

These results indicate that lottery demand is greater among stocks that covary more with inflation and, consequently, the magnitude of the negative lottery premium increases with *iBeta*. This evidence supports our conjecture that investors increase their demand for more speculative assets in an attempt to compensate for the potential adverse impact of high inflation. Our findings also suggest that the inflation risk premium documented in prior studies (e.g., Fama and Schwert (1977); Stulz (1986); Boons et al. (2020)) is likely to partially reflect the overpricing of lottery-type stocks.

3.3. Inflation Dynamics and Portfolio Performance

To tighten the link between inflation and performance of lottery-type investments, we examine the performance of IVOL and MAXRET based Long—Short portfolios during high and low inflationary periods. If inflation induces gambling and increases demand for lottery-type stocks, we expect the returns of IVOL and MAXRET based Long—Short portfolios to be more negative during periods of high expected inflation.

Figure 2 plots the risk-adjusted performance of the Long-Short lottery stock portfolios

during low, medium, and high periods of abnormal expected inflation. We define abnormal expected inflation as the inflation expectation in month t minus the average of inflation expectations over the past ten years.

Consistent with our main conjecture, we find that the Long-Short returns are significantly more negative following months when inflation expectations are high relative to low inflation expectations months. The IVOL Long-Short portfolio earns an average return of -1.365% following high inflation expectation months and -0.524% following months with low expected inflation. The difference between low and high inflationary periods is also large for portfolios sorted on MAXRET. The MAXRET Long-Short portfolio earns an average return of -1.194% following months with high inflation expectations months and -0.225% following months when inflation expectations are low.

To further assess the impact of inflation on the pricing of lottery-type stocks, we examine the performance time series of IVOL and MAXRET based Long-Short portfolios within the high iBeta quintile. Specifically, we consider firms within the top iBeta quintile and plot the 12-month moving average of the returns of High-Low IVOL and High-Low MAXRET strategies within the high iBeta quintile.

Figure 3 shows the Long-Short strategy's performance over time, along with the 12-month moving average of inflation innovations. The figure plots the results for the most recent months just for illustration. The return of the Long-Short strategy is negative for the majority of the sample period. In addition, as expected, it varies inversely with inflation innovations where the underperformance of the strategy is more pronounced during periods of high inflation. In particular, the strategy's performance is persistently negative throughout the early 1980s and around 2001 when inflation spiked.

3.4. Fama-MacBeth Regression Estimates

To ensure that other macroeconomic factors or firm attributes correlated with IVOL or MAXRET do not drive our results, we estimate a series of Fama and MacBeth (1973)

type regressions. If investors increase demand for lottery stocks in response to inflationary pressures, we would expect the negative premium to be larger for stocks that exhibit higher sensitivity to shifts in inflation.

We use data available at the end of each month t to compute IVOL, MAXRET, and iBeta. We then use the values of these lottery proxies and inflation sensitivity to predict returns in month t+1. The interaction between iBeta and the lottery proxies capture the incremental explanatory power of the joint effect of inflation sensitivity and lottery characteristics. We include several control variables to account for the known relation between firm characteristics and stock returns. This set of controls includes the book-to-market ratio, firm size, past returns for the prior 12 months skipping the most recent month, and the returns for the previous month.

Panel A of Table V presents the time-series averages of the coefficient estimates from monthly cross-sectional regressions. Columns (1) and (3) present the baseline results, which support the previously established negative premia for stocks with high IVOL and high MAXRET. Columns (2) and (4) present the estimates from specifications that include additional interaction terms between the lottery characteristic and *iBeta*. To ensure that our results are not sensitive to extreme values, in columns (5) and (6), we present the results from interaction specifications where we use quintile values of IVOL, MAXRET, and *iBeta*. In all specifications, as expected, we find that there is a significantly larger negative premium for lottery stocks with higher sensitivity to inflation.

To facilitate economic interpretation of these findings, we use indicator variables in columns (7) and (8) to capture high values of IVOL, MAXRET, and iBeta. In these specifications, IVOL, MAXRET, and iBeta are set to one if their respective values are above-median, and zero otherwise. We find that, among high IVOL stocks, high iBeta is associated with -0.324% lower average return (see column (7)). The effect is similar when we use MAXRET as the lottery proxy, where among high MAXRET stocks, high iBeta is associated with -0.611% lower return on average (see column (8)). Both interaction terms

are economically meaningful and they are also statistically significant. These results suggest that investors likely increase their demand for lottery stocks when inflation is high, leading to potential mispricing and subsequent correction over the next few months, particularly in market segments that covary strongly with inflation.

Overall, the Fama-MacBeth regression estimates suggest that lottery stocks that covary more strongly with inflation are more overpriced as they earn significantly more negative average return in the following month. Our evidence of greater overpricing of high IVOL and high MAXRET firms within the broad set of high *iBeta* firms is likely due to an increase in demand for lottery stocks during high inflationary periods. This effect persists even when we account for stock-level characteristics that might be correlated with inflation sensitivity and future stock returns.

3.5. Gambling Exposure and Overpricing of Lottery Stocks

To better establish the connection between inflation-induced gambling and mispricing of lottery-type investments, we directly examine whether the negative relation between inflation sensitive lottery stocks and returns is stronger for firms that have greater exposure to gambling and speculative trading activities. To capture stock-level exposure to gambling and speculative trading, we consider two proxies: Retail trading intensity (RTI) and the proportion of Catholic to Protestant religious adherents in a firm's headquarters location (CPRATIO).

Since retail investors are known to exhibit stronger gambling tendencies (Kumar (2009)), we expect the underperformance of high iBeta lottery stocks to be larger for stocks with higher retail trading intensity (RTI). Further, we capture increased exposure to gambling using the ratio of Catholic to Protestant religious adherence in the firm's headquarter county. The Catholic and Protestant traditions present clear views on their acceptance of gambling, where Protestants perceive gambling as a sinful activity while the Catholic tradition is more accepting of gambling. Existing studies find that individual characteristics such as religious

adherence has a significant impact on investment decisions, namely the propensity to gamble (Kumar et al. (2011)).

We follow Boehmer et al. (2021) and use the TAQ data from the Financial Industry Regulatory Authority (FINRA) Trade Reporting Facility (TRF) to identify retail trades from sub-penny price improvements. Specifically, we identify the fraction of the penny associated with the transaction price $(P_{it}): Z_{it} = 100 \times mod(P_{it}, 0.01)$. If Z_{it} is in the range of (0, 0.4) the trade is classified as a retail sell. If Z_{it} is in the range (0.6, 1) the trade is classified as a retail buy. If Z_{it} is in the range (0.4, 0.6) the trade is not considered a retail transaction. We aggregate the total number of retail transactions for firm i in each month t. RTI is computed as the percentage of total trading volume made up of retail trades in each firm-month. We sort firms into high and low buckets based on their relative RTI rank in a given month. The high and low cutoffs are based on median values of RTI each month.

For the CPRATIO tests, we sort counties into high and low buckets based on the relative CPRATIO ranking in a given year, again by median. We then classify firms based on these county CPRATIO buckets. This test relies on the local bias literature which finds that individuals over-invest in local firms (e.g., Seasholes and Zhu (2010); Hong et al. (2008)). We expect high *iBeta* lottery stocks to experience a larger negative premium if a firm is headquartered in a high CPRATIO county.

To test whether the IVOL and MAXRET effects vary with exposure to gambling and speculative trading activity, we expand our Fama-MacBeth specification in Table V and introduce a triple interaction term between *iBeta*, one of our lottery characteristics, and RTI or CPRATIO. A negative coefficient on this triple interaction term would indicate that high *iBeta* lottery stocks with greater exposure to gambling and speculative trading generate more negative returns in the future. For ease of interpretation, we present the results from specifications using indicator variables to capture high values IVOL, MAXRET, *iBeta*, and gambling exposure proxies.

Panel B of Table V presents the results. Consistent with our conjecture, we find that high

iBeta lottery stocks experience larger negative returns if they also have higher RTI. Columns (1) and (2) present the results for specifications that use RTI as measures of gambling exposure, while columns (3) and (4) present the results using CPRATIO as the measure of gambling exposure.

For stocks with high IVOL and high iBeta, we find that high iBeta, high IVOL firms earn -0.469% lower average monthly return if RTI is high (see column (1)). Similarly, high iBeta, high MAXRET firms with high RTI earn -0.675% lower average monthly return (see column (2)). Columns (3) and (4) present the results from a similar Fama-MacBeth specification using CPRATIO as the proxy for exposure to inflation-induced gambling. Again, consistent with our main conjecture, we find that high iBeta lottery stocks experience larger negative returns when a firm is located in a high CPRATIO county.

For stocks with high IVOL and high iBeta, we find that being headquartered in high CPRATIO counties is associated with 0.244% lower average monthly returns (see column (3)) for high IVOL and high iBeta portfolio. Similarly, high iBeta, high MAXRET firms with high RTI earn -0.227% lower average monthly return (see column (4)). This estimate is significant only at the 10% level but the overall pattern is consistent with our conjecture.

Together, RTI and CPRATIO based estimates indicate that exposure to speculative trading exacerbates the mispricing of high iBeta lottery stocks, which generates lower average return in the future. These estimates provide additional support to our main conjecture.

3.6. Evidence Using Intraday and Overnight Returns

In the next set of tests, we further link the observed return patterns to inflation-induced gambling and speculative trading using a return-based proxy for gambling and speculation. We rely on the Lou et al. (2019) methodology that decomposes the close-to-close returns into intraday and overnight components corresponding to less sophisticated noise traders and informed investor clienteles, respectively. Consistent with this interpretation, Chhaochharia et al. (2024) demonstrate that less sophisticated overnight traders are more likely to engage

in gambling activities.

In our setting, these findings imply that the overnight and intraday return patterns of high iBeta, high IVOL and high iBeta, high MAXRET portfolios will differ. Given that the retail clientele are more likely to trade in the period between closes, we expect the returns to high iBeta lottery stocks to experience higher overnight returns. And during the intraday period, we expect the relatively more sophisticated institutional clientele to correct this mispricing generated overnight. Specifically, the findings in Lou et al. (2019) suggest that there are differences in the timing of trading activity among informed and uninformed investors. Better informed institutional investors trade throughout the trading day while retail investors trade during the overnight period. Thus, the trades of more sophisticated arbitrageurs during the intraday period correct the overnight mispricing.

To test this hypothesis, we examine separately the overnight and intraday returns of portfolios double sorted on iBeta and one of the two lottery characteristics. We follow the methodology of Lou et al. (2019) to decompose the close-to-close returns into the intraday and overnight component. Specifically, for each firm i, the intraday return is calculated as the price appreciation between market open and close of the same day s. The overnight return is then imputed based on the intraday return and the standard daily close-to-close return. The price appreciation between market open and close is computed using the volume-weighted average price (VWAP) in the first half hour of trading (9:30 am - 10:00 am). These intraday and overnight returns are then aggregated across all trading days in month t to generate monthly intraday and overnight returns for stock i.

Table VI reports the estimates from Fama-Macbeth regressions, where Panel A presents the effects of lottery characteristics and inflation sensitivity on intraday returns while Panel B presents the effects on overnight returns. Columns (1) and (2) present coefficients from quintile regression specifications where each lottery characteristic and *iBeta* are indicators based on sorting stocks into quintiles, while to facilitate economic interpretation, columns (3) and (4) present coefficients using dummy variables to indicate above and below median

values of lottery characteristics and *iBeta*.

We find that the returns of the high iBeta lottery stock portfolios are significantly negative during the intraday period and positive during the overnight period. The estimates in columns (3) and (4) suggest that, on average, high inflation sensitivity is associated with a 42.1 and 61.4 basis points decline in the intraday returns of high IVOL and MAXRET stocks, respectively. In contrast, high iBeta is associated with a 96.3 and 95.1 basis points average increase in overnight returns for stocks with high IVOL and MAXRET, respectively.

These results suggest that less sophisticated retail investors drive up the returns of lottery stocks when inflation is high, while more sophisticated institutional investors step in to correct this mispricing. These return patterns are aligned with our hypothesis, given that retail investors would exhibit stronger gambling tendencies in response to inflationary pressures. More speculative retail clientele induce price pressure on high *iBeta* lottery stocks while the more risk-averse arbitrageurs correct the mispricing during the trading day.

3.7. More Direct Evidence of Mispricing

An increase in demand for lottery stocks during inflationary periods suggests that these stocks would be more overpriced relative to non-lottery stocks. We test this conjecture directly by examining whether inflation-sensitive lottery stocks exhibit greater mispricing relative to non-lottery stocks because they are relatively more difficult to arbitrage. We use the mispricing (MIS) measure from Stambaugh et al. (2012, 2015) and also consider direct measures of arbitrage costs.¹³ If the negative return predictability reflects mispricing generated by gambling and speculative trading, arbitrage costs and the degree of mispricing should be larger in the top iBeta and lottery proxy quintiles.

Anomalies that form the MIS measure include financial distress (Campbell et al. (2008)), O-score bankruptcy probability (Ohlson (1980)), net stock issues (Ritter (1991); Loughran and Ritter (1995); Fama and French (2008)), composite equity issues (Daniel and Titman

¹³We report results using only one of the arbitrage cost measures, but the results are similar when we consider other related arbitrage cost measures.

(2006)), total accruals (Sloan (1996)), net operating assets (Hirshleifer et al. (2004)), momentum (Jegadeesh and Titman (1993)), gross profitability (Novy-Marx (2013)), asset growth (Cooper et al. (2008)), ROA (Fama and French (2006); Chen et al. (2011)), and investment-to-assets (Titman et al. (2004); Xing (2008)). The aggregate MIS variable is the average value of each stock's decile rank with respect to each of the above 11 variables. Deciles are created such that stocks in the 10th (1st) decile are the most (least) overpriced.

We quantify the average arbitrage cost and MIS for each of the IVOL-iBeta and MAXRET-iBeta double-sorted portfolios. Table VIII presents the estimates. In Panels A and B, we find that MIS is highest among the most inflation-sensitive lottery stocks. Within the subset of high iBeta firms, the average MIS estimate for stocks in the top IVOL and MAXRET quintiles are 6.878 and 6.802, respectively. These estimates are significantly higher than the average MIS for stocks in the bottom IVOL and MAXRET quintiles (= 5.179 and 5.514, respectively). The MIS differentials across the two quintile portfolios are 1.669 and 1.298, respectively, and they are statistically significant at the 1% level.

In addition, within high IVOL (see Panel C) and high MAXRET (see Panel D) firms, inflation sensitivity affects arbitrage cost and mispricing estimates. High *iBeta* firms are more difficult to arbitrage and consequently they have significantly higher MIS estimates. In all four cases, the arbitrage cost estimates, as measured by *BO_Inventory_Value* reveal a similar pattern. High IVOL, high MAXRET, and high *iBeta* portfolios have the lowest *BO_Inventory_Value* and, therefore, the highest arbitrage cost estimates. Overall, these results are consistent with our conjecture that the underperformance of inflation-sensitive lottery-type stocks reflect mispricing.

3.8. Mispricing and Correction Patterns

If our results reflect gambling-induced mispricing, the impact should weaken over time as arbitrage forces correct the potential mispricing. We test this conjecture by examining the portfolio return patterns during the six months following the portfolio formation date. As

before, we consider IVOL and MAXRET based Long-Short portfolios within the subset of top iBeta quintile firms. Similar to the decline in the MIS estimates, we expect the Long-Short portfolio returns to decline in the months following the portfolio formation date.

Table VII presents the difference in average MIS rankings between the long and short portfolios for the six months following portfolio formation. This table also presents the four-factor alpha estimates when there is 1-6 months gap between the the portfolio formation month and the starting month for performance measurement. We find the negative relation between inflation sensitive lottery stocks and returns is significant in the first three months for IVOL-sorted portfolios and two months for MAXRET-sorted portfolios. The alpha in the first month following the portfolio formation month is -1.408%(t-statistic = -5.85) for the IVOL-sorted portfolio and -1.131%(t-statistic = -5.16) for the MAXRET-portfolio. In the second month, the alpha for the IVOL portfolio drops to -0.977%(t-statistic = -2.88). The MAXRET portfolio alpha also drops significantly to -0.534%(t-statistic = -2.06).

Together, these results indicate that gambling-induced mispricing gradually diminishes over time. The mispricing is corrected within the first three months, which suggests that sophisticated arbitrageurs are unable to exploit the gambling-induced mispricing immediately.

3.9. Arbitrage Costs and Inflation-Induced Overpricing

In the next set of tests, we provide additional direct evidence for the mispricing narrative using arbitrage cost measures. Inflation sensitive lottery stocks are more likely to become overpriced if there are factors that prevent arbitrageurs from stepping in to correct the mispricing generated by increased inflation-induced gambling demand. We use a measure that captures the ease of arbitrage to establish this link. Specifically, we test whether arbitrage costs vary across lottery stock portfolios and whether the negative lottery stock premium is greater among stocks with higher arbitrage costs.

We measure the ease of arbitrage using $BO_Inventory_Value$, which measures the ease

with which the shares of a firm can be borrowed. Lower values of $BO_Inventory_Value$ reflect higher arbitrage costs. We first compute the averages of this measure across various double-sorted portfolios. Panel A (B) of Table VIII presents the average values for high iBeta portfolios sorted on IVOL (MAXRET). We find that arbitrage costs are significantly higher for stocks in high IVOL and MAXRET portfolios, relative to low IVOL or MAXRET portfolios. These averages increase monotonically, where the difference between the top and bottom quintile of IVOL and MAXRET portfolios are -0.085 (t-statistic = -13.56) and 0.059 (t-statistic = -9.67), respectively.

We also examine whether arbitrage costs for stocks with high lottery stock characteristics differ across iBeta portfolios. The average arbitrage cost estimates across iBeta portfolios are presented in Panels C and D of Table VIII. Again, we find that arbitrage costs increase as iBeta increases, where the difference in $BO_Inventory_Value$ between the top and bottom iBeta quintile is -0.30 (t-statistic = -5.96) for high IVOL stocks and -0.046 (t-statistic = -7.67) for high MAXRET stocks. These arbitrage cost patterns are consistent with our finding that the negative lottery stock premium is larger in magnitude for stocks with high inflation sensitivity.

Next, we use Fama-MacBeth regressions to examine whether the negative lottery stock premium is larger among stocks with higher arbitrage costs. We introduce a triple interaction term between *iBeta*, IVOL (or MAXRET), and *BO_Inventory_Value* in our baseline Fama-MacBeth specification. We create an indicator for high versus low arbitrage costs based on the median. This triple interaction term quantifies the sensitivity of the high-*iBeta*, high IVOL or MAXRET firms to high arbitrage costs. A negative coefficient estimate on the interaction term would support our conjecture and indicate that higher arbitrage costs amplify mispricing.

Table IX presents the Fama-MacBeth estimates. Columns (1) and (2) present the results using quintile values for IVOL, MAXRET, and *iBeta*. As expected, we find that the lottery stocks have more negative premium when arbitrage costs are high. Specifically, the returns

of inflation-sensitive lottery stocks with high costs of arbitrage are 0.071% lower on average when the portfolios are sorted on IVOL and 0.057% lower when sorted on MAXRET for a given *iBeta* lottery stock portfolio. Columns (3) and (4) present the results using high (low) indicator variables for IVOL, MAXRET, and *iBeta*. We find that high arbitrage costs are associated with a 0.476% and 0.467% lower monthly lottery stock premium when we sort on IVOL and MAXRET, respectively. All coefficient estimates are statistically significant at the 1% level.

Overall, arbitrage cost based sorting results and Fama-MacBeth regression results support our key conjecture that lottery stocks with higher inflation sensitivity are more overpriced because gambling demand increases during periods of high inflation.

3.10. Inflation, Gambling, and Return Comovements

Existing literature has established that gambling generates excess return comovement among stocks with lottery characteristics (Kumar et al. (2016)) due to systematic demand for lottery stocks. In this section, we test whether inflation exacerbates the demand for lottery stocks by examining whether return comovement among lottery stocks increases for stocks with greater inflation sensitivity. We conjecture that inflation-induced gambling behavior will lead to an increase in correlated trading in response to inflationary pressures. If this is the case, we expect excess return comovement to be greater among lottery stocks with a high sensitivity to inflation.

We measure comovement using the Kumar et al. (2016) method, where we estimate time series regressions of excess returns on an equal-weighted index of lottery stocks and the Fama-French three factors. Specifically, we estimate the following time-series regression:

$$r_{it} - r_{ft} = \beta_0 + \beta_1 INDEX_{it} + \beta_2 RMRF_t$$

$$+ \beta_3 SMB_t + \beta_4 HML_t + \varepsilon_{it}$$

$$(4)$$

where INDEX is the return index used to measure the degree of return comovement. We

use three versions of INDEX to capture comovement with lottery stocks: an index of stocks that fall in the top quintile of IVOL, an index of stocks that fall in the top quintile of MAXRET, and an index of stocks that fall into the top quintiles of both IVOL and MAXRET. All indices are equal-weighted. We then use β_1 as our measure of excess return comovement.

As before, we estimate Fama-MacBeth cross-sectional regressions where we regress stocklevel excess return comovement on each of the two lottery stock characteristics, *iBeta*, and the interaction between the two. A positive coefficient on the interaction term would indicate that inflation-sensitive lottery stocks experience greater excess return comovement with the lottery stock index.

Table X presents the results. Consistent with our key conjecture, we find that excess return comovement is greater for high iBeta lottery stocks across all three comovement measures. Panel A presents the results establishing the relation between inflation sensitive lottery stocks and return comovement in the month of portfolio formation. We find, for high iBeta lottery stocks, return comovement in month t is between 0.144 and 0.172 units higher relative to low iBeta non-lottery stocks. The relation persists when predicting comovement in the following month as show in Panel B.¹⁴

Additionally, we test whether greater return comovement predicts returns by adding an interaction term between each of the lottery characteristics, *iBeta*, and the stock-level return comovement measures. We perform Fama-MacBeth cross-sectional regressions similar to the baseline specification, except with an additional triple interaction term. If excess return comovement is driven by a systematic demand for lottery stocks during inflationary periods, we expect greater mispricing among inflation-sensitive lottery stocks that are subject to greater gambling demand induced pressure. We then expect a larger correction in the following month.

Consistent with this conjecture, we find that higher return comovement predicts greater

¹⁴Given that the average value of return comovement is 0.254 for the LOTT index, an increase of 0.144 among inflation sensitive lottery stocks is economically meaningful.

negative returns among inflation-sensitive lottery stocks. The results are presented in Table XI. This evidence supports the hypothesis that inflation induces gambling tendencies, which results in an increase in the demand for lottery stocks. We observe that this systematic demand leads to greater mispricing among inflation sensitive lottery stocks.

Overall, these results provide evidence consistent with our conjecture that high inflation induces correlated trading in lottery stocks. Further, this increase in correlated trading among inflation sensitive lottery stocks is associated with larger negative returns in the following month.

4. Robustness Checks and Alternative Explanations

In this section, we gather additional supportive evidence for our main results and examine alternative explanations for our findings.

4.1. Gambling or Inflation Hedging?

The extant asset pricing literature speaks towards the effectiveness of equities as a hedge against inflation (Bodie (1976); Stulz (1986); Fama and Schwert (1977)). Investors may turn to certain equities with lottery stock characteristics to hedge potential losses in purchasing power due to inflation. This hedging demand could potentially explain our findings of a negative relation between inflation sensitive lottery-type stocks and future returns.

We test this alternative explanation by creating an inflation hedging demand instrument and testing whether an increase in inflation hedging demand predicts the negative returns of inflation sensitive lottery stocks. We follow Addoum et al. (2019) and create an inflation hedging demand instrument (InfHD) by estimating a vector of conditional covariances between inflation innovations, the returns of the Fama-French three portfolios, and the returns of the twenty five portfolios double sorted by lottery characteristics (IVOL and MAXRET) and iBeta. We then scale this vector of covariances by the variance-covariance matrix of all

portfolio returns.

Separately for each lottery proxy, we define the inflation hedging demand instrument as the term corresponding to the covariance of inflation innovations and the portfolio containing stocks that fall into the top quintiles of the respective lottery proxy and *iBeta*. We obtain a time series of *InfHD* using a rolling window of the past 10 years of data to obtain covariances for each month. We use *InfHD* to test whether an increase in inflation hedging demand predicts the returns of various Long—Short portfolios.

We estimate return predictability regressions following Addoum et al. (2019), where we estimate the predictability of *InfHD* for the *iBeta* Lottery stock premium including controls for the dividend yield on the value-weighted CRSP market index over the previous 12 months, the yield on the three-month T-bill, unexpected GDP growth, and the difference between the average yields of bonds with a Moody's rating of AAA and those with a rating of BAA. We find no significant relation between our inflation hedging demand instrument and the returns of Long—Short portfolios, double-sorted on IVOL or MAXRET and *iBeta*. The coefficient on the inflation hedging instrument is positive but statistically insignificant.

This evidence suggests that our findings are unlikely to result from an increase in hedging demand for lottery-type stocks to compensate for inflation-induced loss in purchasing power.

4.2. Split Sample Estimates

The macroeconomic environment has changed significantly between 1963 and 2024. If investors react to inflationary pressures differently across different regimes, our findings might be concentrated within a particular time period. To examine this possibility, we split the sample into two periods and test whether our key results hold in both subsamples. Specifically, we examine whether our lottery proxies and *iBeta* negatively predict returns during pre-1990 and post-1990 periods.

We estimate a series of Fama-MacBeth regressions mirroring our baseline specification in section 4.1. Table XII presents the results. Panel A presents the estimates from estimating

monthly cross-sectional regressions during the pre-1990 sample period, and Panel B present the results for the post-1990 sample period. Columns (1) and (2) present the results from quintile regression specifications, while for ease of economic interpretation, columns (3) and (4) present the results from specifications using indicator variables for above and below median values for these variables.

We find that the interaction of our lottery proxies with iBeta negatively predicts the following month returns in both the pre- and post-1990 subperiods. In the pre-1990 sample, high iBeta firms with above median IVOL is associated with a 0.254% lower average return in the future. This estimate during the post-1990 period is -0.371% (t-statistic = -6.43). Similarly, for high iBeta and high MAXRET firms, the incremental decline in performance during the pre-1990 and post-1990 sample periods are -0.578% (t-statistic = -7.17) and -0.615% (t-statistic = -9.60), respectively.

These estimates indicate that investor response to high inflationary environment is persistent over time. In economic terms, the overpricing magnitudes of lottery-type stocks are similar across both sub-periods and they are also both statistically significant at the 1% level. Thus, regardless of the specific monetary regime, investors increase their demand for speculative investments during high inflationary periods.

4.3. Estimates using Alternative Lottery Measures

To ensure that our results are not specific to our chosen lottery proxies, in the next set of tests, we extend our analysis to four additional ways to define lottery stocks. The alternative lottery proxies include SKEW, ISKEW, ESKEW, and LOTTERY. The first measure, SKEW, is the total skewness of daily returns for a given stock over the past month. The second measure ISKEW is the skewness of residuals, which are obtained from running the four-factor model of Carhart (1997) on daily returns over the past month. Our third measure, ESKEW, is motivated by the evidence in the Boyer et al. (2010) study, which finds that ESKEW is a better predictor of returns compared to idiosyncratic skewness or skewness alone. We

estimate a cross-sectional regression at the end of each month using the most recent five years of data, and these estimates are then used to predict the expected idiosyncratic skewness over the next five years.

Lastly, LOTTERY is a combined measure of our original lottery proxies, IVOL and MAXRET. Specifically, our LOTTERY measure takes the value of one if a stock falls into the top quintile of IVOL and MAXRET in month t-1, and zero otherwise. By combining our lottery proxies, we ensure that the results are driven by their joint properties as opposed to unrelated factors specific to either proxy.

Similar to our baseline tests, we estimate a series of Fama-MacBeth cross-sectional regressions using these four alternative lottery proxies and their interactions with iBeta. The estimates are presented in Appendix Table A.3. Panel A presents the results from quintile regression specifications, and for ease of economic interpretation, Panel B presents the results from specifications that use indicator variables for above and below median values for these variables.

We find that all four alternative lottery characteristics predict lower subsequent returns as inflation sensitivity increases. As shown in Panel B, the magnitude of the interactive effect of high *iBeta* for firms with high values of these alternative lottery characteristics ranges from 18.7 basis points for ESKEW to 103.8 basis points for the combined LOTTERY measure. It is interesting to note that the combined effect is greater than the individual effects of IVOL and MAXRET shown in Table V. Stocks with both high IVOL and high MAXRET are more likely to be perceived as lotteries relative to firms that have high values of only one of these characteristics.

Additionally, for stocks in top quintile of ESKEW, high *iBeta* is associated with a 18.7 basis point reduction in subsequent returns. The smaller magnitude for ESKEW stocks is justified for several reasons. First, ESKEW is a relatively complex metric to compute, making it unlikely that a typical retail investor will select stocks based on ESKEW. Second, ESKEW is based on expected skewness over a longer duration (5 years), while the speculative

demand documented earlier in the paper is driven by shorter investment horizons.

Overall, these results using alternative lottery measures further support the conjecture that investors seek lottery-type investments to compensate for inflation-induced loss in purchasing power. Our key findings are unlikely to be driven by unobserved factors associated with our main lottery proxies, IVOL and MAXRET.

4.4. Impact of Sentiment, Uncertainty, or Inflation Expectations?

One potential concern with our findings is that our *iBeta* estimates could reflect the effects of broader market sentiment or economic conditions rather than inflation sensitivity specifically. To examine this possibility, we re-estimate *iBeta* while controlling for various measures of market sentiment and economic uncertainty. First, we include the sentiment index from Baker and Wurgler (2006) as an additional control. As shown in columns (1) and (2) of Table XII, our key findings remain robust—the interaction between *iBeta* and both lottery proxies (IVOL and MAXRET) continues to be negative and highly significant, with magnitudes similar to our baseline results.

We also examine whether our results reflect the effects of the overall economic environment rather than inflation alone. In columns (3) and (4), we add the NBER recession indicator when estimating iBeta to control for broader economic cycles. The results remain qualitatively similar, with the interaction terms retaining their negative signs (-0.261 for IVOL and -0.542 for MAXRET) and statistical significance. Similarly, in columns (5) and (6), when computing inflation sensitivity, we control for economic policy uncertainty using the Baker et al. (2016) measure. Even after accounting for policy uncertainty, we continue to find that lottery stocks with high inflation sensitivity significantly earn lower returns in the future. The interaction term estimates are -0.345 for IVOL and -0.612 for MAXRET.

As a final robustness check, we use expected inflation rather than realized inflation innovations when computing iBeta (see columns (7) and (8)). Again, the results remain consistent with our main findings—the interaction terms retain their negative signs (-0.328 for IVOL and -0.587 for MAXRET) and economic significance. Together, the results from these additional tests suggest that the greater mispricing of lottery stocks in high inflationary environment do not simply reflect the effects of broader market sentiment, economic conditions, or policy uncertainty.

4.5. Positive and Negative Inflation Betas

To better understand how inflation sensitivity affects the relation between lottery characteristics and future returns, we examine whether the effect differs between stocks with positive and negative inflation betas. Given that our *iBeta* measure is intended to capture investor attention toward high inflation, we posit that both positive and negative values of stock-level inflation sensitivity will increase investor attention. However, it is possible that there is an asymmetry in investor attention and the effects on return predictability between positive and negative *iBeta* stocks. To examine whether this asymmetry exists, we estimate a series of Fama-MacBeth regressions, similar to our baseline specification, where we test the predictability of returns for positive and negative *iBetas* separately.

As shown in Appendix Table A.4., we find that the results are similar between the positive and negative iBeta subsamples, with the magnitude of the iBeta lottery stock premium being slightly stronger among the positive iBeta subsample. For positive iBeta stocks, the interaction coefficients between our lottery proxies and iBeta are -0.305 (t-statistic = -5.17) and -0.609 (t-statistic = -8.89), while the interaction coefficients among negative iBeta stocks are -0.286 (t-statistic = -4.88) and -0.498 (t-statistic = -8.00) for IVOL and MAXRET respectively.

These findings suggest that both positive and negative inflation sensitivity affect the relation between lottery characteristics and future returns. The effect is somewhat stronger for stocks with positive inflation betas, which could reflect investors' differential response to positive versus negative comovement with inflation.

4.6. Estimates Excluding COVID Years

To ensure that our findings are not driven by the abnormal market conditions during the COVID-19 pandemic, we examine whether the relation between inflation sensitivity, lottery characteristics, and returns remains robust when excluding the 2020-2022 period.

As shown in Appendix Table A.5, we find that our key findings remain robust when excluding the COVID years. The interaction terms between iBeta and lottery characteristics continue to be negative and highly significant across different specifications. When using continuous independent variables, the interaction coefficient between IVOL and iBeta is -0.103 (t-statistic = -6.78), while the interaction between MAXRET and iBeta is -0.042 (t-statistic = -8.43). When using quintile rankings, these effects strengthen to -0.072 (t-statistic = -10.77) for IVOL and -0.132 (t-statistic = -16.67) for MAXRET. When using indicator variables, the interaction coefficients are -0.312 (t-statistic = -7.24) and -0.589 (t-statistic = -11.91) for IVOL and MAXRET, respectively.

These findings suggest that the relation between inflation sensitivity and lottery stock returns is not merely an artifact of the unusual market conditions during the COVID-19 pandemic. Instead, it appears to be a persistent feature of stock returns in more normal market environments.

4.7. Controlling for the Fear Index

Finally, to address potential concerns that our results can be driven by general market fear or uncertainty rather than inflation sensitivity specifically, we examine whether our findings remain robust when controlling for the VIX index, commonly known as the market's "fear gauge." The VIX index measures expected market volatility and often spikes during periods of market stress, which could potentially confound our inflation sensitivity results. Similar to how we control for sentiment in Section 4.4., we include the VIX index as an additional control when computing our iBeta estimates.

In untabulated results, we find that controlling for VIX does not materially affect our

main findings. The interaction between iBeta and lottery characteristics remains negative and highly significant. For IVOL, the interaction coefficient is -0.397 (t-statistic = -7.47), while for MAXRET, the interaction coefficient is -0.625 (t-statistic = -10.90). These magnitudes are comparable to our baseline results, suggesting that the relation between inflation sensitivity and lottery stock returns is distinct from general market fear effects.

These findings indicate that the relationship between inflation sensitivity and lottery stock returns is distinct from general market fear or uncertainty as captured by the VIX index. The robustness of our results to VIX controls suggests that greater investment in lottery stocks during high inflation periods is not simply a manifestation of broader market anxiety.

5. Summary and Conclusions

This paper examines the link between inflation and asset prices in certain segments of financial markets that attract gambling and speculative trading. The existing evidence on how U.S. investors respond to high rates of inflation is very limited. It is also not clear how inflation affects financial markets through its systematic impact on investor demand. In this study, we identify a novel gambling channel through which inflation affects investor demand and asset prices.

Our study is motivated by the evidence of increased allocations to risky assets during high inflationary periods (Bonaparte et al. (2024)). If investor risk aversion declines, it is likely that they also exhibit a stronger desire to gamble and engage in speculation, especially when they perceive a loss in their purchasing power. Additionally, if gambling demand shifts are systematic and arbitrage forces are weak, inflation-induced gambling demand could affect asset prices. In particular, Barberis and Huang (2008) asset pricing model predicts that lottery-type investments will become overpriced and earn lower returns in the future, as the mispricing is corrected.

Our results indicate that demand for lottery-type investments increases during high inflationary periods, as risk aversion declines and the preference for skewness becomes stronger. Lottery-type stocks are also more difficult to arbitrage, especially those with high sensitivity to inflation. Using maximum daily return and idiosyncratic volatility as main proxies for lottery-type stocks, we find that inflation-sensitive lottery-type stocks systematically underperform. They become more overpriced during high inflationary periods and earn lower returns in the future. This negative lottery-return relation is stronger for stocks with greater sensitivity to inflation, and also for firms with high retail trading and located in regions with stronger gambling propensity.

We do not find support for alternative explanations for these return patterns, such as inflation hedging. Our results are not time-period specific as investor response to high inflation is persistent over time. We also demonstrate that the greater mispricing of lottery stocks do not reflect the impact of broader market sentiment, economic factors, policy uncertainty, or market anxiety. In addition, we confirm that our results are not driven by the abnormal market conditions during the COVID-19 pandemic.

Together, these findings are consistent with the predictions of the Barberis and Huang (2008) model and indicate that inflation affects asset prices through the gambling channel. There is a dynamic relation between rising inflation and investor preferences. As inflation rises, the allure of potentially high returns outweigh the potential aversion to risk during high inflationary periods, indicating a nuanced and dynamic response to changing economic conditions. Recognizing and understanding this behavioral shift is crucial for financial advisors and policymakers, as it underscores the need for tailored investment approaches that are better aligned with evolving risk preferences of households in a dynamic inflationary landscape.

References

- Addoum, J. M., S. Delikouras, G. M. Korniotis, and A. Kumar (2019). Income hedging, dynamic style preferences, and return predictability. *Journal of Finance* 74(4), 2055–2106.
- Andrei, D., H. Friedman, and N. B. Ozel (2023). Economic uncertainty and investor attention. *Journal of Financial Economics* 149(2), 179–217.
- Baker, M. and J. Wurgler (2006). Investor sentiment and the cross-section of stock returns. Journal of Finance 61(4), 1645–1680.
- Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. Quarterly Journal of Economics 131(4), 1593–1636.
- Bali, T. G., N. Cakici, and R. F. Whitelaw (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics* 99(2), 427–446.
- Barberis, N. and M. Huang (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review 98*(5), 2066–2100.
- Barberis, N., M. Huang, and T. Santos (2001). Prospect theory and asset prices. *Quarterly Journal of Economics* 116(1), 1–53.
- Barberis, N., A. Mukherjee, and B. Wang (2016). Prospect theory and stock returns: An empirical test. *Review of Financial Studies* 29(11), 3068–3107.
- Bekaert, G., E. C. Engstrom, and N. R. Xu (2022). The time variation in risk appetite and uncertainty. *Management Science* 68(6), 3975–4004.
- Bekaert, G., M. Hoerova, and M. L. Duca (2013). Risk, uncertainty and monetary policy. Journal of Monetary Economics 60(7), 771–788.
- Bodie, Z. (1976). Common stocks as a hedge against inflation. *Journal of Finance* 31(2), 459–470.
- Boehmer, E., C. M. Jones, X. Zhang, and X. Zhang (2021). Tracking retail investor activity. Journal of Finance 76(5), 2249–2305.
- Bonaparte, Y., G. M. Korniotis, A. Kumar, and M. Murren Vosse (2024). Monetary policy, inflation hedging, and portfolio choice. *Management Science* 70(9), 6438–6460.

- Boons, M., F. Duarte, F. De Roon, and M. Szymanowska (2020). Time-varying inflation risk and stock returns. *Journal of Financial Economics* 136(2), 444–470.
- Boyer, B., T. Mitton, and K. Vorkink (2010). Expected idiosyncratic skewness. *Review of Financial Studies* 23(1), 169–202.
- Campbell, J. Y. and J. H. Cochrane (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy* 107(2), 205–251.
- Campbell, J. Y., J. Hilscher, and J. Szilagyi (2008). In search of distress risk. *Journal of Finance* 63(6), 2899–2939.
- Capacci, S., E. Randon, and A. E. Scorcu (2017). Are consumers more willing to invest in luck during recessions? *Italian Economic Journal* 3, 25–38.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance* 52(1), 57–82.
- Carroll, C. D. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. Quarterly Journal of Economics 112(1), 1–55.
- Carroll, C. D., R. E. Hall, and S. P. Zeldes (1992). The buffer-stock theory of saving: Some macroeconomic evidence. *Brookings Papers on Economic Activity* 1992(2), 61–156.
- Chen, L., R. Novy-Marx, and L. Zhang (2011). An alternative three-factor model. Working Paper, Available at SSRN: https://ssrn.com/abstract=1418117.
- Chhaochharia, V., J. Guo, X. Han, and A. Kumar (2024). Blinded by lottery preferences? Earnings news, gambling-motivated trading, and informational efficiency. *Working Paper*, *Available at SSRN:* https://ssrn.com/abstract=4595557.
- Cooper, M. J., H. Gulen, and M. J. Schill (2008). Asset growth and the cross-section of stock returns. *Journal of Finance* 63(4), 1609–1651.
- Daniel, K. and S. Titman (2006). Market reactions to tangible and intangible information. Journal of Finance 61(4), 1605–1643.
- Fama, E. F. and K. R. French (2006). The value premium and the CAPM. *Journal of Finance* 61(5), 2163–2185.
- Fama, E. F. and K. R. French (2008). Dissecting anomalies. *Journal of Finance* 63(4), 1653–1678.

- Fama, E. F. and M. R. Gibbons (1984). A comparison of inflation forecasts. *Journal of Monetary Economics* 13(3), 327–348.
- Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81(3), 607–636.
- Fama, E. F. and G. W. Schwert (1977). Asset returns and inflation. *Journal of Financial Economics* 5(2), 115–146.
- Green, T. C. and B.-H. Hwang (2011). Initial public offerings as lotteries: Skewness preference and first-day returns. *Management Science* 58(2), 432–444.
- Guiso, L. and M. Paiella (2008). Risk aversion, wealth, and background risk. *Journal of the European Economic Association* 6(6), 1109–1150.
- Guiso, L., P. Sapienza, and L. Zingales (2018). Time varying risk aversion. *Journal of Financial Economics* 128(3), 403–421.
- Hazell, J., J. Herreno, E. Nakamura, and J. Steinsson (2022). The slope of the Phillips curve: Evidence from US states. *Quarterly Journal of Economics* 137(3), 1299–1344.
- Heaton, J. and D. Lucas (2000). Portfolio choice in the presence of background risk. *The Economic Journal* 110(460), 1–26.
- Hirshleifer, D., K. Hou, S. H. Teoh, and Y. Zhang (2004). Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics* 38, 297–331.
- Hong, H., J. D. Kubik, and J. C. Stein (2008). The only game in town: Stock-price consequences of local bias. *Journal of Financial Economics* 90(1), 20-37.
- Hou, K. and R. K. Loh (2016). Have we solved the idiosyncratic volatility puzzle? *Journal of Financial Economics* 121(1), 167–194.
- Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48(1), 65–91.
- Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica* 47(2), 263–291.
- Kahneman, D. and A. Tversky (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5, 297–323.

- Kaul, G. (1987). Stock returns and inflation: The role of the monetary sector. *Journal of Financial Economics* 18(2), 253–276.
- Kumar, A. (2009). Who gambles in the stock market? Journal of Finance 64(4), 1889–1933.
- Kumar, A., M. Motahari, and R. J. Taffler (2024). Skewness sentiment and market anomalies. *Management Science* 70(7), 4328–4356.
- Kumar, A., J. K. Page, and O. G. Spalt (2011). Religious beliefs, gambling attitudes, and financial market outcomes. *Journal of Financial Economics* 102(3), 671–708.
- Kumar, A., J. K. Page, and O. G. Spalt (2016). Gambling and comovement. *Journal of Financial and Quantitative Analysis* 51(1), 85–111.
- Lou, D., C. Polk, and S. Skouras (2019). A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics* 134(1), 192–213.
- Loughran, T. and J. R. Ritter (1995). The new issues puzzle. *Journal of Finance* 50(1), 23-51.
- Malmendier, U. and S. Nagel (2011). Depression babies: do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics* 126(1), 373–416.
- Menzly, L., T. Santos, and P. Veronesi (2004). Understanding predictability. *Journal of Political Economy* 112(1), 1–47.
- Mikesell, J. L. (1994). State lottery sales and economic activity. *National Tax Journal* 47(1), 165–171.
- Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55(3), 703–708.
- Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics* 108(1), 1–28.
- Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 109–131.
- Ritter, J. R. (1991). The long-run performance of initial public offerings. Journal of Finance 46(1), 3–27.
- Seasholes, M. S. and N. Zhu (2010). Individual investors and local bias. *Journal of Finance* 65(5), 1987–2010.

- Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 289–315.
- Stambaugh, R. F., J. Yu, and Y. Yuan (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics* 104(2), 288–302.
- Stambaugh, R. F., J. Yu, and Y. Yuan (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance* 70(5), 1903–1948.
- Stulz, R. M. (1986). Asset pricing and expected inflation. *Journal of Finance* 41(1), 209–223.
- Titman, S., K. J. Wei, and F. Xie (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis* 39(4), 677–700.
- Vassalou, M. (2000). Exchange rate and foreign inflation risk premiums in global equity returns. *Journal of International Money and Finance* 19(3), 433–470.
- Wachter, J. A. (2006). A consumption-based model of the term structure of interest rates. Journal of Financial economics 79(2), 365–399.
- Xing, Y. (2008). Interpreting the value effect through the q-theory: An empirical investigation. Review of Financial Studies 21(4), 1767–1795.

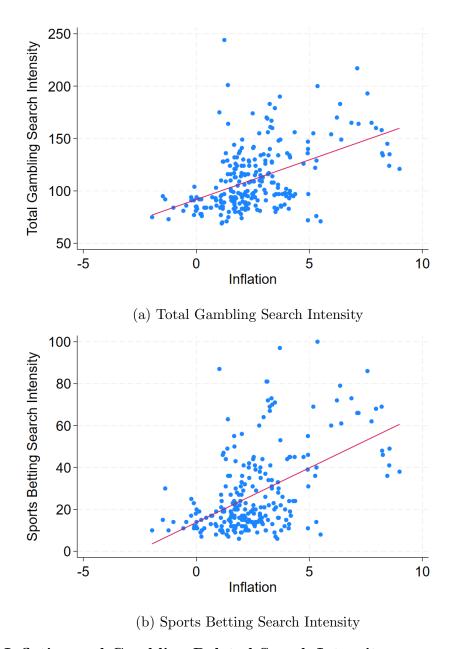


Figure 1: Inflation and Gambling-Related Search Intensity

This figure shows the relation between inflation and internet search intensity of gambling-related terms. Panel A presents a scatter plot and the best fitting line between monthly search intensities for a combination of four gambling-related search terms (i.e., overall gambling search intensity) against the annual change in inflation. The search terms include "gambling," "lottery," and "Powerball," and "sports betting." Panel B presents a scatter plot and the best fitting line between monthly search intensity for the singular term "sports betting" against the annual change in inflation. The sample period is from 2004 to 2024.

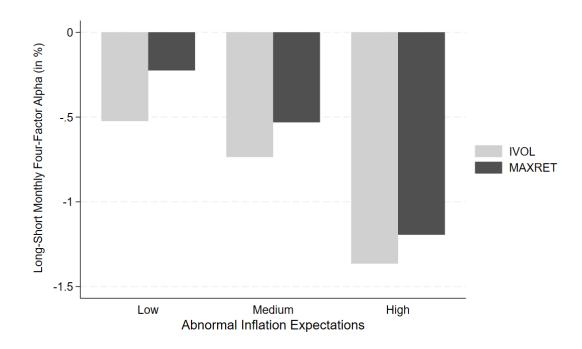


Figure 2: Inflation Expectations and Portfolio Performance

This figure plots the average risk-adjusted returns of portfolios that take a Long position in the top quintile of IVOL or MAXRET and a Short position in the bottom quintile of IVOL or MAXRET. Stocks are sorted based on information available at the end of month t and returns are calculated over the following month. Risk-adjusted returns using the four-factor model of Carhart (1997) are shown. The light (dark) gray bars illustrate the alphas for portfolios sorted on IVOL (MAXRET). We examine the returns of these long-short portfolios over periods of low, medium, and high abnormal expected inflation, where expected inflation is an estimate of expected inflation over the next year generated by the Federal Reserve Bank of Cleveland. Abnormal monthly inflation expectations are measured relative to the past ten years of inflation expectations.

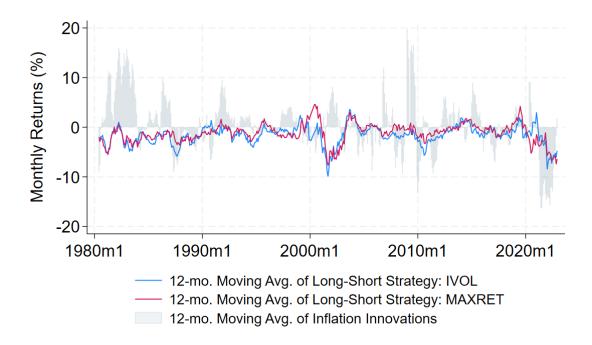


Figure 3: Trading Strategy Performance Time Series

This figure plots the 12-month moving average of risk-adjusted returns of a portfolio that takes a Long position in the top quintile of IVOL or MAXRET and a Short position in the bottom quintile of IVOL or MAXRET. We consider only the stocks within the high iBeta quintile. Stocks are sorted based on information available at the end of month t and returns are calculated over the following month. Risk-adjusted returns using the four-factor model of Carhart (1997) are shown. The blue line indicates the returns of IVOL-based Long-Short portfolio, and the red line indicates the return of MAXRET-based Long-Short portfolio. The light gray bars indicate inflation innovations in month t, filtered using an ARMA(1,1) model. The inflation innovations are scaled by a factor of 1,000 to increase readability of the graph.

Table I: Summary Statistics

This table presents summary statistics for the main variables. Panel A presents statistics for variables related to gambling-related search intensity, inflation, and risk aversion. Panel B presents statistics related to stock-level measures. Panel C presents the average values of monthly stock characteristics for high and low *iBeta* firms. Stocks are categorized as Low (High) *iBeta* if they fall into the bottom (top) quintile of *iBeta* in a given month. Stocks that do not fall into either of these two categories are classified as "Others." Columns (4) and (5) contain statistics for stocks with large positive and negative values of *iBeta*, respectively. Large negative (positive) *iBeta* stocks are those that are in the top 20th percentile of the absolute value of *iBeta*, conditional on negative (positive) *iBeta* values. *iBeta* is defined by regressing a stock's excess returns on monthly inflation innovations and the three Fama-French factors using the past sixty months of data. Inflation innovations are filtered using an ARMA(1,1) model to account for the autogregressive nature of monthly inflation. All variables are defined in Appendix Table A.1. All variables are defined in Appendix Table A.1.

Panel A: Gambling Search Intensity and Macroeconomic Variables

Variable	Mean	StdDev	25th Pctl	Median	75th Pctl
Sports Betting Search Intensity	27.600	19.800	13.000	20.000	37.000
Gambling Search Intensity	35.900	13.300	27.000	31.000	41.000
Lottery Search Intensity	42.500	11.700	32.000	43.000	50.000
Powerball Search Intensity	5.800	7.900	3.000	4.000	5.000
Total Gambling Search Intensity	111.700	30.300	89.000	101.500	129.000
State Lottery Revenue (Per Capita)	\$58.700	\$51.40	\$22.800	\$47.600	\$86.800
Abnormal State Inflation (monthly)	-0.089	1.068	-0.696	-0.069	0.545
% Inflation (monthly)	0.231	0.269	0.110	0.229	0.364
% Inflation (annual)	2.758	1.603	1.715	2.601	3.509
Risk Aversion Index	3.455	2.121	2.254	3.271	4.381

Panel B: Stock-Level Variables

Variable	Mean	StdDev	25th Pctl	Median	75th Pctl
iBeta	1.187	2.961	0.260	0.612	1.304
Intraday Return	0.014	0.397	-0.078	0.003	0.085
Overnight Return	0.016	0.197	-0.044	0.003	0.054
IVOL	2.500	1.661	1.298	2.072	3.278
MAXRET	6.740	4.781	3.209	5.367	9.009
MIS	5.384	2.863	3.000	5.000	8.000
ISKEW	0.157	0.792	-0.266	0.141	0.571
SKEW	0.472	0.581	0.217	0.441	0.693
ESKEW	0.346	0.228	0.221	0.353	0.461
CPRATIO	1.717	1.485	0.518	1.379	2.561
Retail Trade Intensity	0.061	0.059	0.026	0.039	0.070

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Table I – continued from previous page $\,$

Panel C: Portfolio Characteristics

Variable	Others	iBeta Q1	iBeta Q5	iBeta > 0 Q5	iBeta < 0 Q5
VOL	2.902	2.501	3.858	3.809	3.888
IVOL	2.381	2.035	3.217	3.165	3.251
SKEW	0.476	0.419	0.543	0.530	0.553
ISKEW	0.155	0.142	0.184	0.180	0.186
Stock Price	23.271	28.113	12.452	13.483	11.702
Market Beta	0.901	0.851	0.964	0.978	0.954
Firm Size (in \$m)	$2,\!352$	3,845	501	559	452
Book-to-Market	0.879	0.89	0.781	0.778	0.780
Past 12-mo. Return	11.337	10.752	11.953	12.027	11.873
Avg Daily Turnover	0.006	0.005	0.009	0.009	0.009
Retail Trade Intensity	0.057	0.054	0.074	0.071	0.076
MIS	5.212	4.947	6.39	6.355	6.415
BO_Inventory_Value	0.185	0.193	0.126	0.128	0.125
DCBS	1.483	1.353	2.225	2.170	2.264

Table II: Risk Aversion and State Lottery Demand Regression Estimates

This table presents estimates from regressions estimating the effect of inflation on risk aversion and per capita state lottery revenues. The dependent variable in columns (1) to (5) is monthly risk aversion in month t, while the dependent variable in columns (6) and (7) is annual state lottery revenues per capita in 2010 dollars. CPI Change is the percentage change in CPI in month t relative to CPI in month t-12. Adjusted State CPI Change is the monthly state-level inflation minus national inflation in month t. Inflation is the annual state-level innovation in inflation relative to national inflation. Expected CPI Change is an estimate of expected inflation over the next year from the Federal Reserve. The t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. All variables are defined in Appendix Table A.1.

		Risk	Lottery Revenue (6-7)				
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CPI Change	-2.365	-2.036	-2.357	-2.015			
	(-6.58)	(-8.24)	(-6.42)	(-8.00)			
Expected CPI Change					-1.525		
					(-9.20)		
Adjusted State CPI Change						6.067**	6.212***
						(2.16)	(3.72)
Constant	4.002	4.146	4.063	4.137	8.635	59.378***	59.393***
	(31.46)	(8.89)	(11.67)	(8.01)	(11.60)	(7.64)	(341.36)
Year FE	No	Yes	No	Yes	Yes	No	No
Month FE	No	No	Yes	Yes	Yes	No	No
State FE	No	No	No	No	No	No	Yes
N	442	442	442	442	442	589	589
Adjusted R ²	0.090	0.697	0.096	0.703	0.716	0.016	0.737

Table III: Inflation, Lottery Demand, and Individual Investor Portfolios

This table presents estimates from OLS regressions evaluating the extent to which individual investors invest in inflation-sensitive lottery stocks. The dependent variable in all regressions is the excess portfolio weight on stock i in investor j's portfolio in month t relative to stock i's weight in the market portfolio, where we define the CRSP universe as the market portfolio. Experienced Inflation (EI) is a measure of subjective inflation experience based on the investor's individual exposure to local inflation. We create indicator variables for high (low) EI, IVOL, and MAXRET using above (below) median cutoffs and information available at the end of each month. Significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. The definitions for all control variables are in Appendix Table A.1.

	(1)	(2)	(3)	(4)	(5)	(6)
Independent Variable	Full S	Sample	Low I	ncome	High 1	Income
EI	0.288***	0.321***	0.345***	0.399***	0.240***	0.257***
	(6.88)	(7.09)	(5.97)	(6.29)	(4.05)	(4.04)
IVOL	1.068**		0.098		1.840***	
	(2.30)		(0.14)		(2.96)	
$IVOL \times EI$	1.136***		1.739***		0.662*	
	(3.88)		(3.71)		(1.74)	
MAXRET		0.401		-0.322		0.965*
		(1.02)		(-0.53)		(1.86)
$MAXRET \times EI$		0.915***		1.391***		0.548*
		(3.64)		(3.39)		(1.71)
Stock Price	0.053***	0.052***	0.062***	0.060***	0.048***	0.046***
	(18.90)	(18.52)	(13.19)	(12.94)	(15.60)	(15.30)
Market Beta	-0.078***	-0.079***	-0.080***	-0.082***	-0.075***	-0.077***
	(-10.72)	(-10.92)	(-6.75)	(-6.85)	(-10.34)	(-10.54)
$\log(\text{ME})$	-0.024***	-0.025***	-0.025***	-0.026***	-0.023***	-0.024***
	(-31.15)	(-32.46)	(-21.60)	(-22.19)	(-26.66)	(-27.74)
$\log(\mathrm{B/M})$	0.140***	0.126***	0.113***	0.099***	0.163***	0.149***
	(5.13)	(4.78)	(3.50)	(3.15)	(4.41)	(4.13)
RET[-12,-2]	-0.504***	-0.731***	-0.430***	-0.647***	-0.567***	-0.801***
	(-4.75)	(-6.87)	(-3.16)	(-4.73)	(-4.33)	(-6.12)
Systematic Skewness	0.350***	0.334***	0.375	0.360	0.333***	0.314***
	(2.82)	(2.65)	(1.47)	(1.41)	(3.21)	(3.01)
Monthly Volume Turnover	-0.849***	-0.801***	-0.852***	-0.809***	-0.847***	-0.794***
D	(-17.81)	(-16.66)	(-13.36)	(-12.59)	(-16.93)	(-15.93)
Dividend Paying Dummy	0.003***	0.002*	0.005***	0.003**	0.002*	0.000
	(3.43)	(1.82)	(3.12)	(2.10)	(1.86)	(0.45)
Firm Age	0.045***	0.047***	0.044***	0.046***	0.045***	0.048***
00 D K00 D	(25.53)	(26.67)	(17.86)	(18.53)	(20.09)	(20.86)
S&P 500 Dummy	-2.640***	-2.748***	-2.086***	-2.207***	-3.092***	-3.189***
MAGDAOD	(-8.31)	(-8.61)	(-5.01)	(-5.29)	(-6.67)	(-6.85)
NASDAQ Dummy	0.156	0.235	0.813*	0.881*	-0.378	-0.289
C	(0.44)	(0.66)	(1.73)	(1.87)	(-0.74)	(-0.56)
Constant	36.459***	37.740***	37.450***	38.622***	35.710***	37.072***
	(33.76)	(35.33)	(24.80)	(25.69)	(27.24)	(28.30)
Portfolio-Month Obs.	1,439,425	1,439,425	645,734	645,734	793,692	793,692
Adjusted R^2	0.086	0.085	0.078	045,754 0.077	0.095	0.094
Aujusteu N	0.000	0.000	0.010	0.011	0.099	0.094

Table IV: Four-Factor Alpha Estimates for Double-Sorted Portfolios

This table reports the four-factor alpha estimates for double sorted portfolios based on inflation sensitivity (*iBeta*) and measures of lottery-stock characteristics. The portfolios are formed by independently sorting stocks into five portfolios at the end of every month with respect to either IVOL or MAXRET and *iBeta*. Value-weighted returns are then calculated for each of the 25 portfolios. The value-weighted returns are then regressed on the Carhart (1997) four factors. The regression intercept is reported in the table. The *t*-statistics are reported in parentheses. All variables are defined in Appendix Table A.1.

				In	flation Be	ta		
Sorting Variable		All	Low	Q2	Q3	Q4	High	High-Lov
			0.078	0.092	0.054	0.025	-0.180	-0.258
			(2.60)	(2.22)	(1.16)	(0.42)	(-2.12)	(-2.71)
IVOL	Low	0.122	0.080	0.189	0.088	0.120	0.405	0.325
		(3.55)	(1.61)	(3.81)	(1.29)	(1.14)	(2.77)	(2.08)
	2	0.078	0.125	0.071	0.154	0.099	0.001	-0.124
		(1.55)	(1.95)	(0.78)	(1.85)	(1.11)	(0.01)	(-0.81)
	3	0.049	0.083	-0.041	0.117	0.081	0.037	-0.045
		(0.76)	(0.95)	(-0.42)	(0.97)	(0.84)	(0.31)	(-0.32)
	4	-0.248	-0.146	-0.272	-0.382	-0.169	-0.272	-0.126
		(-2.77)	(-0.97)	(-2.23)	(-3.12)	(-1.37)	(-2.04)	(-0.67)
	High	-0.764	-0.482	-0.670	-0.776	-0.524	-1.003	-0.522
		(-5.14)	(-2.78)	(-3.23)	(-3.94)	(-2.80)	(-5.75)	(-2.67)
	$\operatorname{High-Low}$	-0.885	-0.562	-0.859	-0.864	-0.644	-1.408	-0.846
		(-5.35)	(-2.95)	(-3.81)	(-3.98)	(-3.00)	(-5.85)	(-3.20)
MAXRET	Low	0.161	0.086	0.217	0.220	0.193	0.435	0.349
		(3.42)	(1.63)	(3.47)	(3.06)	(1.96)	(3.15)	(2.48)
	2	0.085	0.062	-0.020	-0.009	-0.002	-0.040	-0.102
		(1.57)	(0.98)	(-0.30)	(-0.12)	(-0.02)	(-0.34)	(-0.77)
	3	0.073	0.020	0.068	0.035	-0.017	0.051	0.031
		(1.29)	(0.22)	(0.77)	(0.38)	(-0.21)	(0.42)	(0.21)
	4	-0.113	0.013	-0.098	-0.092	-0.113	-0.425	-0.438
		(-1.24)	(0.10)	(-0.66)	(-0.77)	(-0.95)	(-3.03)	(-2.48)
	High	-0.425	-0.151	-0.482	-0.522	-0.362	-0.696	-0.545
		(-3.85)	(-0.97)	(-3.25)	(-3.55)	(-2.44)	(-4.51)	(-2.85)
	High-Low	-0.579	-0.238	-0.699	-0.742	-0.556	-1.131	-0.894
		(-4.23)	(-1.36)	(-4.07)	(-4.17)	(-2.95)	(-5.16)	(-3.90)

Table V: Baseline Fama-Macbeth Regression Estimates

This table presents estimates from the monthly Fama-MacBeth cross-sectional regressions. At the end of each month, lottery stock characteristics (MAXRET and IVOL) are computed and used to predict returns in the following month. iBeta is computed by regressing excess stock returns at the end of each month t on monthly inflation innovations and the three Fama-French factors using the past sixty months of data. Panel A presents the baseline regressions. Columns (1) through (4) use continuous values of all variables. In columns (5) and (6), IVOL, MAXRET and iBeta represent quintile values, which are defined by sorting stocks into quintile portfolios based on idiosyncratic volatility and maximum daily return information available at the end of month t. In columns (7) and (8), IVOL, MAXRET, and iBeta represent dummy variables, which are indicator variables that take the value of 1 if a stock's idiosyncratic volatility, maximum daily return, and iBeta in month t fall above its respective median in a given month, and 0 otherwise. Stock-level controls include the book-to-market ratio, market value of equity, past returns in the prior 12 months skipping the most recent month, and the returns in the previous month. Panel B presents estimates from monthly Fama-MacBeth cross-sectional regressions where the coefficient of interest is on the interaction between IVOL (or MAXRET), iBeta, and a measure of high gambling exposure. We measure gambling exposure using the proportion of a stock's retail trading intensity (RTI) and the proportion of Catholic-to-Protestant religious adherents in a firm's headquarter county (CPRATIO). Gambling Exposure is an indicator variable that takes the value of 1 if the stock has above median values of RTI or CPRATIO and 0 otherwise. Columns (1) and (2) present the results using RTI as our measure of gambling exposure, and columns (3) and (4) present the results using CPRATIO. We use indicator variables for high (low) IVOL, MAXRET, and iBeta using above (below) median cutoffs and information available at the end of each month. The t-statistics are reported in parentheses below the coefficient estimates. Standard errors are adjusted using the Newey and West (1987) approach with a lag of six. Significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. All variables are defined in Appendix Table A.1.

Panel A: Baseline Fama-MacBeth Regression Estimates								
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
iBeta	-0.023	0.307***	0.098***	0.501***	0.220***	0.506***	0.119***	0.427***
	(-1.12)	(6.51)	(4.06)	(8.84)	(9.30)	(17.39)	(3.48)	(11.89)
IVOL	-0.519***	-0.418***			-0.062		-0.068	
	(-11.48)	(-8.72)			(-1.50)		(-0.60)	
$IVOL \times iBeta$		-0.106***			-0.076***		-0.324***	
MANDEE		(-7.14)	0.400***	0.905***	(-11.14)	0.000***	(-7.44)	1 051***
MAXRET			-0.428***	-0.385***		-0.666***		-1.351***
$\text{MAXRET} \times iBeta$			(-38.05)	(-31.46) -0.044***		(-19.16) -0.137***		(-15.08) $-0.611***$
MAXILI × iDeiu				(-8.88)		(-16.54)		(-12.37)
$\log(B/M)$	-0.801***	-0.793***	-0.948***	-0.935***	-0.751***	-0.893***	-0.720***	-0.827***
0(/ /	(-19.22)	(-19.21)	(-21.85)	(-21.83)	(-18.63)	(-20.99)	(-18.13)	(-20.14)
$\log(ME)$	-0.074***	-0.059**	-0.275***	-0.257***	-0.005	-0.199***	0.031	-0.114***
	(-2.70)	(-2.16)	(-11.20)	(-10.50)	(-0.19)	(-8.44)	(1.26)	(-4.99)
RET[-12,-2]	-0.091	-0.106*	-0.365***	-0.380***	-0.014	-0.215***	-0.010	-0.151**
	(-1.42)	(-1.66)	(-4.61)	(-4.82)	(-0.22)	(-2.69)	(-0.17)	(-2.14)
Ret[-1,0]	0.382***	0.382***	0.399***	0.399***	0.379***	0.392***	0.379***	0.387***
	(89.35)	(89.13)	(84.45)	(84.32)	(86.52)	(84.86)	(89.57)	(88.29)
Constant	1.157***	0.811***	3.565***	3.134***	-0.065	2.329***	-0.339*	0.726***
	(4.81)	(3.46)	(16.79)	(15.50)	(-0.31)	(12.94)	(-1.88)	(4.22)
Average N	2,850	2,850	2,856	2,856	2,802	2,802	2,850	2,856
Adjusted R ²	0.302	0.303	0.313	0.314	0.300	0.308	0.298	0.303

Table V – continued from previous page

Panel B: Extended Fama-MacBeth Regression Estimate	S			
	R	TI	CPR.	ATIO
Independent Variable	(1)	(2)	(3)	(4)
iBeta	0.038	0.211***	-0.019	0.578***
	(0.74)	(3.99)	(-0.36)	(9.30)
Gambling Exposure	-0.068	-0.034	-0.174**	-0.148
	(-0.44)	(-0.21)	(-2.06)	(-1.48)
$iBeta \times Gambling Exposure$	0.369***	0.572***	0.158**	0.193**
	(4.10)	(5.64)	(2.39)	(2.49)
IVOL	-0.015		0.132	
	(-0.08)		(0.80)	
$IVOL \times iBeta$	0.012		-0.362 ****	
	(0.13)		(-4.79)	
$IVOL \times Gambling Exposure$	0.658***		$0.154^{'}$	
· ·	(2.67)		(0.92)	
$IVOL \times iBeta \times Gambling Exposure$	-0.469***		-0.244**	
G P	(-2.96)		(-2.30)	
MAXRET	()	-1.798***	()	-0.651***
		(-10.47)		(-4.05)
$MAXRET \times iBeta$		0.004		-1.133***
		(0.04)		(-11.90)
$MAXRET \times Gambling Exposure$		0.653**		0.083
G P		(2.11)		(0.46)
$MAXRET \times iBeta \times Gambling Exposure$		-0.675****		-0.227*
		(-3.52)		(-1.85)
$\log(\mathrm{B/M})$	-0.521***	-0.597***	-0.779***	-0.921***
108(2)111)	(-12.49)	(-13.56)	(-12.83)	(-14.46)
$\log(\text{ME})$	0.124***	-0.042	0.134***	-0.037
@()	(4.31)	(-1.43)	(4.61)	(-1.31)
RET[-12,-2]	0.001	-0.141	-0.040	-0.228***
	(0.01)	(-0.96)	(-0.52)	(-2.60)
Ret[-1,0]	0.414***	0.421***	0.379***	0.387***
[-7~]	(72.82)	(68.94)	(70.94)	(68.66)
Constant	-1.025***	0.553*	-0.808***	0.020
	(-3.22)	(1.69)	(-3.33)	(0.09)
	(0.22)	(1.00)	(0.00)	(0.00)
Average N	2,550	2,557	2,458	2,462
Adjusted R^2	0.331	0.335	0.296	0.301

Table VI: Performance Estimates Using Intraday and Overnight Returns

This table reports estimates from monthly Fama-MacBeth cross-sectional regressions. At the end of each month, lottery stock characteristics (IVOL and MAXRET) are computed and used to predict returns in the following month. Panel A (Panel B) presents the results from regressing lottery stock characteristics on intraday (overnight) returns. Intraday returns are computed by finding the difference between the value-weighted average price and the close price. Overnight returns are calculated by taking the close-to-close return minus the intraday return. The intraday and overnight returns are decomposed following Lou et al. (2019). In columns (1) and (2), IVOL, MAXRET, and *iBeta* are defined by sorting stocks into quintile portfolios based on the stock's idiosyncratic volatility, maximum daily return, and inflation sensitivity as of the end of the month. In columns (3) and (4), IVOL, MAXRET, and iBeta are indicator variables that take the value of 1 if the value falls above the median in month t and 0 otherwise. All specifications include the baseline controls: book-to-market ratio, market value, past returns for the prior 12 months skipping the most recent month, and the returns for the previous month. Coefficients of the control variables are suppressed for the purpose of presentation. Standard errors are adjusted using the Newey and West (1987) approach with a lag of six. The regression intercept is reported in the table. Significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. All variables are defined in Appendix Table A.1.

Panel A: Intraday Returns	(1)	(2)	(3)	(4)
\overline{iBeta}	0.112*	0.354***	-0.155**	0.029
	(1.82)	(5.08)	(-2.48)	(0.41)
IVOL	0.001	,	0.203	,
	(0.01)		(0.92)	
$IVOL \times iBeta$	-0.100****		-0.576***	
	(-3.98)		(-4.19)	
MaxRet	,	-0.571***	, ,	-1.191***
		(-6.80)		(-5.87)
$MaxRet \times iBeta$		-0.149****		-0.643***
		(-5.08)		(-4.30)
		,		,
Average N	3,297	3,306	3,297	3,306
Adjusted R^2	0.168	0.172	0.166	0.168
Panel B: Overnight Returns	(1)	(2)	(3)	(4)
\overline{iBeta}	-0.339***	-0.111***	0.137***	0.316***
	(-9.11)	(-4.10)	(3.10)	(6.64)
IVOL	0.247***	, ,	0.376**	, ,
	(3.39)		(2.08)	
$IVOL \times iBeta$	0.177***		0.826***	
	(10.49)		(7.68)	
MaxRet	, ,	0.006	, ,	-0.139
		(0.10)		(-0.89)
$MaxRet \times iBeta$		0.126***		0.635***
		(9.06)		(7.19)
Average N	3,297	3,306	3,297	3,306
11 V C 1 (1 E C 1 V	9,491	5,500	9,491	5,500
Adjusted R^2	0.044	0.041	0.041	0.039

Table VII: Mispricing and Correction Patterns

This table presents risk-adjusted excess returns using the four-factor model of Carhart (1997). The alphas are those of a long-short trading strategy where the long portfolio is constructed by selecting stocks that fall into the top quintiles of IVOL (or MAXRET) and the top quintile of iBeta based on data available at the end of month t. The short portfolio is constructed by selecting stocks that fall into the top quintile of iBeta and the bottom quintile of IVOL (or MAXRET). The alphas are presented for the six months following portfolio formation where k represents the number of months following portfolio formation. This table also reports the average MIS spread between the stocks in the long and short legs of the portfolios in the six months following portfolio formation. MIS is a a measure of mispricing from Stambaugh et al. (2015) based on decile ranks of 11 prominent anomalies, where higher values indicate more mispricing. Significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. All variables are defined in Appendix Table A.1.

Panel A: IVOL						
Variable	k = 1	2	3	4	5	k = 6
MIS	1.944	1.902	1.882	1.789	1.699	1.625
	(14.79)	(14.82)	(14.56)	(13.79)	(12.77)	(11.83)
Alpha	-1.408***	-0.977***	-0.622**	-0.412	-0.538*	-0.360
	(-5.85)	(-2.88)	(-2.15)	(-1.20)	(-1.72)	(-1.43)
Mkt-Rf	0.283***	0.191**	-0.025	-0.041	-0.108*	-0.066
	(3.82)	(2.16)	(-0.35)	(-0.47)	(-1.79)	(-0.98)
SMB	1.037***	-0.034	-0.075	-0.298	0.078	0.044
	(11.04)	(-0.30)	(-0.64)	(-1.57)	(0.71)	(0.50)
HML	-0.543***	-0.181	-0.239**	-0.159	-0.169*	-0.066
	(-4.14)	(-1.56)	(-2.13)	(-1.01)	(-1.72)	(-0.72)
MOM	-0.227**	-0.016	-0.041	-0.088	-0.022	-0.106*
	(-2.32)	(-0.13)	(-0.60)	(-0.94)	(-0.29)	(-1.66)
Number of Months	719	718	717	716	715	714
Adjusted \mathbb{R}^2	0.344	0.021	0.009	0.017	0.007	0.005
Panel B: MAXRET						
Variable	k = 1	2	3	4	5	k = 6
MIS	1.291	1.290	1.305	1.219	1.151	1.131
	(8.66)	(8.45)	(8.49)	(7.83)	(7.35)	(7.52)
Alpha	-1.131***	-0.534**	-0.265	-0.273	-0.000	-0.298
	(-5.16)	(-2.06)	(-1.03)	(-0.96)	(-0.00)	(-1.08)
Mkt-Rf	0.289***	0.069	-0.098	-0.084	-0.145**	-0.079
	(3.97)	(1.02)	(-1.57)	(-1.32)	(-2.11)	(-1.26)
SMB	0.782***	-0.190	-0.008	-0.149	0.012	0.160*
	(6.41)	(-1.55)	(-0.09)	(-1.57)	(0.11)	(1.72)
HML	-0.511***	-0.117	-0.373***	-0.095	-0.208**	-0.109
	(-4.59)	(-1.26)	(-3.05)	(-0.80)	(-2.25)	(-1.17)
MOM	-0.102	-0.095	-0.081	0.007	-0.074	-0.022
	(-0.85)	(-1.28)	(-1.07)	(0.08)	(-1.08)	(-0.29)
Number of Months	706	705	704	703	702	701
Adjusted R^2	0.284	0.012	0.025	0.010	0.012	0.008

Table VIII: Mispricing and Arbitrage Cost Estimates

This table reports the average mispricing and arbitrage cost measures for various portfolios sorted on IVOL, MAXRET, and *iBeta*. The portfolios are formed by independently sorting stocks into five portfolios at the end of every month t with respect to either IVOL or MAXRET and *iBeta*. The mispricing and arbitrage cost measures are computed during the portfolio formation month. The mispricing measure (MIS) is the rank of stock-level mispricing as in Stambaugh et al. (2015). BO_Inventory_Value is the value of current inventory on loan in millions. Lower values of BO_Inventory_Value indicate higher arbitrage costs. Panel A reports the mispricing and arbitrage cost estimates for IVOL portfolios within the subset of high *iBeta* firms. Similarly, Panel B reports these estimates for MAXRET portfolios within the subset of high *iBeta* firms. In Panels C and D, we report the estimates for *iBeta* portfolios, within the subset of IVOL and MAXRET firms, respectively. All variables are defined in Appendix Table A.1.

Variable Low IVOL Q2 Q3 Q4 High IVOL High-Low MIS 5.179 5.535 6.017 6.466 6.878 1.699 BO_Inventory_Value 0.170 0.180 0.156 0.125 0.085 -0.085 Panel B: High iBeta Firms, MAXRET Portfolios Variable Low MAXRET Q2 Q3 Q4 High MAXRET High-Low MIS 5.514 5.764 6.089 6.461 6.802 1.288 BO_Inventory_Value 0.153 0.161 0.147 0.125 0.095 -0.059 Panel C: High IVOL Firms, iBeta Portfolios Variable Low iBeta Q2 Q3 Q4 High iBeta High-Low MIS 6.144 6.193 6.173 6.335 6.878 0.734 BO_Inventory_Value 0.115 0.119 0.122 0.110 0.085 -0.030 Variable Low iBeta Portfolios Variable Low iBeta Q2 Q3 Q4	Panel A: High $iBeta$ F	irms, IVOL Portfo	olios				
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Variable	Low IVOL	Q2	Q3	Q4	High IVOL	High-Low
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	MIS	5.179	5.535	6.017	6.466	6.878	1.699
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$							(43.43)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$BO_Inventory_Value$	0.170	0.180	0.156	0.125	0.085	-0.085
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$							(-13.56)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Panel B: High <i>iBeta</i> F	irms, MAXRET P	ortfolios				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Variable	Low MAXRET	Q2	Q3	Q4	High MAXRET	High-Low
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	MIS	5.514	5.764	6.089	6.461	6.802	1.288
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$							(35.45)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$BO_Inventory_Value$	0.153	0.161	0.147	0.125	0.095	-0.059
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$							(-9.67)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Panel C: High IVOL F	irms, <i>iBeta</i> Portfo	lios				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Variable	Low iBeta	Q2	Q3	Q4	High <i>iBeta</i>	High-Low
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	MIS	6.144	6.193	6.173	6.335	6.878	0.734
							(22.87)
	$BO_Inventory_Value$	0.115	0.119	0.122	0.110	0.085	-0.030
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$							(-5.96)
MIS 5.946 5.986 6.008 6.205 6.802 0.856 (26.97) BO_Inventory_Value 0.140 0.142 0.144 0.131 0.095 -0.046	Panel D: High MAXRI	ET Firms, <i>iBeta</i> P	ortfolios				
$BO_Inventory_Value$ 0.140 0.142 0.144 0.131 0.095 (26.97) -0.046	Variable	Low <i>iBeta</i>	Q2	Q3	Q4	High iBeta	High-Low
$BO_Inventory_Value$ 0.140 0.142 0.144 0.131 0.095 -0.046	MIS	5.946	5.986	6.008	6.205	6.802	0.856
<i>u</i>							(26.97)
(-7.67)	$BO_Inventory_Value$	0.140	0.142	0.144	0.131	0.095	-0.046
							(-7.67)

Table IX: Extended Fama-Macbeth Regression Estimates Using Arbitrage Costs

This table presents estimates from monthly Fama-MacBeth cross-sectional regressions. The coefficient of interest is the interaction between IVOL (or MAXRET), iBeta, and BO_Inventory_Value. In columns (1) and (2) IVOL, MAXRET, and iBeta are categorical variables based on quintiles of each respective measure. In columns (3) and (4) IVOL, MAXRET, and iBeta are indicator variables that take the value of 1 if the value falls above the median in month t and 0 otherwise. High Arb.Cost is an indicator variable that take the value of 1 if the measure reflects high arbitrage costs and 0 otherwise. Since lower values of BO_Inventory_Value reflect higher arbitrage costs, the High Arb.Cost indicator takes a value of 1 if BO_Inventory_Value falls below the median and 0 otherwise. At the end of each month, lottery stock characteristics, iBeta, and BO_Inventory_Value are computed and used to predict returns in the following month. Standard errors are adjusted using the Newey and West (1987) approach with a lag of six. Significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. All variables are defined in Appendix Table A.1.

Independent Variable	(1)	(2)	(3)	(4)
iBeta	-0.377***	0.060	0.062	0.341***
	(-4.56)	(0.83)	(1.46)	(7.30)
High Arb. Cost	0.211*	-0.057	0.045	0.001
	(1.85)	(-0.50)	(0.38)	(0.00)
$iBeta \times High Arb. Cost$	0.222***	0.170***	0.121*	0.103*
	(5.81)	(4.95)	(1.80)	(1.67)
IVOL	0.398***		0.551***	
	(3.71)		(2.94)	
$IVOL \times iBeta$	0.133***		0.088	
	(4.34)		(1.17)	
$IVOL \times High Arb.Cost$	-0.165***		-0.331*	
	(-3.91)		(-1.71)	
$IVOL \times iBeta \times High Arb. Cost$	-0.071***		-0.476***	
	(-5.41)		(-3.92)	
MAXRET		-0.620***		-1.483***
		(-7.58)		(-10.02)
$MAXRET \times iBeta$		0.035		-0.084
		(1.45)		(-1.12)
$MAXRET \times High Arb. Cost$		-0.043		0.055
MANDET ID A WILL A LOCAL		(-1.10)		(0.27)
MAXRET \times <i>iBeta</i> \times High Arb. Cost		-0.057***		-0.467***
1 (D (3.6)	0 = 04 ***	(-5.17)	0.000	(-4.35)
$\log(\mathrm{B/M})$	-0.701***	-0.819***	-0.662***	-0.750***
1 (MID)	(-13.90)	(-17.49) -0.272***	(-13.27)	(-15.73)
$\log(\text{ME})$	-0.018		0.027	-0.156***
DET[19 9]	(-0.68) $-0.292**$	(-10.05) -0.578***	(1.20) $-0.269**$	(-6.21) $-0.459***$
RET[-12, -2]	(-2.54)	(-3.79)	(-2.25)	(-3.17)
Ret[-1,0]	(-2.54) 0.418***	(-3.79) 0.428***	(-2.23) $0.416***$	(-3.17) 0.423***
	(87.83)	(84.63)	(87.18)	(85.24)
Constant	-0.537	3.308***	-0.414	1.247***
Computation	(-1.28)	(8.97)	(-1.51)	(4.50)
	(1.20)	(0.31)	(1.01)	(4.00)
Average N	2,364	2,368	2,364	2,368
Adjusted R^2	0.339	0.345	0.335	0.339
· · · · · · · ·				

Table X: Inflation, Gambling, and Return Comovements

Panel A: Dependent Variable: Comovement,

This table presents estimates from Fama-MacBeth cross-sectional regressions that use lottery stock characteristics and *iBeta* to predict stock-level comovement with an equal-weighted lottery stock index. We use information available at the end of month t to predict comovement in month t (Panel A), and comovement in month t+1 (Panel B). Comovement is estimated using an equal weighted index of stocks that fall into the top quintile of IVOL (columns (1) and (2)), the top quintile of MAXRET (columns (3) and (4)), and the top quintiles of both IVOL and MAXRET (columns (5) and (6)). IVOL, MAXRET, and iBeta are indicator variables that take the value of 1 if the value falls above the median in month t and 0 otherwise. All specifications include the baseline controls: book-to-market ratio, market value, past returns for the prior 12 months skipping the most recent month, and the returns for the previous month. Coefficients of the control variables are suppressed for the purpose of presentation. Standard errors are adjusted using the Newey and West (1987) approach with a lag of six. Significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. All variables are defined in Appendix Table A.1.

	IV	OL	MAX	KRET	LO	ГТ	
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	
iBeta	-0.015**	-0.003	-0.009	0.006	-0.014***	-0.001	
IVOL	(-2.38) $0.146***$ (6.73)	(-0.55)	(-1.33) $0.159***$ (6.67)	(0.94)	(-2.67) $0.111***$ (5.65)	(-0.12)	
$IVOL \times iBeta$	0.162***		0.172***		0.150***		
	(14.34)		(13.64)		(14.72)		
MAXRET		0.047**		0.057***		0.034*	
		(2.38)		(2.74)		(1.95)	
$MAXRET \times iBeta$		0.162***		0.169***		0.144***	
		(16.16)		(15.07)		(15.76)	
A NT	2.672	0.070	0.00=	2.62=	0.00=	0.00=	
Average N	2,872	2,872	2,827	2,827	2,827	2,827	
Adjusted R ²	0.043	0.041	0.042	0.040	0.041	0.039	
Panel B: Dependent V	ariable: Con	$movement_{t+}$	-1				
	IV	OL	MAX	KRET	LOTT		
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	
iBeta	0.010	0.027***	0.020***	0.036***	0.011*	0.026***	
IVOL	(1.45) $0.115****$	(3.80)	(2.72) $0.134***$	(4.96)	(1.87) $0.096***$	(4.22)	
	(6.01)		(6.58)		(5.44)		
$IVOL \times iBeta$	0.119***		0.121***		0.106***		
	(11.10)		(10.50)		(10.85)		
MAXRET		0.043**		0.058***		0.035**	
		(2.53)		(3.21)		(2.30)	
$MAXRET \times iBeta$		0.104***		0.107***		0.093***	
	0.010444	(10.60)	0 0 10 4 4 4 4	(10.01)	0 0 1 = 4 + 4	(10.52)	
$Comovement_t$	0.046***	0.048***	0.046***	0.048***	0.045***	0.047***	
	(8.52)	(8.71)	(7.77)	(7.97)	(8.18)	(8.36)	
Avereage N	2,861	2,861	2,812	2,812	2,832	2,832	
Adjusted R ²	0.046	0.045	0.046	0.044	0.044	0.043	
		C					

Table XI: Fama-MacBeth Regression Estimates with Comovement Interactions

This table reports estimates from monthly Fama-MacBeth cross-sectional regressions where we add a triple interaction term between IVOL (and MAXRET), iBeta, and return comovement. The dependent variable in all specifications is the excess return of stock i in month t+1. We use information available at the end of month t to compute IVOL, MAXRET, iBeta, and Comovement. IVOL, MAXRET, iBeta, and Comovement are indicator variables that take the value of 1 if the value falls above the median in month t and 0 otherwise. In columns (1) and (2), comovement is computed by regressing excess returns on an index of stocks that fall in the top quintile of IVOL. In columns (3) and (4), an index of stocks that fall in the top quintile of MAXRET are used to compute comovement. In columns (5) and (6), we use an index of stocks that fall into the top quintiles of both IVOL and MAXRET. All specifications include the baseline controls: book-to-market ratio, market value, past returns for the prior 12 months skipping the most recent month, and the returns for the previous month. Coefficients of the control variables are excluded for the purpose of presentation. Standard errors are adjusted following the Newey and West (1987) approach using a lag of six. Significance at the 10%, 5%, and 1% levels are denoted by *, ***, and ****, respectively. All variables are defined in Appendix Table A.1.

	IVOL		MAX	XRET	LOTT	
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
iBeta	0.252	0.591***	0.156	0.508***	0.248	0.600***
	(1.50)	(3.83)	(0.94)	(3.62)	(1.51)	(3.99)
$iBeta \times Comovement$	-0.226	-0.357**	-0.310**	-0.395***	-0.251*	-0.359***
	(-1.44)	(-2.40)	(-2.02)	(-3.02)	(-1.66)	(-2.62)
Comovement	0.112	0.283***	0.170*	0.314***	0.110	0.251***
****	(1.10)	(2.79)	(1.73)	(3.40)	(1.13)	(2.60)
IVOL	-0.047		-0.127		-0.097	
THOI ID	(-0.21)		(-0.56)		(-0.42)	
$IVOL \times iBeta$	-0.134		-0.025		-0.084	
Wol C	(-1.11)		(-0.20)		(-0.69)	
$IVOL \times Comovement$	-0.018		0.032		0.013	
$IVOL \times iBeta \times Comovement$	(-0.14)		(0.26) $-0.179**$		(0.10) $-0.140**$	
IVOL × <i>ibeta</i> × Comovement	-0.113 (-1.57)		(-2.50)		(-1.97)	
MAXRET	(-1.57)	-1.545***	(-2.50)	-1.559***	(-1.97)	-1.557***
		(-8.43)		(-9.12)		(-8.39)
$MAXRET \times iBeta$		-0.256**		-0.163		-0.216**
		(-2.38)		(-1.63)		(-1.99)
$MAXRET \times Comovement$		0.114		0.132		0.132
		(1.02)		(1.28)		(1.22)
$MAXRET \times iBeta \times Comovement$		-0.224***		-0.270***		-0.235***
		(-3.32)		(-4.28)		(-3.47)
Average N	2,963	2,967	2,818	2,821	2,818	2,821
Adjusted R^2	0.303	0.308	0.302	0.307	0.302	0.307

Table XII: Fama-MacBeth Regressions: Split Sample Estimates

This table reports estimates from monthly Fama-MacBeth cross-sectional regressions on subsamples based on pre- and post-1990 time period cutoffs (Panel A) and from Fama-MacBeth cross-sectional regressions using an additional set of controls when computing iBeta (Panel B). At the end of each month, lottery stock characteristics (MAXRET and IVOL) are computed and used to predict returns in the following month. In Panel A, iBeta is computed by regressing excess stock returns at the end of each month t on monthly inflation innovations and the three Fama-French factors using the past sixty months of data. Columns (1)-(2) and (5)-(6), IVOL, MAXRET, and iBeta represent quintile values, which are defined by sorting stocks into quintile portfolios based on the stock's idiosyncratic volatility, maximum daily return, and inflation sensitivity as of the end of the month. In columns (3)-(4) and (7)-(8), IVOL, MAXRET, and iBeta are indicator variables that take the value of 1 if the value falls above the median in month t and 0 otherwise. In Panel B, we compute iBeta by controlling for Baker and Wurgler (2006) sentiment (columns (1) and (2)), sentiment and NBER recession indicators (columns (3) and (4)), economic policy uncertainty (columns (5) and (6)), and using expected inflation instead of realized inflation (columns (7) and (8)). In all Panel B specifications, IVOL, MAXRET, and iBeta represent an indicator variables that take the value of 1 if the respective measure is above the median in month t and 0 otherwise. All specifications include the baseline controls: book-to-market ratio, market value, past returns for the prior 12 months skipping the most recent month, and the returns for the previous month. Standard errors are adjusted using the Newey and West (1987) approach with a lag of six. Significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. All variables are defined in Appendix Table A.1.

		Pre-1990				Post-1990			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
iBeta	0.205***	0.411***	0.066	0.340***	0.233***	0.584***	0.171***	0.502***	
	(5.75)	(10.50)	(1.37)	(6.94)	(7.37)	(14.84)	(3.57)	(10.16)	
IVOL	-0.334***		-0.826***		0.159***		0.534***		
	(-7.04)		(-7.04)		(3.41)		(3.98)		
IVOL x iBeta	-0.077****		-0.254***		-0.076^{***}		-0.371 ****		
	(-7.35)		(-3.88)		(-8.38)		(-6.43)		
MAXRET	(/	-0.813***	,	-1.693***	,	-0.546***	,	-1.100***	
		(-19.63)		(-16.38)		(-11.46)		(-8.50)	
MAXRET x iBeta		-0.123***		-0.578***		-0.149***		-0.615***	
		(-10.77)		(-7.17)		(-12.78)		(-9.60)	
log(B/M)	-0.800***	-0.910***	-0.738***	-0.822***	-0.712***	-0.879***	-0.692***	-0.816***	
	(-13.87)	(-15.63)	(-12.89)	(-14.44)	(-12.80)	(-14.43)	(-12.40)	(-13.61)	
$\log(\text{ME})$	-0.139***	-0.237***	-0.084**	-0.162***	0.104***	-0.169***	0.126***	-0.073***	
	(-3.30)	(-5.63)	(-2.10)	(-4.05)	(4.29)	(-6.71)	(5.29)	(-2.96)	
RET[-12, -2]	0.153	0.074	0.168*	0.106	-0.150*	-0.450***	-0.130	-0.334***	
- [/]	(1.53)	(0.61)	(1.71)	(0.99)	(-1.89)	(-4.75)	(-1.60)	(-3.70)	
Ret[-1,0]	0.368***	0.384***	0.365***	0.376***	0.388***	0.398***	0.388***	0.394***	
[/-]	(48.96)	(47.53)	(49.15)	(48.12)	(81.51)	(78.67)	(81.66)	(80.10)	
Constant	1.164***	2.665***	0.408	0.893***	-1.065***	2.055***	-0.952***	0.578***	
	(4.20)	(9.78)	(1.53)	(3.28)	(-4.51)	(8.84)	(-4.53)	(2.68)	
Average N	2,336	2,338	2,336	2,338	3,221	3,230	3,221	3,230	
Adjusted R ²	0.284	0.296	0.280	0.287	0.313	0.318	0.311	0.314	

Table XI – continued from previous page

Panel B: Sentiment	and Economi	ic Uncertaint	y Controls					
	Sent.		Sent. & Recession Ind.		EPU		Expected Inflation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
iBeta	0.081***	0.377***	0.082**	0.358***	0.122***	0.451***	0.094**	0.523***
	(2.63)	(11.26)	(2.36)	(9.31)	(2.89)	(10.60)	(1.98)	(9.54)
IVOL	-0.172		-0.231*	, ,	0.033	, ,	-0.070	, ,
	(-1.48)		(-1.71)		(0.35)		(-0.75)	
$IVOL \times iBeta$	-0.332***		-0.261***		-0.345***		-0.328***	
	(-7.28)		(-4.94)		(-7.39)		(-5.69)	
MAXRET	,	-1.481***	, ,	-1.544***	, ,	-1.769***	, ,	-1.817***
		(-16.52)		(-14.37)		(-19.96)		(-20.55)
$MAXRET \times iBeta$		-0.621***		-0.542***		-0.612***		-0.734***
		(-12.07)		(-9.14)		(-12.46)		(-11.75)
log(B/M)	-0.772***	-0.889***	-0.715***	-0.825***	-0.694***	-0.814***	-0.688***	-0.809***
	(-18.15)	(-20.25)	(-15.62)	(-18.25)	(-13.76)	(-15.03)	(-14.34)	(-15.93)
$\log(ME)$	0.035	-0.112***	0.007	-0.136***	0.133***	-0.056**	0.124***	-0.051**
,	(1.28)	(-4.26)	(0.27)	(-5.02)	(6.17)	(-2.41)	(5.61)	(-2.27)
RET[-12, -2]	0.001	-0.129*	0.021	-0.110	-0.112	-0.307***	-0.090	-0.292***
	(0.02)	(-1.85)	(0.29)	(-1.31)	(-1.53)	(-3.80)	(-1.30)	(-3.85)
Ret[-1,0]	0.379***	0.388***	0.382***	0.391***	0.385***	0.391***	0.386***	0.393***
	(82.92)	(81.20)	(73.44)	(72.06)	(86.00)	(85.31)	(88.35)	(86.80)
Constant	-0.313	0.740***	-0.020	1.038***	-0.795***	0.959***	-0.702***	0.938***
	(-1.54)	(3.72)	(-0.09)	(4.79)	(-3.86)	(4.38)	(-3.45)	(4.50)
Average N	3,022	3,028	2,752	2,758	3,242	3,250	3,260	3,268
Adjusted R^2	0.295	0.300	0.291	0.297	0.305	0.308	0.305	0.309

Appendix Table A.1: Variable Definitions

This table defines the variables used in the empirical analyses and also reports the data sources.

Variable	Description	Source
Panel A: Economic Variables		
Inflation	Inflation in the United States. Monthly inflation computed as the monthly change in CPI.	FRED
Inflation Expectations	Estimates of the expected rate of inflation over the next year. Estimates are calculated using a model based on Treasury yields, inflation data, inflation swaps, and survey-based measures of inflation expectations.	Federal Reserve Bank of Cleveland
Overall Gambling Search Intensity	Gambling Interest is defined by taking the sum of search intensities across the following four terms: "gambling," "lottery," "Powerball," and "sports betting."	Google
Risk Aversion	The time-varying risk aversion measure is derived from observable high-frequency financial market data within a noarbitrage framework. It represents the relative risk aversion coefficient of a representative agent in a generalized habit formation model with preference shocks. The measure is constructed as an optimal linear combination of financial instruments, estimated via GMM, including: detrended earnings yield, corporate bond spread (Baa-Aaa), term spread (10-year minus 3-month), realized variance of equity returns, realized variance of corporate bond returns, and risk-neutral equity variance. This combination is designed to span market-wide risk aversion based on the theoretical restrictions of a dynamic exponential affine model.	Bekaert et al. (2022)
Sports Betting Search Intensity	Sports Betting is defined using the monthly search intensity for the term "sports betting." Monthly search intensity is downloaded for the entire period over which Google search volume data is available: January 2004 - October 2024.	Google
State Inflation	State level change in CPI.	Hazell et al. (2022)
State Lottery Revenue	Per capita state level lottery revenue, adjusted to 2010 dollars.	US Census Bureau
Panel B: Stock-Level Variables		
Average Daily Turnover	The average of daily total trading volume divided by shares outstanding over month t .	CRSP
BO_Inventory_Value	Defined as a firm's lendable supply scaled by market capitalization. The total quantity of stock made available by the lenders/institutions in their lending programs. It comes from beneficial owners of the stock like mutual funds, pension funds, and other asset owners.	Markit
BO_On_Loan_Value	Defined as the value of current inventory scaled by the firm's market capitalization.	Markit
Comovement	Computed by performing time-series regressions for each month using of daily excess stock returns as in equation 4. We regress excess returns on an equal-weighted index of lottery stocks and the Fama-French 3 factors. The index of lottery stocks includes either stocks that fall into the top quintile of IVOL, stocks that fall into the top quintile of MAXRET, or stocks that fall into the top quintiles of both IVOL and MAXRET.	CRSP

Variable	Description	Source
Panel B: Stock-Level Variables		
CPRATIO	Defined as the ratio of the Catholic population to the Protestant population in the county of the firm's headquarters.	ARDA
DCBS	Daily Cost of Borrowing Score. This is a bucketed score (1-10) that reflects the cost to borrow the stock charged by lenders from the Prime Brokers in the wholesale market, where 1 reflects cheap and 10 reflects expensive.	Markit
Economic Policy Uncertainty	A monthly measure of economic policy uncertainty from Baker et al. (2016) based on newspaper coverage frequency.	Baker et al. (2016)
Dividend Paying Dummy	Binary indicator that takes a value of 1 if the firm pays a dividend at least once during year t .	CRSP
ESKEW	ESKEW is defined by running a cross-sectional regression at the end of each month using the most recent five years of data. These estimates are then used to predict the expected idiosyncratic skewness over the next five years. Variables used in the predictive regressions include historical estimates of idiosyncratic volatility and idiosyncratic skewness relative to the Fama-French three factor model over the previous five years, momentum as the cumulative returns over months t-12 through t-1, turnover as the average daily turnover in month t-1, small- and medium-sized market capitalization dummies (based on sorts of firms by market capitalization into three groups of small, medium, and large), an industry dummy based on the Fama-French 17 industries, and a NASDAQ dummy. After estimating the model at the end of every month t, we use the pa- rameters together with the most recent data to get out-of-sample expected idiosyncratic skewness estimates for months t+61 through t + 120. Our estimates start in 1988 because detailed data on the trading volume of NASDAQ stocks become available in 1983.	CRSP
iBeta	iBeta is defined by running time series regressions of excess returns on monthly inflation innovations and the three Fama-French factors at the end of each month t using the past sixty months of data. Inflation innovations are defined using an ARMA(1,1) model to account for the autoregressive nature of inflation. The absolute value of the resulting coefficients is our measure of iBeta.	
Intraday Return	The intraday return is calculated as the price appreciation between market open and close of the same day s. The price appreciation between market open and close is computed using the volume-weighted average price (VWAP) in the first half hour of trading (9:30 am - 10:00 am). These returns are then aggregated across all trading days in month t to generate monthly intraday and overnight returns for stock i.	TAQ
ISKEW	Skewness of residuals obtained from running the four-factor model of Carhart (1997) on daily returns for the most recent month.	CRSP
Investor Sentiment	A monthly investor sentiment index from Baker and Wurgler (2006), which is based on the first principal component of six (standardized) sentiment proxies.	Baker and Wurgler (2006)

Variable	Description	Source
Panel B: Stock-Level Variables		
IVOL	Volatility of residuals obtained from running the three-factor model of Fama and French (1993) on daily returns for the most recent month (Stambaugh et al., 2015).	CRSP
LOTTERY	Takes the value of one if the stock falls into the top quintile of IVOL and MAXRET in month t-1, and zero otherwise.	CRSP
Overnight Return	The overnight return is then imputed based on the intraday return and the standard daily close-to-close return. The price appreciation between market open and close is computed using the volume-weighted average price (VWAP) in the first half hour of trading (9:30 am - 10:00 am). These returns are then aggregated across all trading days in month t to generate monthly intraday and overnight returns for stock i.	TAQ
MAXRET	The maximum daily return during the previous month.	CRSP
MIS	Following Stambaugh et al. (2015), MIS is the average of decile ranks of a stock with respect to 11 prominent anomalies. Sorting for each anomaly is performed at the end of every month. Deciles 1 and 10 include stocks that each anomaly strategy predicts will outperform and underperform the most in the following month, respectively. Unlike Stambaugh et al. (2015), we determine our decile cutoffs using our whole sample, not just NYSE stocks. The 11 anomaly strategies considered are accruals (Sloan, 1996), asset growth (Cooper et al., 2008), composite equity issues (Daniel and Titman, 2006), distress (Campbell et al., 2008), gross profitability (Novy-Marx, 2013), investment-to-assets (Titman et al., 2004), momentum (Jegadeesh and Titman, 1993), net operating assets (Hirshleifer et al., 2004), net stock issues (Ritter, 1991; Loughran and Ritter, 1995), O-score (Ohlson, 1980), and return on assets (Fama and French, 2006). We follow the detailed description of Stambaugh et al. (2012, 2015), together with the corresponding anomaly literature, to replicate each strategy.	CRSP and Compustat
Monthly Volume Turnover	Total trading volume over the last month divided by shares outstanding.	CRSP
NBER Recession Ind.	A time series composed of dummy variables that represent periods of expansion and recession. The NBER identifies months of turning points without designating a date within the period that turning points occurred. A value of 1 is a recessionary period, while a value of 0 is an expansionary period.	NBER
RTI	RTI (retail trading intensity) is defined by identifying the fraction of the penny associated with the transaction price $(P_{it}): Z_{it} = 100 * mod(P_{it}, 0.01)$. If Z_{it} is in the range of $(0,0.4)$ the trade is classified as a retail sell. If Z_{it} is in the range $(0.6,1)$ the trade is classified as a retail buy. If Z_{it} is in the range $(0.4,0.6)$ the trade is not considered a retail transaction. We then aggregate the total number of retail transactions for firm i in each month t . We then compute the percentage of total trading volume made up of retail trades in each firm-month. We then sort firms into terciles based on their relative rank in retail trading intensity in a given month.	TAQ
SKEW	Skewness of daily returns for the most recent month.	CRSP
Systematic Skewness	Coefficient of the squared market factor in a regression fitting a two factor $(RMRF$ and $RMRF^2)$ model.	CRSP

Variable	Description	Source
Panel B: Stock-Level Variables		
Total_Demand_Value	Total marked value of borrowed/loaned securities net of double counting scaled by the firm's market capitalization.	Markit
VIX	Monthly prices of the VIX index from 1990 to 2024.	CBOE
VWAF_30_Day	The value-weighted average fee of outstanding loans started in the past $30~\mathrm{days}.$	Markit
Panel C: Household-Level Variabl	es	
Experienced Inflation	A binary indicator based on a weighted average of past realized regional inflation as defined in equation (3). Takes the value of 1 if the weighted average of past experienced inflation is above the median in year t , 0 otherwise.	BLS
Income	Income categories ranging from 0 to 9, where income code 0 corresponds to a household income of \$7,500 or less and income code 9 corresponds to a household income of \$250,000 or more. Low (high) income is defined as households with income codes below (above) 5 (\$62,500).	Discount Brokerage
Panel D: Control Variables		
ln(B/M)	Natural logarithm of the ratio of the book-value and market capitalization of the firm.	COMPUSTAT
ln(Firm Size)	The natural log of firm size defined by the end-of-month market capitalization (price×shares outstanding).	CRSP
Return[-12, -2]	Total monthly stock return over the past 12 months, skipping the most recent month.	CRSP
Return[-1, 0]	Previous month return.	CRSP
Firm Age	Number of years since the stock first appears in CRSP.	CRSP
S&P 500 Dummy	A binary indicator that takes a value of 1 if the stock belongs to the S&P500 index.	CRSP
NASDAQ Dummy	A binary indicator that takes a value of 1 if the stock belongs to the NASDAQ index.	CRSP

Table A.2: Five-Factor Alpha Estimates of Double-Sorted Portfolios

This table reports the five-factor alpha estimates for double sorted portfolios based on inflation sensitivity (iBeta) and measures of lottery-stock characteristics. The portfolios are formed by independently sorting stocks into five portfolios at the end of every month with respect to either IVOL or MAXRET and iBeta. Value-weighted returns are then calculated for each of the 25 portfolios. The value-weighted returns are then regressed on the Fama-French five factors. The regression intercept is reported in the table. The t-statistics are reported in parentheses. All variables are defined in Appendix Table A.1.

				Ir	nflation Be	eta		
Sorting Variable		Full Sample	Low	2	3	4	High	High-Low
			0.036	0.059	0.006	0.028	0.066	0.030
			(1.29)	(1.76)	(0.15)	(0.43)	(0.84)	(0.33)
IVOL	Low	0.056	0.014	0.122	0.004	-0.024	0.346	0.332
		(1.61)	(0.29)	(2.40)	(0.05)	(-0.22)	(2.10)	(1.92)
	2	0.043	0.087	0.016	0.073	0.112	0.146	0.059
		(0.75)	(1.23)	(0.18)	(0.82)	(1.21)	(1.11)	(0.38)
	3	0.142	0.089	0.044	0.181	0.176	0.280	0.192
		(2.27)	(0.99)	(0.45)	(1.45)	(1.80)	(2.26)	(1.31)
	4	-0.128	-0.103	-0.280	-0.315	-0.128	-0.014	0.089
		(-1.56)	(-0.69)	(-2.35)	(-2.73)	(-1.03)	(-0.12)	(0.46)
	High	-0.626	-0.433	-0.645	-0.746	-0.510	-0.731	-0.298
		(-4.94)	(-2.48)	(-3.13)	(-4.04)	(-2.95)	(-4.87)	(-1.63)
	High-Low	-0.682	-0.447	-0.767	-0.749	-0.485	-1.077	-0.630
		(-4.76)	(-2.39)	(-3.47)	(-3.55)	(-2.34)	(-4.66)	(-2.44)
MAXRET	Low	0.063	0.011	0.136	0.079	0.056	0.358	0.347
		(1.40)	(0.20)	(2.21)	(1.12)	(0.54)	(2.40)	(2.26)
	2	0.048	0.022	-0.026	-0.021	-0.041	0.104	0.082
		(1.04)	(0.33)	(-0.38)	(-0.31)	(-0.37)	(0.77)	(0.54)
	3	0.109	0.074	0.048	0.018	0.032	0.229	0.155
		(1.97)	(0.84)	(0.50)	(0.19)	(0.36)	(1.99)	(1.12)
	4	0.044	0.055	0.028	-0.001	0.005	-0.114	-0.169
		(0.52)	(0.43)	(0.19)	(-0.01)	(0.04)	(-0.85)	(-0.94)
	High	-0.257	-0.109	-0.453	-0.447	-0.292	-0.375	-0.265
		(-2.69)	(-0.74)	(-3.06)	(-3.13)	(-2.14)	(-2.63)	(-1.36)
	High-Low	-0.324	-0.120	-0.590	-0.526	-0.348	-0.732	-0.612
		(-2.77)	(-0.75)	(-3.54)	(-3.22)	(-2.00)	(-3.64)	(-2.67)

Table A.3: Fama-MacBeth Regression Estimates Using Other Lottery Measures

This table reports estimates from monthly Fama-MacBeth cross-sectional regressions using four alternative lottery-stock proxies: SKEW, ISKEW, ESKEW, and LOTTERY. At the end of each month, each of the alternative lottery proxies are computed and used to predict returns in the following month. Panel A (Panel B) presents the results for specifications using quintile (median) cutoffs for each lottery proxy and *iBeta*. Standard errors are adjusted following the Newey and West (1987) approach using a lag of six. Significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. All variables are defined in Appendix Table A.1.

Panel A: Quintile Cutoffs				
	(1)	(2)	(3)	(4)
Independent Variable	SKEW	ISKEW	ESKEW	LOTTERY
iBeta	0.134***	0.465***	0.001	0.075***
	(5.67)	(16.93)	(0.02)	(5.07)
Lottery Proxy	0.078***	-0.217***	0.062	-1.514***
	(4.61)	(-11.15)	(1.31)	(-10.11)
Lottery Proxy \times $iBeta$	-0.069***	-0.181***	-0.025***	-0.533***
	(-10.75)	(-22.07)	(-2.61)	(-12.55)
Average N	2840	2824	1475	5149
Adjusted R^2	0.288	0.302	0.29	0.297
Panel B: Median Cutoffs				
	(1)	(2)	(3)	(4)
Independent Variable	SKEW	ISKEW	ESKEW	LOTTERY
iBeta	0.376***	1.368***	0.122	0.483***
	(5.67)	(16.19)	(1.35)	(12.05)
Lottery Proxy	0.254***	-0.212***	0.304***	-0.625***
	(4.67)	(-3.40)	(3.15)	(-5.68)
Lottery Proxy \times $iBeta$	-0.365***	-1.034***	-0.187***	-1.038***
	(-8.78)	(-20.00)	(-3.38)	(-14.99)
Arrono mo N	0.040	0.004	1 475	E 140
Adjusted D^2	2,840	2,824	1,475	5,149
Adjusted R^2	0.288	0.299	0.288	0.297

Table A.4: Fama-MacBeth Regression Estimates Using Positive and Negative iBeta Subsamples

This table reports estimates from monthly Fama-MacBeth cross-sectional regressions on samples that include only stocks with positive and negative iBeta as of month t. At the end of each month, lottery stock characteristics (MAXRET and IVOL) are computed and used to predict returns in the following month. iBeta is computed by regressing excess stock returns at the end of each month t on monthly inflation innovations and the three Fama-French factors using the past sixty months of data. Columns (1) and (2) present the result for regressions using only stocks with positive iBeta as of month t. Columns (3) and (4) present the result for regressions using only stocks with negative iBeta as of month t. Standard errors are adjusted following the Newey and West (1987) approach using a lag of six. Significance at the 10%, 5%, and 1% levels are denoted by *, ***, and ****, respectively. All variables are defined in Appendix Table A.1.

	Positiv	e <i>iBeta</i>	Negativ	ve iBeta
	(1)	(2)	(3)	(4)
iBeta	0.092**	0.421***	0.123***	0.394***
	(2.22)	(9.05)	(3.28)	(9.51)
IVOL	-0.391***		-0.421***	
	(-4.17)		(-4.35)	
IVOL x $iBeta$	-0.305***		-0.286***	
	(-5.17)		(-4.88)	
MAXRET		-1.954***		-1.998***
		(-24.93)		(-25.30)
${\rm MAXRET} \ {\rm x} \ iBeta$		-0.609***		-0.498***
		(-8.89)		(-8.00)
$\log(\mathrm{B/M})$	-0.729***	-0.839***	-0.705***	-0.806***
	(-18.13)	(-20.20)	(-16.45)	(-18.36)
$\log(ME)$	0.041	-0.106***	0.019	-0.122***
	(1.65)	(-4.56)	(0.74)	(-5.05)
RET[-12,-2]	-0.097	-0.239***	0.015	-0.118
	(-1.50)	(-3.34)	(0.19)	(-1.37)
Ret[-1,0]	0.383***	0.391***	0.383***	0.391***
	(85.01)	(84.05)	(84.76)	(83.83)
Constant	-0.245	1.128***	-0.193	1.171***
	(-1.26)	(6.03)	(-0.99)	(6.16)
Average N	1,463	1,466	1,387	1,390
Adjusted R ²	0.301	0.305	0.303	0.307

Table A.5: Fama-MacBeth Regression Estimates Excluding COVID Period

This table reports estimates from monthly Fama-MacBeth cross-sectional regressions excluding the COVID period (2020-2022). At the end of each month, lottery stock characteristics (MAXRET and IVOL) are computed and used to predict returns in the following month. *iBeta* is computed by regressing excess stock returns at the end of each month t on monthly inflation innovations and the three Fama-French factors using the past sixty months of data. Columns (1) through (4) use continuous values of all variables. In columns (5) and (6), IVOL, MAXRET and *iBeta* represent quintile values, which are defined by sorting stocks into quintile portfolios based on idiosyncratic volatility and maximum daily return information available at the end of month t. In columns (7) and (8), IVOL, MAXRET, and *iBeta* represent dummy variables, which are indicator variables that take the value of 1 if a stock's idiosyncratic volatility, maximum daily return, and *iBeta* in month t fall above its respective median in a given month, and 0 otherwise. Stock-level controls include the book-to-market ratio, market value of equity, past returns in the prior 12 months skipping the most recent month, and the returns in the previous month. Standard errors are adjusted following the Newey and West (1987) approach using a lag of six. Significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. All variables are defined in Appendix Table A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
iBeta	-0.029	0.285***	0.091***	0.470***	0.201***	0.478***	0.097***	0.395***
	(-1.48)	(6.23)	(3.71)	(8.33)	(9.22)	(18.28)	(3.07)	(12.18)
IVOL	-0.523***	-0.426***			-0.088**		-0.127	
	(-11.03)	(-8.50)			(-2.16)		(-1.15)	
IVOL x $iBeta$		-0.103***			-0.072***		-0.312***	
		(-6.78)			(-10.77)		(-7.24)	
MAXRET			-0.431***	-0.390***		-0.696***		-1.420***
			(-37.47)	(-31.12)		(-22.36)		(-17.47)
${\it MAXRET} \ {\it x} \ {\it iBeta}$				-0.042***		-0.132***		-0.589***
				(-8.43)		(-16.67)		(-11.91)
$\log(\mathrm{B/M})$	-0.816***	-0.809***	-0.965***	-0.953***	-0.775***	-0.920***	-0.737***	-0.845***
	(-19.45)	(-19.46)	(-22.02)	(-22.03)	(-19.42)	(-21.90)	(-18.62)	(-20.59)
$\log(\text{ME})$	-0.070**	-0.056*	-0.273***	-0.256***	-0.007	-0.202***	0.030	-0.115***
	(-2.44)	(-1.95)	(-10.78)	(-10.13)	(-0.24)	(-8.23)	(1.17)	(-4.84)
$_{\rm RET[-12,-2]}$	-0.082	-0.097	-0.350***	-0.364***	-0.019	-0.217***	-0.004	-0.140**
	(-1.30)	(-1.55)	(-4.39)	(-4.60)	(-0.31)	(-2.78)	(-0.07)	(-1.98)
Ret[-1,0]	0.381***	0.381***	0.398***	0.398***	0.379***	0.392***	0.378***	0.386***
	(85.46)	(85.26)	(80.61)	(80.49)	(85.67)	(83.42)	(85.59)	(84.46)
Constant	1.092***	0.765***	3.510***	3.099***	-0.012	2.391***	-0.320*	0.743***
	(4.57)	(3.25)	(16.53)	(15.24)	(-0.06)	(13.00)	(-1.74)	(4.26)
Average N	2,876	2,876	2,882	2,882	2,876	2,882	2,876	2,882
Adjusted R ²	0.300	0.301	0.312	0.313	0.299	0.307	0.296	0.301