The Inflation Gamble*

Yosef Bonaparte, George M. Korniotis, Alok Kumar, and Melina Vosse

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Abstract: This paper identifies a new link between inflation and asset prices. We conjecture that lottery-type investments become attractive to investors when inflation rises, as they feel "poorer" and attempt to mitigate inflation-induced loss in purchasing power. Consistent with this conjecture, we find high inflation lowers risk aversion, strengthens skewness preference, and increases demand for lottery-like investments. Due to increased gambling demand, lottery-type stocks become overpriced and earn lower future returns. This relation is stronger for inflation-sensitive lottery stocks that are harder to arbitrage. Collectively, these findings indicate that gambling demand in inflationary environments generates predictable patterns in stock returns.

Keywords: Inflation, skewness preference, lottery stocks, gambling, mispricing, idiosyncratic volatility.

JEL classification: G12, G14, G41.

*Please address correspondence to Alok Kumar, Miami Herbert Business School, 5250 University Drive, Coral Gables, FL 33146; akumar@miami.edu, 305-284-1882. Yosef Bonaparte is at the University of Colorado at Denver and can be reached at yosef.bonaparte@ucdenver.edu, 303-315-8483. George M. Korniotis is at Miami Herbert Business School and can be reached at gkorniotis@miami.edu, 305-284-5728. Melina Vosse is at the University of San Diego and can be reached at mvosse@sandiego.edu, 619-260-2400. We thank Turan Bali, Jiangxue Feng, William Goetzmann, Clifton Green, Jiaqi Guo, Byoung-Hyoun Hwang, Charles Lee, Mehrshad Motahari, Anh Tran, and seminar participants at Tulane University and University of Miami for helpful comments and useful suggestions. All remaining errors and omissions are ours.

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

Inflation, while often stable, can exhibit substantial variation over time, as evidenced by the sharp increase observed in recent years. For example, the annual inflation rate in the U.S. crossed 9% in June 2022. How do investors and various other financial market participants react to inflation-induced shocks that potentially reduce their purchasing power? Do their systematic portfolio adjustments create correlated demand shifts that affect prices of inflation-sensitive assets?

Traditional economic theory posits that investors should reduce their exposure to risky assets during high inflationary periods as uncertainty about the value of future income streams increases (e.g., Carroll et al. (1992), Carroll (1997)). Financial experts, including Warren Buffett, have likened inflation to a tax on capital. Traditional advice for dealing with this tax often includes hedges such as commodities, Treasury Inflation-Protected Securities (TIPS), or real assets. In contrast to these predictions, Bonaparte et al. (2024) find that U.S. households increase their allocations to equities when inflation rises, as exposure to certain sectors may be an effective hedge against inflation.

This paper proposes an alternative behavioral channel that may affect investment decisions and asset prices during high inflationary periods. Specifically, we posit that high levels of inflation induce an increase in demand for high-risk, high-reward assets as investors seek to at least partially compensate for perceived loss in purchasing power. Our conjecture is motivated by the observation that a small chance of winning a large prize is more tempting to individuals during economic downturns, especially because gambling instruments have low prices (e.g., Mikesell (1994), Capacci et al. (2017)).[1] In a similar manner, certain speculative investments can become attractive to investors who feel "poorer" as inflation erodes their purchasing power.[2] These investors may view even a small potential of extreme returns as

[1]Several media articles provide anecdotal evidence of increased short-term borrowing and gambling activities 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 New Jersey: 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/`.

[2]Research in psychology finds that financial hardship and perceptions of poverty can increase gambling

an attractive means to partially offset the perceived loss induced by rising prices.[3]

At the aggregate level, if these inflation-induced demand shifts are systematic, they can also affect the prices of stocks that may be perceived as lotteries. In particular, if arbitrage forces are not very powerful during high inflationary periods as economic uncertainty rises, lottery-type stocks would become overpriced. And this mispricing may not get corrected immediately, generating lower average returns in the future.

These conjectures are consistent with the theoretical predictions of the Barberis and Huang (2008) asset pricing model. In related studies, Green and Hwang (2011) examine the predictions of the Barberis and Huang (2008) model using IPOs as lotteries, and Barberis et al. (2016) test those theoretical predictions more directly using distributions of past return to capture the gambling behavior of investors. Our study extends the predictions of the Barberis and Huang (2008) model to a novel economic setting where inflation is high and both risk-taking and gambling propensities of investors increase.

We begin our empirical analysis by examining whether risk-taking and gambling propensities are higher during periods of high inflation. If investors perceive a reduction in purchasing power, their risk aversion could decline and speculative trading intensity may increase. Using the aggregate monthly risk aversion estimates from Bekaert et al. (2022), consistent with our conjecture, we find a negative relation between inflation and risk aversion. We also observe that per-capita state-level lottery revenue is higher in U.S. states with higher levels of inflation. Further, interest in gambling activities such as sports betting, as revealed through Google Trends search intensity, is at elevated levels 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 investors behave in a similar manner when they expect or experience higher levels of inflation, aggregate exposure to lottery-type investments may systematically increase. Han et al. (2022) find that social interactions generate an attraction for skewness.

propensity. Individuals who feel relatively "poor" are more prone to gambling, using it as a means to restore a sense of justice or control (Callan et al. (2008)). Likewise, Haisley and Mostafa (2008) find that lower-income individuals are more inclined to purchase lottery tickets, often framing them as a "poor man's investment" to increase upward mobility. Beckert and Lutter (2013) further demonstrate that lottery participation is disproportionately higher among the poor, who likely perceive gambling as one of the few means to improve their financial standing.

[3]High inflation can amplify risk-taking propensity and gambling motives through multiple mechanisms. In particular, investors with prospect-theoretic preferences will increase their risk-taking propensity as they move into the "loss" domain of the value function (Kahneman and Tversky (1979)). Notably, investors in high inflationary environments may perceive a loss due to a decline in their purchasing power even when they do not actually lose money. Further, if investors assign larger probability weights to extreme returns, they will find lottery-type investments more attractive (Kahneman and Tversky (1992)).

As investors learn of their peers' "big wins," these assets can become more salient, subsequently increasing the chance that investors follow the herd and invest in lottery stocks in hopes of achieving a similar outcome. In this scenario, correlated trading activities of inflation-sensitive investors may influence stock prices of lottery-type stocks with high inflation sensitivity. We use a variety of tests to examine this key asset pricing conjecture.

Specifically, we use past return distributions to identify stocks with lottery characteristics. 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. Consequently, the absolute value of return sensitivity to inflation can identify firms that attract greater investor attention and speculative trading activity when inflation rises.

To identify firms with high inflation-induced gambling demand, we compute firm-level inflation sensitivity by regressing each firm's past sixty months of returns on inflation innovations and the three Fama-French factors. This inflation exposure measure captures the sensitivity of a firm's stock returns to inflation innovations and is likely to be correlated with the unobserved inflation-induced gambling demand. In particular, returns of firms with high inflation sensitivity would react more strongly to inflation-induced gambling demand and are more likely to be overpriced.

We begin our empirical analysis by testing whether the negative lottery stock premium is larger in magnitude following periods of high inflation. Using information available at the end of the prior month, we form value-weighted monthly Long−Short portfolios based on one of the lottery characteristics, IVOL or MAXRET. We find that portfolios that are long high IVOL (MAXRET) stocks and short low IVOL (MAXRET) exhibit significantly more negative risk-adjusted abnormal returns following periods of high inflation. This evidence suggests that the demand for lottery-type stocks is greater during high inflationary periods.

We further test the relation between inflation and lottery stock returns by computing abnormal returns of these Long−Short portfolios starting in the portfolio formation month and over the subsequent six months. If speculative trading activity is greater during periods of high inflation, we expect the abnormal returns of the lottery stock portfolios to be

[4] In 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.

positively related to inflation and to subsequently reverse as the mispricing gets corrected. Consistent with this conjecture, we find that abnormal returns of the lottery stock portfolios are significantly more positive during high inflation months relative to low inflation months. We also find that the return correction is more pronounced following high inflation periods.

Next, we conduct our core empirical analysis by forming monthly portfolios double sorted on inflation sensitivity (*IS*) and one of the lottery characteristics and measuring portfolio returns in the following month. We posit that high *IS* stocks attract more attention during changing inflation environments and, therefore, are most likely to attract speculative trading behavior. We find that the high IVOL portfolio underperforms the low IVOL portfolio within each *IS* quintile, but the gap is the largest for the highest *IS* 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 -0.145% (t-statistic $= -0.90$) for the lowest *IS* quintile, and this magnitude jumps to -0.696% (t-statistic $= -4.53$) for the highest *IS* quintile. The average difference of -0.551% per month is statistically significant with a t-statistic of -2.85. This evidence is consistent with our key conjecture that high inflation increases the appetite for lottery stocks and, consequently, inflation-sensitive lottery stocks become 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 sensitivity is more pronounced among firms with higher retail trading.

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 recent studies (e.g., Stambaugh et al. (2015), 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 inflation sensitivity quintile, we find a similar pattern. The overpricing of inflation-sensitive lottery stocks gets corrected within 8 (2) months for IVOL (MAXRET) sorted portfolios, 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, we demonstrate that 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 demand, and changes in the investment opportunity set (e.g., Fama and Schwert (1977); Kaul

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

(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 become more risk-seeking 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 non-fundamental 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$\leq$ Standard Industrial Classification $\leq$ 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.

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

We posit that gambling demand is likely concentrated among lottery stocks that receive more attention when inflation is high. To identify these particular lottery stocks, we compute a time-varying conditional inflation sensitivity measure that allows us to identify stocks with returns that exhibit greater covariance with inflation. 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 using the past 60 months of data. 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, we denote this sensitivity measure as IS.[8]

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

[6] The 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)).

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

[8] For robustness, we compute IS 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.

[9] We also examine the effects of positive and negative IS estimates separately and find similar results.

attention is likely associated with both increases in positive and negative return covariances, which is captured by the absolute value of the inflation sensitivity measure.

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

We find that high *IS* stocks are more volatile and have higher levels of skewness, compared to low *IS* stocks, with volatility of 3.858% and 2.502% for high and low *IS* stocks respectively. Similarly, high *IS* stocks have an average skewness of 0.254, as compared to 0.197 for low *IS* stocks. They also have smaller average market capitalization ($502 million versus $3,842 million) and lower average stock price ($12.46 versus $28.12). Recent examples of high *IS* stocks include Allbirds and Vaxxinity, which both exhibited *IS* values in the top 10^{th} percentiles during peak inflation in 2022. These stocks were also mentioned on channels like reddit's wallstreetbets during this time period, which provides support for *IS* capturing stocks that garnered high attention during periods of changing inflation.

We report measures of retail trading intensity and arbitrage costs for the three *IS* categories. Consistent with our assumption, we find that high *IS* 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 *IS* firms have higher mispricing. Finally, we find that rolling estimates of *IS* slopes significantly predict subsequent inflation sensitivity, confirming that *IS* precisely captures the covariance of stock returns with inflation rather than merely reflecting noise.

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.

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 Fama and French (1993) three 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) and idiosyncratic skewness (ISKEW) 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 as investors are 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 monthly 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 in month t relative to one year ago.

During the 2004-2024 period, we find a positive relation between inflation and gambling. The correlation between annual inflation and the 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 inflation. 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:

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

where $RiskAversion_t$ 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. We also filter inflation using an ARMA(1,1) process to account for the autocorrelation in the time series. For robustness, we consider different measures of inflation, including expected inflation estimates. The coefficient θ represents the sensitivity of risk aversion to inflation. We also include additional controls for macroeconomic conditions such as the monthly VIX index and the federal effective funds rate. 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 negatively correlated with monthly inflation. Specifically, a one standard deviation change in inflation is associated with a 1.3 to 3.4% decrease in the monthly risk aversion index, relative to its mean.[10] 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.

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 corresponds to an increase in demand for state lotteries. We use the annual state lottery revenues per capita and excess state-level inflation to estimate the following regression model:

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

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 also include additional time-varying state-level controls to account for local macroeconomic conditions that may be correlated with state inflation and lottery revenues such as state-level population growth and unemployment rates. 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 locally experienced differences in inflation impact lottery demand, providing evidence for the mechanism underlying our prediction that inflation increases demand for gambling-related investments.

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

[10] We compute the economic magnitude of the impact as $100 \times \frac{-0.717 \times 0.142}{2.992} = -3.4\%$.

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 11.30 to 12.46% increase in real per capita state lottery revenue, relative to its mean value.[11] This evidence suggests that local inflation shifts have a meaningful impact on state-level lottery activity, supporting our conjecture that perceived inflation increases the demand for lotteries.

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 greater sensitivity to inflation allocate a larger portion of their holdings to stocks with lottery characteristics. We obtain data on the portfolio holdings of investors at a large discount brokerage house over the 1991 to 1996 period.

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,

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

where,

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

I^R_{t-k} 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

[11] We compute the economic magnitude of the impact as $100 \times \frac{6.212\times 1.068}{58.7} = 11.30\%$.

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 exposure leads investors to 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 larger weights to lottery stocks based on household income. If inflation increases the propensity to gamble as investors hope for a large payoff to partially compensate for purchasing power losses, investors with lower income will exhibit greater loss sensitivity because they are more likely to feel high inflation-induced "pain". 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 exposure assign a significantly larger weight to lottery stocks relative to those with higher incomes. Specifically, low-income households with high inflation sensitivity 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 direct 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. Inflation Dynamics and Portfolio Performance

In this section, we test our main conjecture, which posits a link between inflation and the performance of lottery-type investments. To establish the link between inflation and the 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 returns of IVOL and MAXRET based Long−Short portfolios to be more negative during periods of high inflation.

Therefore, we examine the performance of our long-short lottery portfolios starting from the portfolio formation month and following the performance over the subsequent six months. During periods of high inflation, we expect the demand for lottery stocks to increase, causing the returns of these stocks to increase. This relation is expected to reverse as mispricing gets corrected in subsequent months. To test this prediction, we analyze the abnormal returns of the long-short lottery stock portfolios following periods of high inflation and low inflation separately. We categorize high and low inflation using terciles of unexpected inflation, where unexpected inflation is calculated by taking the realized year-over-year percentage change in CPI and subtracting the value of expected inflation for that month based on the University of Michigan Survey of Consumers. High (low) inflation months are classified as months that fall in the top (bottom) tercile of unexpected inflation.

The results are presented in Table IV. As predicted, we find that the abnormal returns of the long-short IVOL and MAXRET portfolios are positive and significant in the month of portfolio formation when unexpected inflation is high. These positive returns are followed by a significant reversal in the six months following portfolio formation. The reversal pattern remains negative and significant through month five for the IVOL sorted portfolios, while the negative abnormal returns lose significance after month four for the MAXRET sorted portfolios.

During low inflation months, the long-short IVOL strategy yields a positive but insignificant abnormal return suggesting that low inflation periods do not spur as much excess demand for high IVOL stocks. The IVOL sorted portfolios exhibit negative and significant returns in the two months following portfolio formation, however this effect is likely due to the correction of residual mispricing among IVOL portfolios and not our gambling channel. The long-short MAXRET portfolio is positive and significant during low inflation months. However, both the formation-month returns and subsequent reversals are greater during high inflation months, suggesting that demand for high MAXRET stocks—and therefore mispricing—is amplified during these periods.

For robustness, we perform time series regressions of excess returns on various lottery stock characteristics (IVOL and MAXRET), unexpected inflation, a set of stock-level controls, as well as firm, year, and month fixed effects. The results are presented in Table IA.2 in the Internet Appendix. For ease of interpretation, we present results for continuous values of monthly unexpected inflation, as well as categorical versions of unexpected inflation where months are sorted into above or below median, terciles, and quintiles.[12]

Consistent with our conjecture, we find that returns of lottery stock portfolios are negative and statistically significant following months with larger inflation surprises. In months with above median inflation surprises, lottery stock portfolios experience −0.281% and −0.185% lower average returns in the following month (see columns (7) and (8)). The results are statistically and economically significant for all variations of inflation surprise variables[13].

We also test whether inflation induced gambling exhibits sensitivity to inflation persistence. We expect gambling tendency to increase following months of persistently high inflation, as the adverse effects of price increases on real purchasing power may take time to materialize. We run additional time series regressions where we replace our measures of unexpected inflation with indicators that take the value of one if year-over-year inflation has been greater than 2% for 1, 3, and 6 months. In untabulated results, we find that the lottery stock portfolios are significantly more negative following months when inflation was above 2% for at least 6 months relative to months when inflation was high for a shorter period.

We also test the importance of expected versus unexpected inflation. We posit that gambling demand is likely to be greater during months with higher unexpected inflation, since the surprise in CPI is likely to increase the salience of price increases. We again perform time series regressions similar to those presented in Table IA.2, where we interact the lottery stock characteristics with measures of expected and unexpected inflation. In untabulated results, we find that the unexpected portion of inflation is a stronger predictor of gambling demand among lottery stocks. When we include both expected and unexpected inflation together, only the interactions between our lottery stock measures and unexpected inflation remain significant.

3.3. Sorting Results

In this section, we analyze the performance of portfolios sorted on *IS* and one of the two main lottery proxies (IVOL and MAXRET). Our use of *IS* as a key sorting variable is motivated by the observation that not all lottery-type stocks attract equal investor attention during inflationary periods. Stocks with higher inflation sensitivity are more likely to capture attention as inflation changes, making them more susceptible to gambling-induced demand. Since high *IS* stocks attract more attention during periods of rising inflation, we expect gambling behavior to be more prevalent among these stocks and therefore expect the negative

[12]To prevent look ahead bias, months are sorted based on monthly observations up to month t.

[13]The results are robust to alternative measures of inflation including quarterly and annual moving averages of both year-over-year changes in CPI as well as month-over-month changes in CPI.

lottery stock premium to be more pronounced. If our conjecture is correct, the negative lottery premium should be most pronounced among high *IS* stocks.

We begin by independently sorting stocks into quintiles based on the absolute value of their inflation sensitivities 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.[14]

Table V 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 on our lottery proxies indicate that high IVOL, and high MAXRET portfolios are overpriced. consistent with the evidence in prior studies, the monthly alpha difference between high and low IVOL and MAXRET portfolios are −0.940 (t-statistic = −5.52) and −0.577 (t-statistic = −4.21), respectively.[15]

The single sort results on *IS* also show that high *IS* stocks are overpriced relative to low *IS* stocks. However, the return pattern is not monotonic as we move from the lowest *IS* to the highest *IS* quintile. More notably, the only quintile that is overpriced is the highest quintile. This finding emphasizes our motivation for using *IS* to capture gambling demand. Stocks with the greatest sensitivity to inflation—high *IS* stocks—attract greater investor attention following changes in inflation, reflecting the increase covariance between returns and inflation. The mispricing caused by this increased attention is then corrected in the following month.

Examining how returns of lottery stock portfolios vary with *IS*, we find that the degree of overpricing of the high IVOL portfolio is greatest in the top *IS* quintile. The alpha estimate of the high IVOL portfolio in the low *IS* quintile is −0.447 (t-statistic = −2.31), while the alpha in the high *IS* quintile is −1.017 (t-statistic = −5.45). Similarly, the alpha estimates of the high MAXRET portfolio in the low and high *IS* quintiles are −0.145 (t-statistic = −0.90) and −0.696 (t-statistic = −4.53), respectively. Moreover, we find that the performance spread between low and high IVOL portfolios is largest for the highest *IS* quintile (alpha difference = −1.303, t-statistic = −5.09). The pattern is similar when we examine portfolios sorted on MAXRET. The performance spread across low and high MAXRET portfolios in the highest IS quintile is = −1.136 with a t-statistic of −5.19.

[14]Among our twenty five double sorted portfolios, we find that the average number of stocks in each portfolio increases (decreases) with *IS* among high (low) IVOL and MAXRET stocks. We also find a similar pattern in the average total market cap of each portfolio as a percentage of the overall market. We find that the excess value-weighted returns of high (low) IVOL and MAXRET portfolios decrease (increase) with *IS*, but the standard deviation of these portfolios increases with *IS* regardless of the level of IVOL or MAXRET.

[15]Our results are similar when we compute alphas using the Fama-French five-factor model. See the estimates reported in Appendix Table IA.1.

To further assess the impact of inflation on the pricing of lottery-type stocks, we again examine the performance time series of IVOL and MAXRET based Long−Short portfolios, focusing on stocks within the highest *IS* quintile. Specifically, we consider firms within the top *IS* quintile and plot the 12-month moving average of the returns of High−Low IVOL and High−Low MAXRET strategies within the high *IS* quintile. We focus on the top *IS* quintile because stocks with greater return sensitivity to inflation are those that receive the most attention in response to changes in inflation.

Figure 2 shows the Long−Short strategy's performance over time, along with unexpected inflation in month t. The figure plots the results for the most recent months 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 unexpected inflation 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 2022 when inflation spiked.

These results indicate that lottery demand is greater among stocks that exhibit more sensitivity to inflation and are more likely to attract investor attention, with the magnitude of the negative lottery premium being greatest among the most inflation-sensitive stocks. This evidence supports our conjecture that investors increase their speculative demand for such assets when inflation rises. 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)) may partially reflect the overpricing of stocks with lottery-like characteristics.

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 *IS*. We then use the values of these lottery proxies and inflation sensitivity to predict returns in month $t + 1$. The interaction between *IS* and the lottery proxies captures 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 VI 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 *IS*. 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 *IS*. 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 *IS*. In these specifications, IVOL, MAXRET, and *IS* are set to one if their respective values are above-median, and zero otherwise. We find that, among high IVOL stocks, high *IS* is associated with -0.150% lower average return (see column (7)). The effect is similar when we use MAXRET as the lottery proxy, where among high MAXRET stocks, high *IS* is associated with -0.135% lower return on average (see column (8)). Both interaction terms are statistically and economically 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 *IS* 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 retail trading intensity (RTI) as a proxy for stock-level gambling propensity.

Since retail investors are known to exhibit stronger gambling tendencies (Kumar (2009)), we expect the underperformance of high *IS* lottery stocks to be larger for stocks with higher retail trading intensity (RTI). 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 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.

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 VI and introduce a triple interaction term between *IS*, one of our lottery characteristics, and RTI. A negative coefficient on this triple interaction term would indicate that high *IS* 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, *IS*, and gambling exposure proxies.

Panel B of Table VI presents the results. Consistent with our conjecture, we find that high *IS* lottery stocks experience larger negative returns if they also have higher RTI. Columns (1) and (2) present the results for specifications that use continuous values of RTI, while columns (3) and (4) present the results using indicator values for above versus below median RTI.

For stocks with high IVOL and high *IS*, we find that high *IS*, high IVOL firms earn -0.073% lower average monthly return if RTI is high (see column (3)). Similarly, high IS, high MAXRET firms with high RTI earn -0.056% 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, these results indicate that exposure to speculative trading exacerbates the mispricing of high *IS* 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.

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.

In our setting, these findings imply that the overnight and intraday return patterns of high *IS*, high IVOL and high *IS*, 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 *IS* 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.

To test this hypothesis, we examine separately the overnight and intraday returns of portfolios double sorted on *IS* 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 VII 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 *IS* 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 *IS*.

We find that the returns of the high *IS* 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 51.1 and 39.1 basis points decline in the intraday returns of high IVOL and MAXRET stocks, respectively. In contrast, high *IS* is associated with a 88.6 and 78.8 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 *IS* 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.[16] 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 *IS* 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 (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-*IS* and MAXRET-*IS* 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

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

of high *IS* firms, the average MIS estimate for stocks in the top IVOL and MAXRET quintiles are 6.890 and 6.800, respectively. These estimates are significantly higher than the average MIS for stocks in the bottom IVOL and MAXRET quintiles (= 5.171 and 5.514, respectively). The MIS differentials across the two quintile portfolios are 1.719 and 1.285, 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 *IS* 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 *IS* 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 *IS* 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 IX 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 but weakening in the first six months for IVOL-sorted portfolios. The abnormal return is negative for MAXRET-sorted portfolios, and loses significance after two months. The alpha in the first month following the portfolio formation month is -1.265%(t-statistic = -4.92) for the IVOL-sorted portfolio and -1.136%(t-statistic = -5.19) for the MAXRET-portfolio. In the second month, the alpha for the IVOL portfolio drops to -1.066%(t-statistic = -4.36). The MAXRET portfolio alpha also drops significantly to -0.768%(t-statistic = -3.19).

Together, these results indicate that gambling-induced mispricing eventually diminishes over time. The mispricing correction begins immediately and continues over the next six months, with the negative abnormal returns weakening but remaining significant for IVOL sorted portfolios through month eight and for MAXRET through month two.[17] This correction pattern suggests that limits to arbitrage prevent sophisticated investors from fully exploiting the gambling induced mispricing.

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 *IS* 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 *IS* portfolios. The average arbitrage cost estimates across *IS* portfolios are presented in Panels C and D of Table VIII. Again, we find that arbitrage costs increase as *IS* increases, where the difference in $BO\_Inventory\_Value$ between the top and bottom *IS* 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 *IS*, 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-*IS*,

[17] We find that the negative abnormal return becomes insignificant at $k = 9$ for the IVOL sorted portfolios.

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 X presents the Fama-MacBeth estimates. Columns (1) and (2) present the results using quintile values for IVOL, MAXRET, and *IS*. As expected, we find that the lottery stocks have a larger negative premium when arbitrage costs are high. Specifically, the returns of inflation-sensitive lottery stocks with high costs of arbitrage are 0.061% lower on average when the portfolios are sorted on IVOL and 0.032% lower when sorted on MAXRET for a given *IS* lottery stock portfolio. Columns (3) and (4) present the results using high (low) indicator variables for IVOL, MAXRET, and *IS*. We find that high arbitrage costs are associated with a 0.570% and 0.335% 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 Comovement

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:

$$\begin{aligned} r_{it} - r_{ft} = \beta_0 + \beta_1 INDEX_{it} + \beta_2 RMRF_t \\ + \beta_3 SMB_t + \beta_4 HML_t + \varepsilon_{it} \end{aligned} \tag{4}$$

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 stock-level excess return comovement on each of the two lottery stock characteristics, *IS*, 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 XI presents the results. Consistent with our key conjecture, we find that excess return comovement is greater for high *IS* 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 *IS* lottery stocks, return comovement in month t is between 0.144 and 0.169 units higher relative to low *IS* non-lottery stocks. The relation persists when predicting comovement in the following month as show in Panel B.[18]

Additionally, we test whether greater return comovement predicts returns by adding an interaction term between each of the lottery characteristics, *IS*, 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 negative returns among inflation-sensitive lottery stocks. The results are presented in Table XII. 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.

[18]Given that the average value of return comovement is 0.260 for the LOTT index, an increase of 0.144 among inflation sensitive lottery stocks is economically meaningful.

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 *IS*. 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 *IS*. 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 *IS* 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 *IS*. 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. 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 three additional ways to define lottery stocks. The alternative lottery proxies include ISKEW, ESKEW, and LOTTERY. The first 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 second 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 *IS*. The estimates are presented in Table IA.3 in the Internet Appendix. 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 three alternative lottery characteristics predict lower subsequent returns as inflation sensitivity increases. As shown in Panel B, the magnitude of the interactive effect of high *IS* for firms with high values of these alternative lottery characteristics ranges from 11.1 basis points (monthly) for ISKEW to 18.2 basis points (monthly) for the ESKEW. The combined effect falls in the middle of the individual effects of IVOL and MAXRET shown in Table VI. Therefore, stocks with both high IVOL and high MAXRET are more likely to be perceived as lotteries due to their joint properties, rather than due to unrelated characteristics that are merely correlated with inflation.

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.

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

One potential concern with our findings is that our *IS* estimates could reflect the effects of broader market sentiment or economic conditions rather than inflation sensitivity specifically. To examine this possibility, we re-estimate *IS* 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) in Table XIII, our key findings remain robust—the interaction between *IS* 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 *IS* to control for broader economic cycles. The results remain qualitatively similar, with the interaction terms retaining their negative signs (-0.095 for IVOL and -0.127 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 -0.202 for IVOL and -0.194 for MAXRET.

As a final robustness check, we use expected inflation rather than realized inflation innovations when computing *IS* (see columns (7) and (8)). Again, the results remain consistent with our main findings—the interaction terms retain their negative signs (-0.210 for IVOL and -0.235 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.

4.4. Positive and Negative Inflation Sensitivity

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 values of *IS*. Given that our *IS* 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 *IS* 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 *IS* separately.

As shown in Table IA.4 in the Internet Appendix, we find that the results are similar between the positive and negative *IS* subsamples, with the magnitude of the *IS* lottery stock premium being slightly stronger among the positive *IS* subsample. For positive *IS* stocks, the interaction coefficients between our lottery proxies and *IS* are −0.088 (t-statistic = −3.03) and −0.078 (t-statistic = −2.72), while the interaction coefficients among negative *IS* stocks are −0.099 (t-statistic =− 4.18) and −0.077 (t-statistic = −3.07) 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 effects are qualitatively similar when comparing the effect of *IS* on the negative lottery stock premium between positive and negative *IS* stocks.

4.5. 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 Table IA.5 in the Internet Appendix, we find that our key findings remain robust when excluding the COVID years. The interaction terms between *IS* and lottery characteristics continue to be negative and highly significant across different specifications. When using continuous independent variables, the interaction coefficient between IVOL and *IS* is −0.048 (t-statistic = −2.46), while the interaction between MAXRET and *IS* is −0.011 (t-statistic = −1.92). When using quintile rankings, these effects strengthen to −0.043 (t-statistic = −5.13) for IVOL and −0.036 (t-statistic = −4.47) for MAXRET. When using indicator variables, the interaction coefficients are −0.163 (t-statistic = −2.97) and −0.132 (t-statistic = −2.63) 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.

4.6. 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 4.3., we include the VIX index as an additional control when computing our *IS* estimates.

In untabulated results, we find that controlling for VIX does not materially affect our main findings. The interaction between *IS* and lottery characteristics remains negative and highly significant. For IVOL, the interaction coefficient is -0.270 (t-statistic $= -3.94$), while for MAXRET, the interaction coefficient is -0.224 (t-statistic $= -3.92$). 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.

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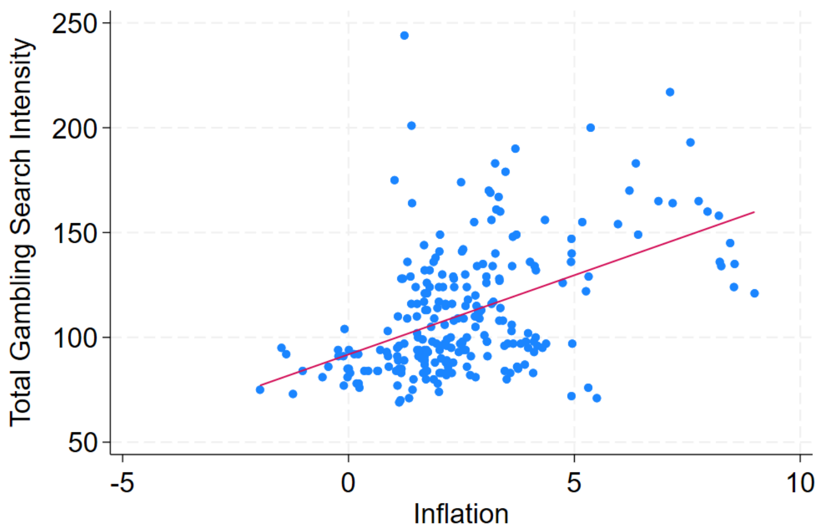
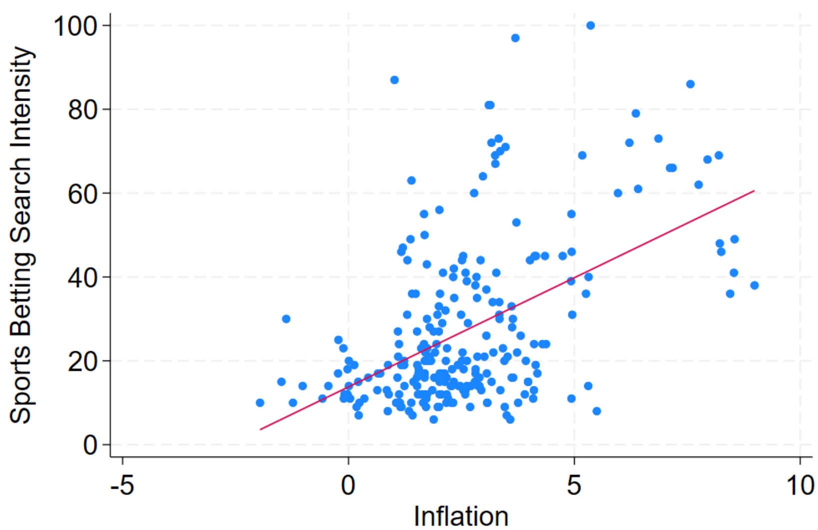


(a) Total Gambling Search Intensity



(b) Sports Betting Search Intensity

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.

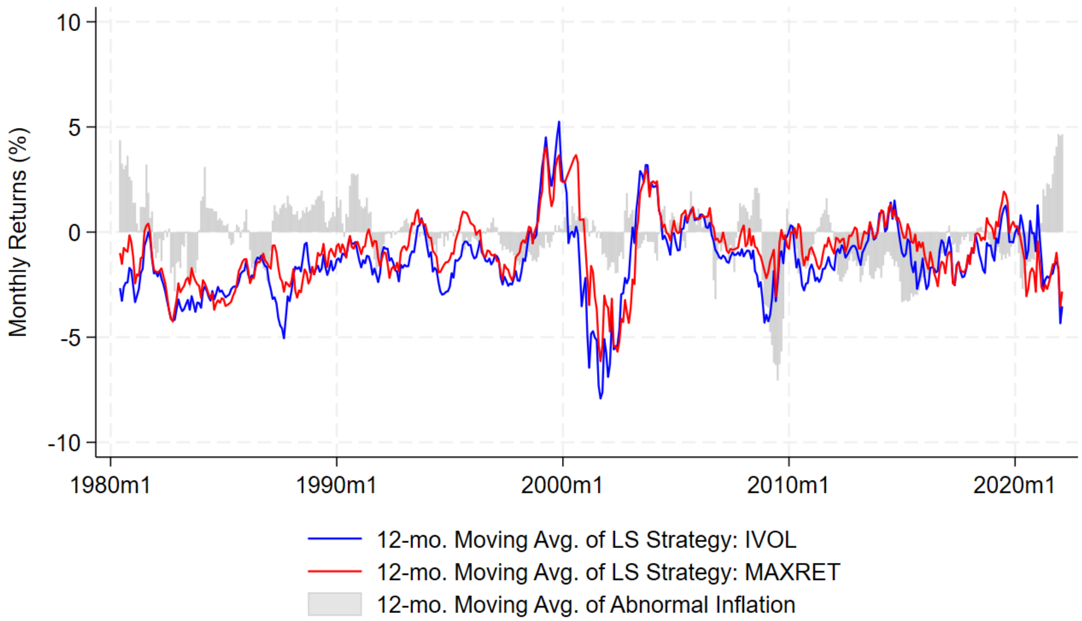


Figure 2: **Trading Strategy Performance Time Series**

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 *IS* 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 unexpected inflation in month t.

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 *IS* firms. Stocks are categorized as Low (High) *IS* if they fall into the bottom (top) quintile of *IS* 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 *IS*, respectively. Large negative (positive) *IS* stocks are those that are in the top 20th percentile of the absolute value of *IS*, conditional on negative (positive) *IS* values. *IS* 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.

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 Innovation	0.008	0.142	-0.062	0.006	0.074
Expected Inflation	3.110	0.670	2.700	3.000	3.300
Risk Aversion Index	2.992	0.667	2.626	2.812	3.081

Panel B: Stock-Level Variables

Variable	Mean	StdDev	25th Pctl	Median	75th Pctl
IS	1.211	5.474	0.260	0.612	1.305
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	2.592	1.714	1.351	2.152	3.397
MAXRET	6.740	4.781	3.209	5.367	9.009
MIS	5.384	2.863	3.000	5.000	8.000
ISKEW	0.175	0.835	−0.262	0.157	0.603
SKEW	0.218	0.951	−0.245	0.197	0.680
ESKEW	0.346	0.229	0.221	0.353	0.462
Retail Trade Intensity	0.061	0.059	0.026	0.039	0.070

Continued on next page...

Table I – continued from previous page

Panel C: Portfolio Characteristics

Variable	Others	IS Q1	IS Q5	$IS > 0$ Q5	$IS < 0$ Q5
VOL	2.902	2.502	3.858	3.805	3.89
IVOL	2.468	2.11	3.334	3.279	3.369
SKEW	0.215	0.197	0.254	0.251	0.257
ISKEW	0.173	0.159	0.204	0.201	0.207
Stock Price	23.266	28.123	12.458	13.481	11.704
Market Beta	0.901	0.851	0.964	0.976	0.954
Firm Size	2352.228	3842.011	501.673	560.532	449.039
Book-to-Market	0.879	0.89	0.781	0.778	0.779
Past 12-mo. Return	11.314	10.742	11.772	11.856	11.685
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	5.213	4.946	6.388	6.35	6.415
BO_Inventory_Value	0.185	0.193	0.126	0.128	0.125
DCBS	1.483	1.353	2.224	2.17	2.263

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 (4) is monthly risk aversion in month t, while the dependent variable in columns (5) and (6) is annual state lottery revenues per capita in 2010 dollars. $Inflation$ is the percentage change in CPI in month t relative to CPI in month $t-12$. $Inflation$ is also filtered using an ARMA(1,1) process to account for the serial correlation in the time series of inflation. $Inflation\ Expectation$ is the value of expected inflation from the University of Michigan Survey of Consumers. *Adjusted State CPI Change* is the monthly state-level inflation minus national inflation in month t. Additional controls in columns (1) through (4) include the monthly VIX index and the Federal Effective Funds Rate. Additonal controls in columns (5) and (6) are state-level controls for population growth and unemployment. We use Newey-West HAC adjusted standard errors with 12 lags in columns (1) through (4) and state-by-year clustered standard errors in columns (5) and (6). 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 Aversion (1−4)				Lottery Revenue (5−6)	
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Inflation	−0.717*	−0.694*	−0.266***			
	(−1.73)	(−1.66)	(−2.82)			
Inflation Expectation				−0.120***		
				(−2.94)		
Adjusted State Inflation					6.212*	6.850**
					(2.03)	(2.37)
Constant	2.895***	2.904***	1.138***	1.491***	59.393***	79.887***
	(160.83)	(31.93)	(3.65)	(5.86)	(14.92)	(5.65)
Additional Controls	No	No	Yes	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	No	No
Month FE	No	Yes	Yes	Yes	No	No
State FE	No	No	No	No	Yes	Yes
N	463	463	420	420	589	589
R$\hat{2}$	0.493	0.513	0.901	0.902	0.721	0.734

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 Sample		Low Income		High 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 × 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 × 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(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(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***
	(−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***
	(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***
	(−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
	(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	0.077	0.095	0.094

Table IV: **K-Month Four-Factor Alpha Estimates for Single-Sorted Portfolios**

This table reports the four-factor alpha estimates for long-short portfolios sorted on our two 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. Value-weighted returns are then calculated for each of the 5 portfolios. The long portfolio contains stocks that fall in the top quintile of IVOL or MAXRET, and the short portfolio contains stocks that fall in the bottom quintile of IVOL or MAXRET. The value-weighted returns of the long-short portfolios are then regressed on the Carhart (1997) four factors. The regression intercepts are reported in the table, starting at the end of the portfolio formation month (k=0) to six months following portfolio formation (k=6). In Panel A (Panel B), we restrict the sample to portfolios formed during high (low) inflation months. We classify high and low inflation months based on terciles of unexpected inflation, where high (low) inflation months are those in the top (bottom) tercile of unexpected inflation. The *t*-statistics are reported in parentheses. All variables are defined in Appendix Table A.1.

Panel A: High Inflation Months							
	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5	k = 6
IVOL	1.933***	−1.156***	−1.279***	−1.748***	−1.094***	−0.905**	−0.456
	(2.95)	(−2.79)	(−3.64)	(−3.76)	(−3.03)	(−2.51)	(−1.27)
Number of Months	183	152	137	124	120	115	109
R^2	0.607	0.621	0.596	0.662	0.657	0.637	0.592
MAXRET	10.530***	−0.627*	−1.031***	−0.687*	−0.985***	−0.330	−0.355
	(20.62)	(−1.91)	(−3.30)	(−1.94)	(−2.61)	(−1.17)	(−1.19)
Number of Months	176	150	135	122	115	106	102
R^2	0.611	0.517	0.663	0.641	0.567	0.579	0.609
Panel B: Low Inflation Months							
	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5	k = 6
IVOL	0.081	−0.850***	−0.725**	−0.625	−0.549	−0.521	−0.361
	(0.12)	(−3.00)	(−2.18)	(−1.48)	(−1.56)	(−1.60)	(−1.16)
Number of Months	183	158	143	133	121	110	108
R^2	0.491	0.519	0.550	0.511	0.561	0.606	0.592
MAXRET	9.717***	−0.827***	−0.663**	−0.483	−0.539	−0.217	−0.557*
	(19.23)	(−2.70)	(−2.48)	(−1.33)	(−1.47)	(−0.71)	(−1.67)
Number of Months	167	143	126	116	107	92	88
R^2	0.593	0.534	0.640	0.598	0.650	0.608	0.619

Table V: **Four-Factor Alpha Estimates for Double-Sorted Portfolios**

This table reports the four-factor alpha estimates for double sorted portfolios based on inflation sensitivity (*IS*) 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 *IS*. 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.

			Inflation Sensitivity					
Sorting Variable		All	Low	Q2	Q3	Q4	High	High−Low
			0.078	0.070	0.062	0.035	−0.203	**−0.281**
			(2.58)	(1.77)	(1.36)	(0.57)	(−2.36)	**(−2.92)**
IVOL	Low	0.116	0.078	0.163	0.114	0.136	0.286	0.208
		(3.25)	(1.50)	(3.01)	(1.65)	(1.35)	(1.98)	(1.37)
	2	0.094	0.171	0.028	0.118	0.108	0.036	−0.135
		(2.01)	(2.51)	(0.33)	(1.47)	(1.24)	(0.27)	(−0.84)
	3	0.031	0.048	−0.012	0.085	0.028	−0.006	−0.054
		(0.50)	(0.57)	(−0.14)	(0.74)	(0.28)	(−0.05)	(−0.37)
	4	−0.257	−0.184	−0.196	−0.253	−0.093	−0.337	−0.154
		(−2.66)	(−1.21)	(−1.41)	(−1.85)	(−0.72)	(−2.75)	(−0.90)
	High	−0.824	**−0.447**	−0.918	−0.885	−0.477	**−1.017**	−0.569
		(−5.44)	**(−2.31)**	(−4.48)	(−4.72)	(−2.50)	**(−5.45)**	(−2.38)
	High−Low	−0.940	−0.525	−1.081	−1.000	−0.613	−1.303	**−0.778**
		(−5.52)	(−2.47)	(−4.83)	(−4.81)	(−2.79)	(−5.09)	**(−2.59)**
MAXRET	Low	0.156	0.085	0.195	0.225	0.179	0.440	0.355
		(3.32)	(1.59)	(3.18)	(3.07)	(1.82)	(3.19)	(2.51)
	2	0.083	0.057	−0.019	0.001	0.014	−0.093	−0.151
		(1.54)	(0.91)	(−0.28)	(0.01)	(0.14)	(−0.78)	(−1.14)
	3	0.071	0.022	0.089	0.011	−0.001	0.032	0.010
		(1.25)	(0.24)	(0.99)	(0.12)	(−0.01)	(0.26)	(0.07)
	4	−0.119	0.000	−0.104	−0.078	−0.093	−0.460	−0.460
		(−1.30)	(0.00)	(−0.71)	(−0.63)	(−0.77)	(−3.29)	(−2.61)
	High	−0.428	**−0.145**	−0.553	−0.536	−0.298	**−0.696**	−0.551
		(−3.86)	**(−0.90)**	(−3.78)	(−3.77)	(−1.94)	**(−4.53)**	(−2.85)
	High − Low	−0.577	−0.230	−0.748	−0.762	−0.477	−1.136	**−0.906**
		(−4.21)	(−1.28)	(−4.42)	(−4.37)	(−2.53)	(−5.19)	**(−3.92)**

Table VI: **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. *IS* 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 *IS* 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 *IS* represent dummy variables, which are indicator variables that take the value of 1 if a stock's idiosyncratic volatility, maximum daily return, and *IS* 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), *IS*, and retail trading intensity (RTI). Columns (1) and (2) present the results using the continous values of RTI as our measure of gambling exposure. In columns (3) and (4) we use an indicator variable for RTI where RTI takes the value of 1 if the retail trading intensity is above the median for a given stock in a given month and zero otherwise. 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)
IS	−0.017	0.142**	−0.029	0.096	0.128***	0.108***	0.079	0.064
	(−0.55)	(2.18)	(−0.88)	(1.59)	(4.55)	(3.96)	(1.55)	(1.32)
IVOL	−0.262***	−0.221***			−0.054		−0.190	
	(−6.27)	(−4.53)			(−1.07)		(−1.43)	
IVOL × *IS*		−0.045**			−0.042***		−0.150***	
		(−2.49)			(−5.05)		(−2.83)	
MAXRET			−0.074***	−0.064***		−0.062		−0.180
			(−6.06)	(−4.60)		(−1.33)		(−1.57)
MAXRET × *IS*				−0.011**		−0.038***		−0.135***
				(−2.06)		(−4.84)		(−2.81)
log(B/M)	0.747***	0.751***	0.758***	0.764***	0.774***	0.796***	0.824***	0.838***
	(4.80)	(4.85)	(4.87)	(4.93)	(5.03)	(5.16)	(5.23)	(5.31)
log(ME)	−0.107***	−0.100***	−0.086***	−0.081***	−0.077***	−0.069**	−0.060*	−0.055*
	(−3.66)	(−3.45)	(−2.74)	(−2.62)	(−2.68)	(−2.23)	(−1.95)	(−1.69)
RET[−12, −2]	0.716***	0.708***	0.703***	0.702***	0.762***	0.735***	0.781***	0.749***
	(7.02)	(6.98)	(6.91)	(6.89)	(7.60)	(7.24)	(7.65)	(7.35)
RET[−1, 0]	−0.033***	−0.033***	−0.029***	−0.029***	−0.034***	−0.030***	−0.034***	−0.032***
	(−9.89)	(−9.85)	(−8.33)	(−8.26)	(−10.23)	(−8.77)	(−10.35)	(−9.40)
Constant	1.381***	1.212***	1.107***	0.981***	0.752***	0.727***	0.537*	0.521*
	(4.81)	(4.42)	(3.64)	(3.33)	(3.09)	(2.79)	(1.87)	(1.73)
Average N	2,838	2,838	2,844	2,844	2,838	2,844	2,838	2,844
Adjusted R^2	0.044	0.045	0.043	0.044	0.044	0.043	0.041	0.041

Table VI – continued from previous page

Panel B: Extended Fama-MacBeth Regression Estimates				
Independent Variable	(1)	(2)	(3)	(4)
IS	-0.095	-0.089	-0.044	-0.070
	(-1.55)	(-1.44)	(-0.76)	(-1.18)
RTI	0.453	1.650	0.031	0.114
	(0.19)	(0.66)	(0.15)	(0.48)
IS × RTI	2.035**	0.783	0.212***	0.116
	(2.20)	(0.93)	(2.94)	(1.34)
IVOL	-0.173*		-0.152*	
	(-1.90)		(-1.66)	
IVOL × *IS*	0.030		0.013	
	(1.55)		(0.69)	
IVOL × RTI	-0.633		-0.047	
	(-0.96)		(-0.60)	
IVOL × *IS* × RTI	-0.758***		-0.073***	
	(-2.96)		(-2.80)	
MAXRET		-0.165*		-0.161**
		(-1.81)		(-2.03)
MAXRET × *IS*		0.033*		0.022
		(1.83)		(1.36)
MAXRET × RTI		-0.720		-0.044
		(-0.80)		(-0.45)
MAXRET × *IS* × RTI		-0.527**		-0.056*
		(-2.00)		(-1.67)
log(B/M)	0.270	0.277	0.242	0.250
	(1.09)	(1.13)	(1.03)	(1.07)
log(ME)	-0.055*	-0.027	-0.019	0.008
	(-1.72)	(-0.71)	(-0.68)	(0.26)
RET[-12,-2]	0.509***	0.491***	0.522***	0.509***
	(3.06)	(2.97)	(3.09)	(3.01)
RET[-1,0]	-0.007	-0.002	-0.008*	-0.004
	(-1.39)	(-0.49)	(-1.75)	(-0.74)
Constant	1.717***	1.471***	1.362***	1.191***
	(4.26)	(3.35)	(4.10)	(3.37)
Average N	2,453	2,456	2,453	2,456
Adjusted R^2	0.031	0.031	0.027	0.028

Table VII: **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 *IS* 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 *IS* 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)
IS	0.065	0.027	−0.259***	−0.333***
	(1.05)	(0.45)	(−3.67)	(−4.92)
IVOL	−0.204**		−0.354	
	(−2.21)		(−1.40)	
IVOL × *IS*	−0.092***		−0.511***	
	(−3.72)		(−3.84)	
MAXRET		−0.196**		−0.432*
		(−1.98)		(−1.93)
MAXRET × *IS*		−0.085***		−0.391***
		(−3.13)		(−2.79)
Average N	3,289	3,296	3,289	3,296
Adjusted R^2	0.030	0.030	0.027	0.027
Panel B: Overnight Returns	**(1)**	**(2)**	**(3)**	**(4)**
IS	−0.342***	−0.236***	0.177***	0.249***
	(−9.35)	(−8.09)	(3.13)	(4.15)
IVOL	0.241***		0.304	
	(2.76)		(1.42)	
IVOL × *IS*	0.186***		0.886***	
	(10.87)		(8.74)	
MAXRET		0.238***		0.326*
		(3.23)		(1.80)
MAXRET × *IS*		0.161***		0.788***
		(10.65)		(8.20)
Average N	3,289	3,296	3,289	3,296
Adjusted R^2	0.026	0.025	0.023	0.023

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 *IS*. 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 *IS*. 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 IS firms. Similarly, Panel B reports these estimates for MAXRET portfolios within the subset of high IS firms. In Panels C and D, we report the estimates for IS portfolios, within the subset of IVOL and MAXRET firms, respectively. All variables are defined in Appendix Table A.1.

Panel A: High IS Firms, IVOL Portfolios						
Variable	Low IVOL	Q2	Q3	Q4	High IVOL	High−Low
MIS	5.171	5.518	6.024	6.452	6.890	1.719
						(43.29)
$BO\_Inventory\_Value$	0.173	0.183	0.156	0.124	0.085	−0.088
						(−13.70)
Panel B: High IS Firms, MAXRET Portfolios						
Variable	Low MAXRET	Q2	Q3	Q4	High MAXRET	High−Low
MIS	5.514	5.762	6.091	6.454	6.800	1.285
						(35.23)
$BO\_Inventory\_Value$	0.154	0.161	0.146	0.125	0.095	−0.059
						(−9.64)
Panel C: High IVOL Firms, *IS* Portfolios						
Variable	Low IS	Q2	Q3	Q4	High IS	High−Low
MIS	6.166	6.197	6.194	6.344	6.890	0.724
						(22.42)
$BO\_Inventory\_Value$	0.116	0.120	0.125	0.114	0.085	−0.031
						(−6.07)
Panel D: High MAXRET Firms, *IS* Portfolios						
Variable	Low IS	Q2	Q3	Q4	High IS	High−Low
MIS	5.953	5.984	6.008	6.209	6.800	0.846
						(26.96)
$BO\_Inventory\_Value$	0.140	0.142	0.145	0.131	0.094	−0.046
						(−7.70)

Table IX: **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 *IS* 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 *IS* 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	1.698	1.683	1.657	1.583	1.542	1.509
	(41.06)	(40.59)	(40.58)	(39.15)	(37.99)	(36.71)
Alpha	−1.265***	−1.066***	−0.902***	−0.568**	−0.783***	−0.706***
	(−4.92)	(−4.36)	(−3.27)	(−2.00)	(−3.16)	(−3.12)
Mkt − Rf	0.336***	0.309***	0.293***	0.248***	0.294***	0.306***
	(4.63)	(4.55)	(3.95)	(3.01)	(4.65)	(4.50)
SMB	1.131***	1.117***	0.957***	0.986***	1.005***	0.841***
	(12.29)	(8.62)	(8.04)	(7.66)	(7.40)	(7.08)
HML	−0.544***	−0.667***	−0.569***	−0.586***	−0.578***	−0.383***
	(−4.06)	(−5.35)	(−4.68)	(−4.50)	(−5.07)	(−3.32)
MOM	−0.189*	−0.145	−0.164*	−0.204**	−0.102	−0.067
	(−1.80)	(−1.35)	(−1.69)	(−2.11)	(−0.84)	(−0.62)
Number of Months	705	699	682	676	674	659
R^2	0.390	0.416	0.347	0.309	0.340	0.312
Panel B: MAXRET						
Variable	$k=1$	2	3	4	5	$k=6$
MIS	1.072	1.070	1.065	0.997	0.973	0.960
	(31.55)	(31.32)	(31.26)	(30.03)	(29.48)	(28.93)
Alpha	−1.136***	−0.768***	−0.375	−0.310	−0.323	−0.256
	(−5.19)	(−3.19)	(−1.57)	(−1.58)	(−1.30)	(−1.20)
Mkt − Rf	0.293***	0.348***	0.293***	0.215***	0.297***	0.276***
	(4.02)	(5.29)	(4.69)	(3.08)	(4.56)	(3.81)
SMB	0.793***	0.750***	0.737***	0.738***	0.854***	0.736***
	(6.42)	(6.87)	(7.14)	(6.83)	(6.90)	(5.52)
HML	−0.507***	−0.525***	−0.540***	−0.628***	−0.518***	−0.521***
	(−4.48)	(−5.03)	(−4.34)	(−4.44)	(−4.08)	(−3.84)
MOM	−0.104	−0.064	−0.200*	−0.178	0.064	−0.108
	(−0.85)	(−0.66)	(−1.75)	(−1.52)	(0.54)	(−0.83)
Number of Months	701	688	680	685	667	654
R^2	0.284	0.329	0.309	0.283	0.326	0.283

Table X: **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), IS, and $BO\_Inventory\_Value$. In columns (1) and (2) IVOL, MAXRET, and IS are categorical variables based on quintiles of each respective measure. In columns (3) and (4) IVOL, MAXRET, and IS 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, *IS*, 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.

Indepndent Variable	(1)	(2)	(3)	(4)
IS	−0.023	0.136	0.341***	0.369***
	(−0.24)	(1.33)	(4.51)	(4.78)
High Arb. Cost	0.302*	0.748***	0.844***	1.173***
	(1.76)	(4.05)	(4.45)	(6.46)
IS x High Arb. Cost	0.208***	0.087*	0.265**	0.099
	(4.24)	(1.68)	(2.32)	(0.94)
IVOL	0.294**		0.877***	
	(2.53)		(4.06)	
IVOL x *IS*	0.028		−0.163	
	(0.99)		(−1.53)	
IVOL x High Arb. Cost	0.143***		0.885***	
	(3.38)		(3.67)	
IVOL x *IS* x High Arb. Cost	−0.061***		−0.570***	
	(−4.66)		(−4.04)	
MAXRET		0.296**		0.644***
		(2.56)		(3.14)
MAXRET x *IS*		−0.002		−0.165*
		(−0.08)		(−1.72)
MAXRET x High Arb. Cost		0.034		0.441
		(0.69)		(1.63)
MAXRET x *IS* x High Arb. Cost		−0.032**		−0.335**
		(−2.24)		(−2.31)
log(B/M)	1.820***	1.789***	1.800***	1.768***
	(6.98)	(6.78)	(6.91)	(6.73)
log(ME)	−0.897***	−0.829***	−0.842***	−0.793***
	(−17.08)	(−17.59)	(−17.68)	(−17.24)
RET[−12,−2]	0.118	0.057	0.105	0.053
	(0.70)	(0.32)	(0.59)	(0.30)
RET[−1,0]	−0.016***	−0.019***	−0.016***	−0.018***
	(−4.37)	(−4.59)	(−4.17)	(−4.46)
Constant	−8.421***	−8.237***	−6.912***	−6.527***
	(−11.05)	(−10.92)	(−11.79)	(−10.99)
Average N	2,360	2,364	2,360	2,364
Adjusted R^2	0.040	0.040	0.036	0.036

Table XI: **Inflation, Gambling, and Return Comovement**

This table presents estimates from Fama-MacBeth cross-sectional regressions that use lottery stock characteristics and *IS* 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 *IS* 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.

Panel A: Dependent Variable: Comovement$_t$						
	IVOL		MAXRET		LOTT	
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
IS	−0.010*	0.009	−0.001	0.020***	−0.006	0.011**
	(−1.78)	(1.53)	(−0.24)	(3.16)	(−1.21)	(2.08)
IVOL	0.160***		0.177***		0.132***	
	(7.04)		(7.42)		(6.64)	
IVOL × *IS*	0.163***		0.169***		0.144***	
	(15.13)		(14.38)		(14.70)	
MAXRET		0.030		0.041*		0.020
		(1.44)		(1.88)		(1.12)
MAXRET × *IS*		0.159***		0.164***		0.141***
		(16.15)		(14.91)		(15.46)
Average N	2,859	2,859	2,815	2,815	2,815	2,815
Adjusted R^2	0.051	0.048	0.050	0.047	0.048	0.046

Panel B: Dependent Variable: Comovement$_{t+1}$						
	IVOL		MAXRET		LOTT	
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
IS	0.014**	0.024***	0.024***	0.033***	0.015**	0.023***
	(2.11)	(3.24)	(3.42)	(4.45)	(2.58)	(3.75)
IVOL	0.144***		0.165***		0.122***	
	(7.45)		(8.13)		(6.84)	
IVOL × *IS*	0.114***		0.116***		0.103***	
	(10.61)		(10.14)		(10.39)	
MAXRET		0.090***		0.107***		0.075***
		(5.45)		(6.06)		(5.03)
MAXRET × *IS*		0.110***		0.113***		0.099***
		(11.53)		(10.72)		(11.26)
Comovement$_{t-1}$	0.049***	0.051***	0.049***	0.051***	0.048***	0.049***
	(9.27)	(9.47)	(8.51)	(8.70)	(8.85)	(9.05)
Average N	2,849	2,849	2,804	2,804	2,804	2,804
Adjusted R^2	0.039	0.037	0.038	0.036	0.037	0.035

Table XII: **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), *IS*, 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, *IS*, and Comovement. IVOL, MAXRET, *IS*, 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		MAXRET		LOTT	
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
IS	0.818***	0.710***	0.691***	0.578***	0.842***	0.693***
	(3.85)	(3.47)	(3.41)	(3.13)	(4.26)	(3.67)
IS × Comovement	−0.413**	−0.457**	−0.488***	−0.522***	−0.373**	−0.471***
	(−2.11)	(−2.38)	(−2.80)	(−3.21)	(−2.20)	(−2.82)
Comovement	0.165	0.192	0.233**	0.260**	0.133	0.182
	(1.33)	(1.54)	(2.10)	(2.37)	(1.21)	(1.62)
IVOL	0.961***		0.855***		0.977***	
	(3.71)		(3.40)		(3.97)	
IVOL × *IS*	−0.227		−0.104		−0.213	
	(−1.62)		(−0.77)		(−1.61)	
IVOL × Comovement	0.216		0.275**		0.195	
	(1.54)		(2.13)		(1.54)	
IVOL × *IS* × Comovement	−0.150*		−0.215***		−0.144*	
	(−1.75)		(−2.80)		(−1.91)	
MAXRET		0.555**		0.468**		0.507**
		(2.32)		(2.13)		(2.20)
MAXRET × *IS*		−0.113		0.009		−0.065
		(−0.85)		(0.07)		(−0.50)
MAXRET × Comovement		0.280**		0.331***		0.305**
		(2.17)		(2.82)		(2.52)
MAXRET × *IS* × Comovement		−0.183**		−0.248***		−0.198**
		(−2.22)		(−3.26)		(−2.53)
Average N	2,846	2,850	2,802	2,805	2,802	2,805
Adjusted $\hat{R2}$	0.048	0.047	0.046	0.045	0.046	0.045

Table XIII: **Fama-MacBeth Regressions: Controlling for Sentiment**

This table reports estimates from monthly Fama-MacBeth cross-sectional regressions using an additional set of controls when computing *IS*. At the end of each month, lottery stock characteristics (MAXRET and IVOL) are computed and used to predict returns in the following month. We compute *IS* 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 specifications, IVOL, MAXRET, and *IS* 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.

	Sent.		Sent. & Recession Ind.		EPU		Expected Inflation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS	0.060	0.058	0.058	0.084	0.026	0.012	0.024	0.023
	(1.26)	(1.20)	(1.06)	(1.53)	(0.44)	(0.19)	(0.35)	(0.32)
IVOL	−0.322***		−0.271**		−0.347**		−0.343**	
	(−2.74)		(−2.13)		(−2.38)		(−2.58)	
IVOL × *IS*	−0.170***		−0.082*		−0.215***		−0.231***	
	(−3.06)		(−1.65)		(−3.39)		(−4.06)	
MAXRET		−0.307***		−0.262**		−0.317**		−0.304**
		(−2.90)		(−2.25)		(−2.34)		(−2.51)
MAXRET × *IS*		−0.167***		−0.130**		−0.193***		−0.240***
		(−3.24)		(−2.32)		(−3.40)		(−4.19)
log(B/M)	0.847***	0.863***	1.033***	1.035***	0.858***	0.875***	0.910***	0.925***
	(4.91)	(4.99)	(5.53)	(5.55)	(4.50)	(4.53)	(4.92)	(4.97)
log(M/E)	−0.075**	−0.071*	−0.075**	−0.074**	0.003	0.007	−0.005	−0.001
	(−2.15)	(−1.94)	(−2.06)	(−1.98)	(0.10)	(0.24)	(−0.18)	(−0.03)
RET[−12,−2]	0.793***	0.765***	0.617***	0.589***	0.639***	0.602***	0.679***	0.643***
	(7.27)	(7.03)	(4.56)	(4.36)	(5.75)	(5.45)	(6.14)	(5.84)
RET[−1,0]	−0.038***	−0.036***	−0.043***	−0.040***	−0.019***	−0.017***	−0.022***	−0.020***
	(−10.96)	(−10.06)	(−10.03)	(−9.31)	(−6.68)	(−5.64)	(−7.59)	(−6.53)
Constant	0.674*	0.655*	0.706*	0.717*	0.400	0.370	0.464	0.431
	(1.90)	(1.76)	(1.70)	(1.67)	(1.26)	(1.07)	(1.42)	(1.25)
Average N	3,008	3,013	2,747	2,751	3,231	3,238	3,246	3,253
Adjusted $\hat{R2}$	0.041	0.040	0.037	0.036	0.030	0.030	0.032	0.031

Appendix

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 (monthly)	Inflation in the United States. Monthly inflation computed as the month over month change in CPI.	FRED
Inflation (annual)	Inflation in the United States. Annual inflation computed as the percentage change in CPI relative to one year ago.	FRED
Inflation Expectations	Median expected price change next 12 months.	Surveys of Consumers, UMich
Unexpected Inflation	Calculated by taking inflation (annual) and subtracting inflation expectation from 12 months prior.	FRED & UMich Survey of Consumers
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 no-arbitrage 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
Adjusted State Inflation	State level change in CPI relative to one year ago minus nationwide change in CPI relative to one year ago.	Hazell et al. (2022)
State Lottery Revenue	Per capita state level lottery revenue, adjusted to 2010 dollars.	US Census Bureau

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Table A1 – *Continued from previous page*

Variable	Description	Source
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
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

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Table A1 – *Continued from previous page*

Variable	Description	Source
Inflation Sensitivity (*IS*)	IS 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 IS.	
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 Fama and French (1993) three-Factor model 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)
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 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

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Table A1 – *Continued from previous page*

Variable	Description	Source
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

Continued on next page

Table A1 – *Continued from previous page*

Variable	Description	Source
VIX	Monthly prices of the VIX index from 1990 to 2024.	CBOE
Panel C: Household-Level Variables		
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(ME)	The natural log of market capitalization.	CRSP
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

Internet Appendix

Table IA.1: Five-Factor Alpha Estimates of Double-Sorted Portfolios

This table reports the five-factor alpha estimates for double sorted portfolios based on inflation sensitivity (IS) 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 IS. 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.

Sorting Variable		Full Sample	Inflation Sensitivity Low	2	3	4	High	High−Low
			0.038	0.044	0.011	0.035	0.048	0.010
			(1.39)	(1.40)	(0.25)	(0.52)	(0.60)	(0.11)
IVOL	Low	0.044	0.010	0.095	0.006	−0.014	0.160	0.149
		(1.27)	(0.21)	(1.74)	(0.08)	(−0.14)	(1.04)	(0.93)
	2	0.064	0.126	−0.003	0.036	0.102	0.219	0.092
		(1.29)	(1.81)	(−0.04)	(0.42)	(1.20)	(1.57)	(0.54)
	3	0.133	0.059	−0.005	0.176	0.145	0.240	0.181
		(2.12)	(0.66)	(−0.05)	(1.36)	(1.45)	(1.83)	(1.18)
	4	−0.128	−0.128	−0.149	−0.154	−0.048	−0.065	0.063
		(−1.48)	(−0.89)	(−0.94)	(−1.20)	(−0.36)	(−0.55)	(0.36)
	High	−0.656	−0.406	−0.880	−0.822	−0.473	−0.717	−0.312
		(−5.12)	(−1.93)	(−4.53)	(−4.63)	(−2.70)	(−4.62)	(−1.39)
	High − Low	−0.699	−0.416	−0.975	−0.828	−0.458	−0.877	−0.461
		(−4.87)	(−1.86)	(−4.63)	(−4.12)	(−2.27)	(−4.06)	(−1.63)
MAXRET	Low	0.059	0.009	0.129	0.073	0.032	0.367	0.358
		(1.32)	(0.16)	(2.11)	(1.02)	(0.31)	(2.48)	(2.34)
	2	0.045	0.023	−0.027	−0.015	−0.022	0.032	0.009
		(0.97)	(0.33)	(−0.38)	(−0.23)	(−0.20)	(0.24)	(0.06)
	3	0.107	0.070	0.068	−0.002	0.038	0.214	0.144
		(1.93)	(0.82)	(0.68)	(−0.02)	(0.42)	(1.85)	(1.05)
	4	0.044	0.057	0.010	0.025	0.022	−0.139	−0.196
		(0.52)	(0.44)	(0.07)	(0.22)	(0.18)	(−1.06)	(−1.11)
	High	−0.256	−0.047	−0.522	−0.440	−0.254	−0.377	−0.330
		(−2.68)	(−0.30)	(−3.72)	(−3.31)	(−1.80)	(−2.70)	(−1.61)
	High − Low	−0.320	−0.056	−0.651	−0.513	−0.287	−0.744	−0.689
		(−2.73)	(−0.33)	(−4.00)	(−3.28)	(−1.74)	(−3.72)	(−2.93)

Table IA.2: Time Series Regression Estimates: Lottery Characteristics and Inflation

This table reports coefficients from time series regressions of stock excess returns on various lottery characteristics, inflation surprises, a set of stock-level controls, as well as firm, year, and month fixed effects. At the end of each month, lottery stock characteristics (MAXRET and IVOL) are computed and used to predict returns in the following month. *Inflation Surprise* is defined as the difference between realized monthly inflation and the expected inflation for that month from the University of Michigan Survey of Consumers. The dependent variable is the stock's excess return in the following month. Standard errors are clustered at the firm-month level. The t-statistics are reported in parentheses. All variables are defined in Appendix Table A.1.

	Continuous		Quintiles		Terciles		Median	
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unexpected Inflation	−0.535*	−0.634**	−0.314	−0.426	−0.653	−0.847*	−0.286	−0.579
	(−1.90)	(−2.25)	(−1.14)	(−1.57)	(−1.43)	(−1.85)	(−0.51)	(−1.06)
IVOL	0.384***		0.739***		0.811***		0.818***	
	(8.91)		(6.06)		(5.20)		(4.72)	
IVOL × Unexpected Inflation	−0.094***		−0.114***		−0.207***		−0.281**	
	(−3.30)		(−2.83)		(−2.68)		(−2.31)	
MAXRET		0.203***		0.443***		0.495***		0.486***
		(4.73)		(4.02)		(3.63)		(3.11)
MAXRET × Unexpected Inflation		−0.063**		−0.078**		−0.143**		−0.185*
		(−2.50)		(−2.29)		(−2.26)		(−1.75)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,716,296	1,716,296	1,716,296	1,716,296	1,716,296	1,716,296	1,716,296	1,716,296
Adjusted R$\hat{2}$	0.060	0.059	0.060	0.059	0.060	0.059	0.059	0.058

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

This table reports estimates from monthly Fama-MacBeth cross-sectional regressions using three alternative lottery-stock proxies: 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 *IS*. 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)
Independent Variable	ISKEW	ESKEW	LOTTERY
IS	0.002	0.156***	0.010
	(0.07)	(4.04)	(0.49)
Lottery Proxy	0.041**	−0.391***	−0.456***
	(2.49)	(−7.03)	(−3.37)
Lottery Proxy ×*IS*	−0.013**	−0.036***	−0.055**
	(−2.51)	(−3.29)	(−2.38)
Average N	2,838	1,476	2,844
Adjusted R^2	0.036	0.042	0.041

Panel B: Median Cutoffs

	(1)	(2)	(3)
Independent Variable	ISKEW	ESKEW	LOTTERY
IS	0.112	0.382***	0.075
	(1.46)	(3.51)	(1.49)
Lottery Proxy	0.144***	-0.735***	-0.326**
	(2.70)	(-5.70)	(-2.39)
Lottery Proxy x IS	-0.111***	-0.182***	-0.146***
	(-3.04)	(-2.60)	(-2.60)
Average N	2,838	1,476	2,844
Adjusted R^2	0.036	0.038	0.041

Table IA.4: Fama-MacBeth Regression Estimates Using Positive and Negative *IS* Subsamples

This table reports estimates from monthly Fama-MacBeth cross-sectional regressions on samples that include only stocks with positive and negative *IS* 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. *IS* 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 *IS* as of month t. Columns (3) and (4) present the result for regressions using only stocks with negative *IS* 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.

	Positive *IS*		Negative *IS*	
	(1)	(2)	(3)	(4)
IS	0.261***	0.222**	0.320***	0.260***
	(3.05)	(2.55)	(4.24)	(3.15)
IVOL	−0.119**		−0.153***	
	(−2.53)		(−3.21)	
IVOL x IS	−0.088***		−0.099***	
	(−3.03)		(−4.18)	
MAXRET		−0.120***		−0.163***
		(−2.84)		(−3.68)
MAXRET x IS		−0.078***		−0.077***
		(−2.72)		(−3.07)
log(B/M)	0.775***	0.791***	0.799***	0.832***
	(5.01)	(5.11)	(4.75)	(4.97)
log(Me)	−0.072**	−0.068**	−0.078***	−0.067**
	(−2.34)	(−2.05)	(−2.62)	(−2.16)
RET[−12,−2]	0.715***	0.677***	0.819***	0.791***
	(7.32)	(6.86)	(7.09)	(6.70)
RET[−1,0]	−0.034***	−0.031***	−0.033***	−0.029***
	(−10.13)	(−8.78)	(−8.75)	(−7.35)
Constant	0.939***	0.900***	0.990***	0.948***
	(3.47)	(3.11)	(3.63)	(3.34)
Average N	1,457	1,460	1,381	1,384
Adjusted R^2	0.044	0.043	0.046	0.046

Table IA.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. *IS* 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 *IS* 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 *IS* represent dummy variables, which are indicator variables that take the value of 1 if a stock's idiosyncratic volatility, maximum daily return, and *IS* 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.

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS	−0.016	0.144**	−0.023	0.095	0.125***	0.100***	0.066	0.051
	(−0.50)	(2.23)	(−0.69)	(1.56)	(4.50)	(3.66)	(1.30)	(1.05)
IVOL	−0.259***	−0.216***			−0.043		−0.146	
	(−6.06)	(−4.35)			(−0.84)		(−1.08)	
IVOL $\times$*IS*		−0.048**			−0.043***		−0.163***	
		(−2.46)			(−5.13)		(−2.97)	
MAXRET			−0.074***	−0.064***		−0.065		−0.185
			(−5.96)	(−4.57)		(−1.39)		(−1.54)
MAXRET $\times$*IS*				−0.011*		−0.036***		−0.132***
				(−1.92)		(−4.47)		(−2.63)
log(B/M)	0.716***	0.721***	0.723***	0.729***	0.740***	0.759***	0.790***	0.799***
	(4.58)	(4.63)	(4.65)	(4.70)	(4.79)	(4.92)	(5.00)	(5.07)
log(ME)	−0.108***	−0.101***	−0.091***	−0.086***	−0.079***	−0.074**	−0.062*	−0.061*
	(−3.56)	(−3.34)	(−2.81)	(−2.69)	(−2.64)	(−2.34)	(−1.95)	(−1.83)
RET[−12,−2]	0.722***	0.713***	0.703***	0.701***	0.765***	0.735***	0.783***	0.746***
	(6.90)	(6.86)	(6.70)	(6.67)	(7.48)	(7.05)	(7.48)	(7.12)
RET[−1,0]	−0.035***	−0.035***	−0.030***	−0.030***	−0.036***	−0.032***	−0.035***	−0.033***
	(−10.18)	(−10.13)	(−8.68)	(−8.61)	(−10.48)	(−9.14)	(−10.64)	(−9.72)
Constant	1.348***	1.179***	1.131***	1.009***	0.740***	0.776***	0.552*	0.577*
	(4.62)	(4.19)	(3.67)	(3.37)	(2.92)	(2.92)	(1.90)	(1.90)
Average N	2,863	2,863	2,869	2,869	2,863	2,869	2,863	2,869
Adjusted R^2	0.043	0.044	0.042	0.043	0.043	0.043	0.040	0.040