Motivated Extrapolative Beliefs

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This study investigates the relationship between investors' prior gains or losses and their adoption of extrapolative beliefs. Our findings indicate that investors facing prior losses tend to rely on optimistic extrapolative beliefs, whereas those experiencing prior gains adopt pessimistic extrapolative beliefs. These results support the theory of motivated beliefs. The interaction between the capital gain overhang and extrapolative beliefs results in noteworthy mispricing, yielding monthly returns of approximately 1%. Motivated extrapolative beliefs comove with investors' survey expectations and trading behavior, and help explain momentum anomalies.

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1 Introduction

Traditional economic theory assumes investors could form unbiased beliefs based on Bayesian updating according to their information set. However, recent work documents that the expectations measured by surveys or other data are inconsistent with the expected returns in the model. One of the most convincing expectation biases is return extrapolation (Barberis (2018)), i.e., investors form their beliefs according to past returns, with more weight on recent returns. With extrapolative beliefs, investors tend to overreact to past returns, and extrapolative beliefs can negatively predict future returns. (See Greenwood and Shleifer (2014); (Da et al., 2021)). Previous studies show that return extrapolation could help explain the facts on excess volatility ((Barberis et al., 2015); (Jin & Sui, 2021)), return predictability ((Cassella & Gulen, 2018); (Da et al., 2021)), bubbles ((Barberis et al., 2018); (Liao et al., 2021); (Pan et al., 2021)), and overreaction-related anomalies ((He et al., 2020)). However, how investors rely on extrapolation to form their expectations is less explored in the literature.

A growing literature on motivated beliefs argues that people often believe what they want to believe ((Kunda, 1990); (Caplin & Leahy, 2001); (Bénabou & Tirole, 2002); (Bénabou, 2015); (Bénabou & Tirole, 2016)). With motivated beliefs, people may hold unrealistically optimistic beliefs about their IQ, appearance, and so forth. People ignore negative signals to make them feel better, even though that may make them more informed. ((Eil & Rao, 2011); (Zimmermann, 2020)[2].

Motivated by the motivated beliefs theory, this paper investigates how prior gains or losses relative to the reference price (we refer to purchase price here) affects the salience of extrapolative signals and how the motivated extrapolative beliefs affect the cross-sectional anomalies.

Intuition and Conceptual Framework

Suppose investors maximize their expected utility, encompassing an S-shape realization utility (Ingersoll and Jin (2013)) anticipated utility, which can generate additional utility by avoiding potential losses or realizing additional gains according to the S-shape utility function. Investors form their beliefs

[2] The motivated inattention to the negative information may lead to behavioral biases when making serious decisions. Some papers focus on the biased decisions on moral justification. See Konow, J. (2000) , Dana and Kuang (2007), Gino and Weber (2016) , Gneezy, Serra-Garcia, and van Veldhuizen (2020) , Saccardo & Serra-Garcia (2020), Bosch-Rosa and Heinemann (2021) for more discussions.

based on fundamentals and an extrapolative perception of the preceding price trajectory. They update their beliefs by assigning weights to the extrapolative signal and the fundamental information ((Barberis et al., 2018)):

$$E_t[\Delta P] = d \times X_t + (1 - d) \times Fundamental,$$

where the X_t is the extrapolative signal, specified by an exponentially weighted average of past returns, $X_t = \sum_{k=1}^{t} \theta^{k-1}\, Ret_{t-k}$.

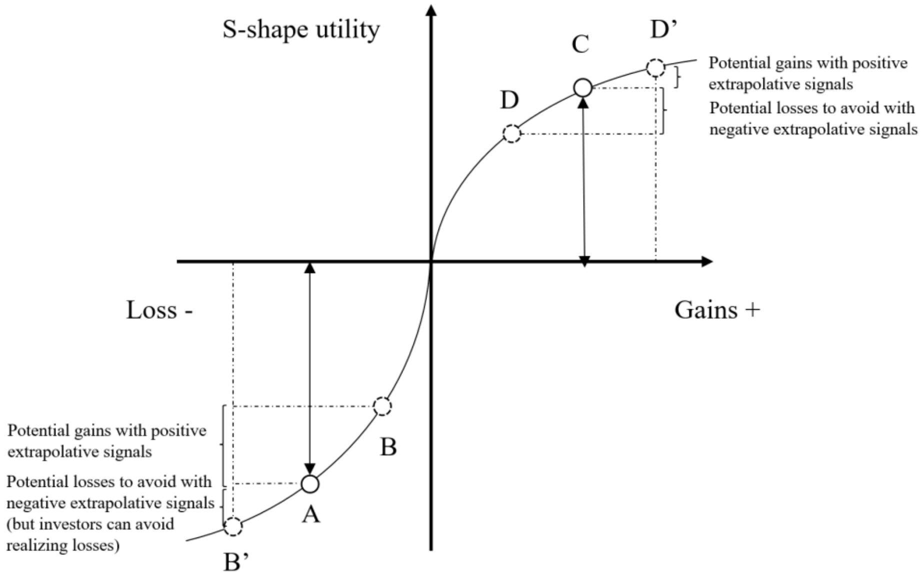

Figure 1: Prospect theory (PT) and potential gains or losses with different extrapolative signals.

Because realizing losses is painful, the investor tends to stick to holding the stocks with paper loss, which is well-documented as the disposition effect ((Shefrin & Statman, 1985); (Odean, 1998); Barberis and Xiong (2012)). An S-shape realization utility function indicates that investors are risk-seeking when facing losses. Assume an investor holds a stock at point A in Figure 1. Consider two scenarios: in the first scenario, a positive extrapolative signal X_{pos} is received, indicating a potential price increase to point B. In the second scenario, a negative extrapolative signal X_{neg} is received, suggesting a price decline to point B'. let $X_{pos} = |X_{neg}|$. In both scenarios, the investor assigns a weight d on the extrapolative signal to form her expectations.

Since the utility function is convex, compared with the potential losses to avoid when receiving the negative signal, putting more weight on the positive signal can generate a higher potential gain.

Furthermore, suppose an investor wants to get the utility gains by avoiding potential losses when facing a negative signal. In that case, she must sell the stock and realize the current losses, which may lead to more disutility and decrease the degree of belief distortion. Overall, stocks with high and positive extrapolative beliefs and low and negative capital gain overhang are thus expected to have a higher *d*, subject to excess demand and lower future returns.

Conversely, paper gains and a downward-trend stock price can motivate investors to realize their gains. Let us assume the investor is currently at point C, indicating a profitable position. Consider two extrapolation signals: one that can decrease the price to point D and another to increase it to point D'. Given the concave nature of the utility function, the investor derives greater utility from avoiding potential losses compared to realizing potential gains when the absolute values of X_{pos} and X_{neg} are the same. To strengthen their confidence and appear more "astute" in decision-making, the investor can adopt a more pessimistic belief by assigning a larger d to the negative extrapolative signal and subsequently selling stocks promptly.

In summary, extrapolative beliefs can be motivated by the status of investors' capital gain overhang. Investors tend to overreact to the positive extrapolative signal in the loss region, while in the gain region, they may excessively amplify a pessimistic extrapolative signal. Considering asset pricing implications, our first testable hypothesis is that stocks with pessimistic extrapolative beliefs and high capital gain overhang interactively have *higher* future returns, while stocks with optimistic extrapolative beliefs and low capital gain overhang yield *lower* future returns. Because the investors can be more loss-averse in the loss domain and can keep avoiding the realization of losses, the interaction effects may be more pronounced in the loss domain.

Since it is hard to estimate d directly, we mainly focus on the pricing implications. To examine our conjectures, we construct the firm-level extrapolation proxy, namely EXTV (the value of extrapolative beliefs), which is calculated by an exponential decay model following (Da et al., 2021) and (Li & Yang, 2022), and (Wang, 2022). We follow (Grinblatt & Han, 2005) to construct the CGO[3], as the proxy of

[3] In the Internet Appendix, we compare the Capital Gain Overhang (CGO) with actual transaction data. The outcomes suggest that the CGO can effectively act as a validated proxy for representing the capital gain overhang at an individual stock level.

unrealized profit.

The empirical tests begin with portfolio double sorting. It is shown that the correlation between these two variables is only -0.001 in the cross-section, which validates the double-sorting analysis. At the end of each month *t*-1, we independently sort the stocks into $5 \times 5 = 25$ portfolios according to their EXTV and CGO. We use CGO1 and EXTV1 to represent the lowest quintiles of CGO and EXTV, respectively. We find that capital gain overhang plays an important role in the return predictability of EXTV. In the value-weighted double-sorted and low-CGO (CGO1) portfolios, the stocks in EXTV5 generate an FF5 alpha of -1.231% per month [*t*= -5.79], while the stocks in EXTV1 only earn an insignificant FF5 alpha of 0.102% per month. In the high-CGO (CGO5) portfolios, the stocks in EXTV1 earn an average FF5 alpha of 0.609% [*t*= 5.31], while the stocks in EXTV5 generate an insignificant FF5 alpha of -0.021%. A similar pattern can be observed within equal-weighted portfolios, where the main difference is that alphas of stocks in CGO5 and EXTV5 even turn out to be positive rather than negative. These results are consistent with our hypothesis that investors at loss (gains) overreact to positive (negative) extrapolative signals.

We further use the EXTV3 group as the alternative benchmark. The return spread of EXTV (1-3) is more pronounced within the CGO5 group. In CGO5, the equal(value)-weighted EXTV (1-3)'s FF5 (Fama-French) alpha is 0.718% (0.371%) [*t*= 6.55 (0.78)]. The equal(value)-weighted EXTV's FF5 alpha is 0.331% (0.144%) [*t*= 2.82 (1.85)] in CGO1. The FF5 alpha spread of (1-3) between CGO5 and CGO1 is 0.387% (0.226%) [*t*= 2.87 (1.18)]. These patterns indicate that investors react more to the low and negative extrapolative beliefs among high and positive CGO stocks. Likewise, the return spread of EXTV (3-5) is more pronounced within the CGO1 group. In CGO1, the equal(value)-weighted EXTV (3-5)'s FF5 (Fama-French) alpha is 0.983% (1.189%) [*t*=7.46 (5.34)]. The equal(value)-weighted EXTV's FF5 alpha is 0.194% (0.260%) [*t*=1.73 (1.59)] in CGO5. The return spread of (3-5) between CGO5 and CGO1 is -0.789% (-0.929%) [*t*= -4.59 (-3.59)]. These patterns indicate that investors react more to the high and positive extrapolative beliefs among low and negative CGO stocks. Overall, the equal(value)-weighted return spread induced by the asymmetric distortion of extrapolative beliefs can generate a significant FF5 alpha of 1.176% (1.155%).

A long-short strategy, namely XRP (extrapolative beliefs motivated by reference price) is accordingly constructed, which longs the stocks in the (CGO5 and EXTV1) portfolios and shorts the stocks in the (CGO1 and EXTV5) portfolios. This strategy could earn both economically and statistically significant monthly returns of 2.284% (t=11.91, equal-weighted) and 1.646% (t=5.97, value-weighted). The FF5 adjusted alphas are 2.388% and 1.848%, respectively.

We then define the interaction effect as the return spread between portfolios with low EXTV and high CGO (EXTV1 and CGO5, denoted as *Motivated pessimism*) and portfolios with high EXTV and low CGO (EXTV5 and CGO1, denoted as *Motivated optimism*), net of the pure effects caused by CGO and EXTV. To better identify the interaction effect, we use two specifications. The first one is to control the EXTV and CGO into the Fama-Macbeth predictive regressions, which absorb the pure effect of EXTV and CGO. The second one is to decompose the returns into the pure effect of EXTV, the pure effect of CGO, and the interaction effect between EXTV and CGO, following (Huang et al., 2021). These two methods get similar results. Without other control variables, the interaction effect is 0.920% (t=8.40) in the first specification and 1.181% (t=6.30) in the second specification. After adding controls, the interaction effects are 0.695% (t=6.82) in the first specification and 0.707% (t=4.52) in the second specification. These findings suggest that current paper losses or gains can motivate extrapolative beliefs with an both economically and statistically significant magnitude.

Several additional analyses are conducted to strengthen the mispricing argument. It is shown that the interaction effect is more pronounced within high idiosyncratic volatility, small market capitalization, and low institutional holding stocks. The stocks with high idiosyncratic risk and low market capitalization are more likely subjected to the limit of arbitrage ((Stambaugh et al., 2015), which leads to more mispricing. The influence of group work compared with individual decisions remains debatable in decision theory. On the one hand, group work could make the choices follow the standard game-theoretic predictions more closely (See (Charness & Sutter, 2012) for more surveys and Barahona et al. (2022)) by reducing biases, cognitive limitations, and social considerations. In comparison, groupthink could also be exposed to shared heuristics ((Tversky & Kahneman, 1974); (Bénabou, 2013)). Our results show that the interaction effect is more pronounced within stocks with lower institutional holdings. We also find that household investors are more susceptible to this belief distortion bias. These findings shed light on the positive side of groupthink.

To better pin down the economic mechanism of motivated beliefs, this study examines the impact of the reference purchase price on belief distortion in aggregate market survey expectations and cross-sectional trading behavior. Empirical analysis reveals that motivated optimistic belief is positively associated with the dispersion of bullish and bearish expectations and the order imbalance. In contrast, motivated pessimistic belief negatively relates to expectation dispersion and order imbalance. These findings, supported by both time-series and cross-sectional evidence, support the motivated belief hypothesis, suggesting that investors' expectations can be influenced by their positions and tend to align with directions that bolster their confidence. Additional evidence derived from the actual transaction data utilized by a large discount broker (LDB) further substantiates our argument, which is presented in the Appendix.

We next explore two alternative explanations related to reference-dependent preferences (RDP) for our empirical results. The first explanation posits that extrapolative beliefs may be associated with a gambling preference. As investors in the gain region tend to be risk-averse but become risk-seeking in the loss region, they are inclined to favor lottery-like stocks when experiencing losses. This lottery-reference-dependent preference relationship could account for the observed empirical results regarding the effect of motivated optimistic beliefs. However, this explanation fails to elucidate the observation that the pricing pattern of low and negative extrapolative beliefs is more pronounced within high-CGO stocks. The second explanation revolves around the biased risk-return trade-off induced by reference-dependent preferences, as proposed by (Wang et al., 2017). (Atmaz, 2021) proposes a channel that stock prices will be more sensitive to fundamental variance shocks with higher extrapolative returns. Higher (lower) extrapolative belief is combined with lower (higher) expected fundamental variance and less (more) volatile returns. In line with the risk-return trade-off and reference-dependent preference relation, capital gains investors exhibit higher risk aversion and tend to steer clear of stocks with low extrapolative beliefs (EXTV). As a result, stocks with high CGO and low EXTV experience further underpricing. However, it is hard to explain why investors facing prior losses exhibit a higher demand for high-EXTV stocks. Although both explanations can partially account for the empirical findings, they may work together to provide a more comprehensive explanation. We conduct several (Fama & MacBeth, 1973) regressions controlling for the lottery-RDP and risk-return trade-off-RDP effect. The results confirm that the empirical findings are unlikely to be driven by RDP-related explanations. Moreover, our findings remain robust when excluding NASDAQ and illiquid stocks and employing weighted-least-squares (WLS) Fama-Macbeth regressions.

Given the economic significance of mispricing, the following question is, who are trading on or against the motivated belief bias? To address this question, we follow (Koijen & Yogo, 2019) to construct a stock-quarter-investor level holding change dataset[4], classifying investors into households, banks, insurance companies, mutual funds, investment advisors, and pension funds. We follow (McLean et al., 2022) to examine how different types of investors respond to the mispricing. Our findings indicate that households are prone to the motivated extrapolation bias, making them the "dumb money" participants. Institutional investors, on the other hand, generally align their trading activities with the motivated optimistic belief but do not significantly trade based on the motivated pessimistic belief that leads to underpricing. The only consistent "smart money" participants, in terms of their response to the motivated belief bias, are investment advisors (who are likely to be the hedge funds).

In addition to the substantial magnitude of mispricing, we further argue that motivated extrapolative beliefs can help explain the momentum effect. Liao et al., (2021) propose a related theoretical framework. Although our paper shares similarities with theirs, there are notable distinctions. Their empirical investigation focuses on the mechanism of excessive trading volume during market bubbles and crashes. In contrast, we emphasize the interaction between extrapolative beliefs and reference prices, which plays a vital role. The interplay between extrapolative beliefs and reference prices can amplify the *mean-reversion* belief updating process, providing a potentially superior fit to price dynamics and inducing the momentum effect.

To examine this conjecture, we first decompose the momentum strategies in the cross-section

[4] It is shown that XRP can generate a persistent return after portfolio formation for up to at least ten months. See Table A5 and Figure 1.

following (Hou & Loh, 2016)[5] and (Guo et al., 2022). Our findings indicate that XRP acting as an enhanced CGO[6] can contribute to explaining the momentum effect in the cross-section. Specifically, XRP significantly explains the return predictability of MOM (6, 2) (cumulative returns from month *t*-6 to *t*-2) at 86.3% (t=4.59). In comparison, neither EXTV, CGO alone, nor the combination of EXTV and CGO achieves the same explanatory power, which suggests that the interaction effect matters. When examining the MOM (12, 2) (cumulative returns from month *t*-12 to *t*-2), the explanatory power of all candidates weakens. XRP explains 69.1% of the variation, higher than CGO's 54.2%, EXTV's 0.2%, and the combination of CGO and EXTV's 52.5%. Nevertheless, XRP helps substantially shrink the coefficients of different momentum strategies.

We then conduct factor-spanning tests on momentum-related anomalies: 41 anomalies in the momentum category of Lu Zhang's personal website, UMD factor from Kenneth French's personal website, and UMD_IND from Novy-Marx's personal website. It is shown that 40 out of 41 momentum anomalies' alphas are significant relative to the Fama-French five-factor model; 14 out of 41 momentum anomalies' alphas are significant relative to Hou, Xue, and Zhang Q4 factor ((Hou et al., 2015)); 6 out of 41 for Hou, Mo, Xue, and Zhang Q5 factor model ((Hou et al., 2019) and (Hou et al., 2021)). Our results demonstrate that a simple two-factor model consisting of the market factor and the XRP strategy can explain 30 out of the 43 test strategies. The performance slightly exceeds that of the Q4 factor model but falls short of the effectiveness of the Q5 factor model. The unexplained strategies are mainly customer or supplier momentum strategies and industry lead-lag effect strategies, indicating different economic intuitions. The traditional momentum strategies are well-explained, exhibiting small and insignificant alphas. Conversely, neither CGO nor EXTV, individually or in combination, provide an adequate explanation for most momentum-related strategies (30, 43, and 34 failing to explain, respectively). We do not assert XRP as a new common pricing factor, although we look forward to formally testing the property in future research. Overall, both the cross-section decomposition and time-

[5] Hou and Loh (2016) show that only the candidates that could capture the relationship between momentum and future returns are attributed explanatory power in the Hou and Loh decomposition method.

[6] The construction of XRP for cross-sectional tests differs slightly from the previous strategy. Specifically, XRP is constructed as the disparity between the cross-sectional rank of CGO and EXTV (both normalized in [0, 1], uniformly). This methodology allows for direct and equitable comparison among the candidates in explaining momentum under the Hou and Loh test. We also refer to this as XRP for consistency when there is no confusion.

series spanning tests support our hypothesis that XRP can contribute to explaining momentum.

Our study contributes to the growing literature on belief formation, especially on motivated beliefs in the financial market. Prior empirical research on motivated beliefs in trading environments has primarily relied on laboratory experiments; see (Kuhnen & Knutson, 2011), (Mayraz, 2011), (Kuhnen et al., 2017), and (Trutmann et al., 2022). (Cassella et al., 2022) emphasize the significance of a motivated belief framework in understanding the formation of aggregate expectations. They use professional forecast data to demonstrate that forecasters react more strongly to good than bad news. When considering investment decisions, (Cueva & Iturbe-Ormaetxe, 2021) provides experimental evidence that purchasing a stock induces optimistically biased expectations when its price falls below the purchase price. Similarly, (Gödker et al., 2021) find that the experiment participants exhibit an increased distortion of optimistic beliefs in response to more observed negative outcomes. (Trutmann et al., 2022) also discovers that in contrast to risk-neutral Bayesian investors, participants in their experiment exhibit a disposition effect, displaying stronger updates from unfavorable information when experiencing gains and stronger updates from favorable information when experiencing losses.

Although laboratory experiments can help identify causal effects, a gap exists between laboratory experiments and more general settings. How motivated beliefs affect the real stock market has yet to be thoroughly investigated. Our study reveals that investors are more inclined to form expectations about stocks based on positively extrapolated beliefs when facing losses. At the same time, they are more inclined to form expectations based on negatively extrapolated beliefs when making profits. The interaction effect of extrapolative beliefs and investment position can result in significant mispricing, which may require considerable time to correct. To our best knowledge, this study is among the first to examine the implications of motivated beliefs in the cross-sectional stock market within a real-world context.

Our paper also contributes to the rapidly growing literature on extrapolation. Previous studies have shown that extrapolation plays an important role in asset prices, such as Lakonishok et al. (1994) on value premium, (La Porta, 1996), (Bordalo et al., 2019a); Bordalo et al. (2019b) on long-term earnings forecasts, Cassella and Gulen (2018) on price-scaled variables' return predictability, He et al. (2020) on overreaction-related anomalies, Pan et al. (2021) on extrapolative market participation and momentum and value effect, Liu et al. (2021) on risk-return trade-offs. Unlike these studies, our paper investigates how capital gain motivates extrapolative beliefs, providing insights into the extent to which investors rely on extrapolation to form their expectations. The motivated beliefs theory also relates to investors' strategic memory, which is closely linked to the question of how far back individuals look when making judgments about the future, as proposed by (Barberis, 2018). However, this aspect is beyond the scope of this paper and can be reserved for further research.

This paper is also related to the literature on momentum effects. The most closely related papers are (Liao et al., 2021) and (Pan et al., 2021), which shed light on how extrapolation induces momentum and reversal effects. The former argues that the disposition effect leads shareholders to sell stocks with capital gains, while extrapolators are more likely to purchase stocks with strong past performance. This mechanism can produce an enormous trading volume in the bubble period. The latter study suggests that extrapolative market participation can cause prices to be persistently overpriced (overreaction momentum), followed by a subsequent reversal. Unlike their argument, our study suggests that the combination of capital gain overhang and extrapolation can jointly explain momentum in the cross-sectional decomposition and factor-spanning tests. Our empirical extends their work to further understand momentum effects.

The rest of the paper is organized as follows. Section 2 provides a detailed description of the data source, variable construction, and the results of portfolio analysis. Section 3 presents the findings regarding the interaction effect of XRP. Section 4 discusses the economic mechanism and presents additional robustness tests. Section 5 extends our studies on the explanatory power of XRP on momentum. Section 6 concludes the paper.

2 Data, Variable Construction, and Portfolio Analysis

2.1 Data Source and Main Variables

The data utilized in this study are sourced from various sources. Stock returns and financial information are retrieved from CRSP and Compustat, respectively. Institutional holdings data are obtained from the Thomson Reuters Institutional Holdings Database (S34 file). The investor-type file used in (Koijen & Yogo, 2019) is acquired from Koijen's website. Order imbalance data are collected from the TAQ database. We also collect the common factors, such as Fama-French three, Carhart-four, and five factors from Kenneth French's personal website, Hou, Xue and Zhang (HXZ) Q factors from Lu Zhang's personal website, Daniel, Hirshleifer, and Sun (DHS) three factors from Lin Sun's personal website, and Stambaugh and Yuan (SY) mispricing factors from Stambaugh's personal website. A compilation of 41 momentum-related anomalies are downloaded from Lu Zhang's personal website. The market-level predictors, such as DP (dividend-to-price), EP (earnings-to-price), and Rf (risk-free rate), are obtained from Goyal's personal website. The unemployment rate is from the Federal Reserve Bank of St. Louis. The stock trading data covers the period from January 1960 to December 2021. The institutional holdings data spans from Q1, 1980 to Q4, 2017, which is the same as (Koijen & Yogo, 2019).

We use the turnover-based measure from (Grinblatt & Han, 2005) to measure the average purchase price as the reference price. At the end of last week *s* in month *t*, the reference price for each stock i is defined as:

$$RP_{i,t} = \frac{1}{k}\sum_{n=1}^{T}\left(V_{i,s-n}\prod_{\tau=1}^{n-1}(1 - V_{i,s-n+\tau})\right)P_{i,s-n} \tag{1}$$

where $P_{i,s}$ is the stock price at the end of week *s*; $V_{i,s}$ is the week *s*'s turnover ratio, calculated as weekly trading volume divided by the number of outstanding shares; $T = 260$ weeks, i.e., the past five years; and k denotes the sum of weights calculated from turnover ratio to make the weights sum to one. We adjust the trading volume of Nasdaq stocks following (Gao & Ritter, 2010). Then CGO is computed as:

$$CGO_{i,t} = \frac{P_{i,s-1} - RP_{i,t}}{P_{i,s-1}} \tag{2}$$

The stocks are required to have at least 100 weeks of non-missing data in the past five years and have prices above 5 dollars at the end of month *t*. Then our test period starts from February 1965.

To measure the extrapolative beliefs, we follow Wang (2021) to construct EXTV with parameters $\lambda = 0.75, \mathrm{L} = 49$ days, where EXTV is defined as:

$$EXTV_{i,t} = \sum_{l=1}^{L} w_l \, R_{i,t-l} \tag{3}$$

where $R_{i,t-l}$ is stock *i*'s daily return at day *t-l*, and $w_l = \lambda^{l-1} / \sum_{k=0}^{L-1} \lambda^k$.

We also follow (Gulen & Woeppel, 2022) to construct price-path convexity as the proxy of extrapolative beliefs. The price convexity is defined as:

$$Convexity_{i,t} = \frac{\frac{PRC_{first,i,t}+PRC_{last,i,t}}{2} - PRC_{avg,i,t}}{PRC_{avg,i,t}} \tag{4}$$

where $PRC_{first,i,t}$, $PRC_{last,i,t}$, and $PRC_{avg,i,t}$ are the first, last, and average price of stock i in month *t*. (Gulen & Woeppel, 2022) show that the price convexity could be decomposed as:

$$Convexity_{i,t} = \frac{N}{2PRC_{avg,i,t}} [\frac{N\Delta P_{i,N} + (N-1)\Delta P_{i,N-1} + \cdots + P_{i,1}}{N + N - 1 + \ldots + 1} - \frac{P_{i,N} - P_{i,0}}{N}] \tag{5}$$

The convexity assigns the decay weights on past returns as $\frac{N}{\sum_{j=1}^{j=N} j}, \frac{N-1}{\sum_{j=1}^{j=N} j}, \ldots, \frac{1}{\sum_{j=1}^{j=N} j}$ from the recent one to distant one, which is slightly different from the exponential decay model to describe extrapolative beliefs in literature. The price convexity captures the return extrapolation beyond the return over the same month. Thus, it could provide the robustness check on both parameter sensitivity and the effect of returns over the same month[7].

In our empirical analysis, we also control for other characteristics that are documented to predict future returns, such as Size (the logarithm of market capitalization), logBM (the logarithm of book-to-market ratio), Gross Profitability (gross profitability-to-asset ratio, following (Novy-Marx, 2013)), Asset Growth (the growth rate of total assets), MOM (12, 2) (the cumulative returns from month *t*-12 to *t*-2, we denote MOM (m, n) as the cumulative returns from month *t-m* to *t-n* in this paper), IVOL

[7] Due to space limitations, the robustness tests on convexity are available on request but not in the current version.

(idiosyncratic risks calculated by residuals from Fama-French Three-Factor model), Skew (return skewness), and Kurt (return kurtosis). These variables are defined explicitly in Table A.

2.2 Summary Statistics and Single Sorts

Table 1 presents a summary of the main variables in our study. The correlation between EXTV and CGO is only -0.001 in the cross-section, suggesting that the double-sorting outcomes are not significantly influenced by the correlation between these two variables. Furthermore, CGO correlates with cumulative returns, specifically MOM (12, 2) and MOM (6, 2). (Grinblatt & Han, 2005) argue that momentum is a noisy proxy for CGO. They are very similar by construction, where the CGO is calculated by the price changes relative to the average historical purchase price divided by the current price, and the MOM is calculated by the cumulative returns. Additionally, EXTV is associated with contemporary one-month returns (Lagged return), which may raise concerns that our findings could be driven by past performance rather than extrapolative beliefs. Nonetheless, we address this concern by employing convexity, a variable weakly correlated with contemporary monthly returns, which yields similar results.

Table A1 presents the results of the single sorting based on EXTV and CGO. Our results indicate a significant negative relationship between EXTV and future returns, consistent with previous literature. This suggests that investors with extrapolative beliefs tend to be excessively optimistic or pessimistic, leading to suboptimal investment decisions. The return spread between the highest EXTV quintile and the lowest one is -0.818%. CGO positively and significantly predicts future returns, which aligns with the disposition effect and PT/MA argument proposed by (Grinblatt & Han, 2005). Furthermore, the characteristics shown in each portfolio indicate no significant correlation between these two variables.

2.3 Double Sorting

At the end of each month t-1, we sort the stocks into $5 \times 5 = 25$ portfolios according to their EXTV and CGO, independently. Here EXTV1 or CGO1 denotes the lowest quintile of EXTV- or CGO-sorted portfolios, and EXTV5 and CGO5 denote the highest quintile for convenience. The portfolios are rebalanced monthly. Panel A of Table 2 presents the portfolios' characteristics. The first block shows no issue of having an insufficient number of stocks in the extreme portfolios. It is noted that the CGO1-

EXTV5 portfolio contains a higher percentage of stocks, amounting to 4.70%, larger than the conditional 4%. This indicates that portfolios featuring low CGO but high EXTV can coexist. On average, the portfolios of CGO1-CGO2 are at a loss, while CGO4-CGO5 are at a gain.

Panel B and Panel C of Table 2 present the equal-weighted and value-weighted portfolio performance. According to our first hypothesis, investors tend to update their beliefs more according to the positive and high extrapolative signal when they are in the loss domain. And they tend to react more to negative and low extrapolative signals in the gain domain.

Consistent with this hypothesis, we find that capital gain overhang plays an important role in the return predictability of EXTV. In the value-weighted double-sorted and low-CGO (CGO1) portfolios, the stocks in EXTV5 generate an FF5 alpha of -1.231% per month [*t*= -5.79], while the stocks in EXTV1 only earn an insignificant FF5 alpha of 0.102% per month. In the high-CGO (CGO5) portfolios, the stocks in EXTV1 earn an average FF5 alpha of 0.609% [*t*= 5.31], while the stocks in EXTV5 generate an insignificant FF5 alpha of -0.021%. A similar pattern can be observed within equal-weighted portfolios, where the main difference is that alphas of stocks in CGO5 and EXTV5 even turn out to be positive rather than negative.

Next, we use the EXTV3 group as the alternative benchmark. The return spread of EXTV (Low-3) is more pronounced within the CGO5 group. In CGO5, the equal(value)-weighted EXTV(Low-3)'s FF5 (Fama-French) alpha is 0.718% (0.371%) [*t*= 6.55 (0.78)]. The equal(value)-weighted EXTV's FF5 alpha is 0.331% (0.144%) [*t*= 2.82 (1.85)] in CGO1. The FF5 alpha spread of (Low-3) between CGO5 and CGO1 is 0.387% (0.226%) [*t*= 2.87 (1.18)]. These patterns indicate that investors react more to the low and negative extrapolative beliefs among high and positive CGO stocks.

Likewise, the return spread of EXTV (3-High) is more pronounced within the CGO1 group. In CGO1, the equal(value)-weighted EXTV(3-High)'s FF5 (Fama-French) alpha is 0.983% (1.189%) [*t*=7.46 (5.34)]. The equal(value)-weighted EXTV's FF5 alpha is 0.194% (0.260%) [*t*=1.73 (1.59)] in CGO5. The return spread of (3-High) between CGO5 and CGO1 is -0.789% (-0.929%) [*t*= -4.59 (-3.59)]. These patterns indicate that investors react more to the high and positive extrapolative beliefs among low and negative CGO stocks. Overall, the equal(value)-weighted return spread induced by the asymmetric distortion of extrapolative beliefs can generate a significant FF5 alpha of 1.176% (1.155%).

Furthermore, a long-short strategy, referred to as XRP, involves longing stocks in the (CGO5 and EXTV1) portfolios and shorting stocks in the (CGO1 and EXTV5) portfolios. This strategy can earn a both economically and statistically significant monthly return of 2.284% (t=11.91, equal-weighted) and 1.646% (t=5.97, value-weighted). The FF5 adjusted alphas are 2.388% and 1.848% for the equal-weighted and value-weighted portfolios, respectively.

The results of dependent sorting are presented in Table A2. The dependent-sorting method could enhance the performance of the XRP strategy. The raw return for XRP, first sorted by CGO, is 1.792%, while the CAPM, FF3, and FF5 alphas are 1.923%, 2.097%, and 2.017%, respectively. When XRP is first sorted by EXTV, the raw return is 1.718%, and the CAPM, FF3, and FF5 alphas are 1.866%, 2.045%, and 1.954%, respectively. Additional robustness checks on the XRP strategy using other factor models are presented in Table A3. As the December tax-loss selling effect may lead to a reversal of the disposition effect in January, we exclude returns from January in our tests. The results, shown in Table A4, demonstrate that excluding the January effect can enhance the performance of the XRP strategy: the equal-weighted XRP achieves returns of 2.532% (raw return), 2.550% (CAPM), 2.616% (FF3), and 2.596% (FF5) while the value-weighted XRP yields returns of 1.853 % (raw return), 1.960 % (CAPM), 2.056% (FF3), and 1.961% (FF5), respectively. Figure 2 displays the buy-and-hold returns of the XRP strategy, revealing that the mispricing correction is most pronounced in the initial two periods and persists for a while. Table A5 presents the results of the performance persistence of the XRP strategy.

3 Return Decomposition

The portfolio analyses provide preliminary results on how extrapolative beliefs motivated by the status of paper gains or losses affect asset prices. To investigate the interaction effects further, we employ two specifications of Fama-Macbeth regressions.

3.1 Fama-Macbeth Regressions Controlling for EXTV and CGO

The interaction effect is defined as the return spread between portfolios with low EXTV and high CGO (EXTV1 and CGO5, referred to as *Motivated pessimism*) and portfolios with high EXTV and low

CGO (EXTV5 and CGO1, referred to as *Motivated optimism*) while controlling for the pure independent effects of CGO and EXTV. These two dummy variables, *Motivated pessimism* and *Motivated optimism* in Fama-Macbeth predictive regressions without other controls, can identify the return of XRP. To better examine the interaction effect, we introduce the variables EXTV and CGO into the regressions, absorbing the independent pure effect of EXTV and CGO. If no interaction effect exists, the coefficients associated with *Motivated pessimism* and *Motivated optimism* should be insignificant. Conversely, suppose investors' beliefs are distorted towards either overly optimistic or pessimistic extrapolative beliefs driven by potential capital gain. In that case, the coefficients are expected to exhibit significance, and so is their difference.

Table 3 presents the results of Fama-Macbeth regressions. Regardless of whether EXTV or CGO is controlled for, the coefficients of *Motivated optimism* and *Motivated pessimism* are highly significant. The differences between the coefficients, as indicated in the first three columns, amount to 2.282%, 2.482%, and 1.832%, respectively, which is consistent with the equal-weighted XRP strategy. By excluding the pure effects of CGO and EXTV, the interaction effect diminishes to 1.044%, 0.978%, and 0.753%, respectively. Thus, the interaction effect accounts for approximately 40% of the XRP strategy and holds economic and statistical significance. Additional robustness checks using different thresholds (30% and 10%) are reported in Table A6.

3.2 Return Decomposition Method

The second approach for return decomposition follows the methodology proposed by (Huang et al., 2021). We decompose the average returns of 25 portfolios sorted by CGO (CGO 1-5) and EXTV (EXTV 1-5) into four components. The first is the benchmark component, which is neutral to CGO and EXTV. The second one is the pure CGO effect, which exclusively relates to the rankings of CGO. The third one is the pure EXTV effect, which is only related to the rankings of EXTV. The fourth one is the interaction effect, i.e., the effect of motivated extrapolative beliefs.

The return of each portfolio can be expressed as a combination of the four components. Table A7 tabulates the detailed specification of return decomposition for reference. The center of the 5×5 matrix, i.e., EXTV 3 and CGO 3, serves as the benchmark component denoted as μ. The difference between other portfolios' returns and the benchmark return is induced by CGO, EXTV, and their interaction. When considering the pricing pattern of CGO, CGO 2-4 are treated as a unified group, denoted as $A_{..}$. The common component of high-CGO stocks is represented as A_H, while A_L represents the common component for low-CGO stocks. The pure EXTV effect is denoted as $E_{..}$. The common components shared by 1-5 EXTV-ranking portfolios are denoted as E_{bb}, E_b, 0, E_g, E_{gg}, where b represents "bad past performance", and g indicates "good past performance." Then the pure effect of CGO is measured as $A_h - A_l$. The pure effect of EXTV is computed as $E_{gg} - E_{bb}$.

In the presence of extrapolative beliefs motivated by the capital gain overhang, we anticipate the existence of an interaction effect stemming from unrealized gains coupled with pessimistic extrapolative beliefs or unrealized losses paired with optimistic extrapolative beliefs. Alternatively, if no interaction effect is present, the return spread observed in the portfolio analysis would be solely attributed to the aforementioned pure CGO and EXTV effects. We identify the interaction effects as $I_{gg,h}$ and $I_{bb,l}$. Furthermore, as (Cueva & Iturbe-Ormaetxe, 2021) demonstrate, when the price falls below the purchase price, optimistic expectations may be induced, which is more pronounced than the magnitude of pessimistic expectations motivated by paper gain. Hence, we expect a higher $I_{gg,l}$ than $I_{bb,h}$. The interaction effects can be calculated as $I_{gg,l} - I_{bb,h}$.

Following (Huang et al., 2021), we run Fama-Macbeth regressions to estimate the four components in each month. Then we conduct time-series regressions to examine the pure extrapolative effect, CGO effect, and interaction effect with Fama-French risk factors. Appendix A7 provides a detailed explanation of the decomposition approach. The main distinction between these two methods lies in the benchmark portfolios employed. In the former method, the benchmark consists of stocks with zero CGO and zero EXTV, while in the latter method, the benchmark comprises stocks with intermediate CGO and EXTV after ruling out their respective effects.

Table 4 presents the decomposition results. Panel A shows that the interaction effects are 1.181% (raw return, t=6.30), 1.169% (CAPM, t=6.22), 1.140% (FF3, t=5.83), and 1.089 (FF5, t=5.40). The results are consistent with those in Table 3. Additionally, the results indicate that after filtering out the interaction effect, the coefficients of both pure EXTV and CGO diminish, particularly for EXTV. This suggests that motivated extrapolative beliefs play a significant role in the pricing power of EXTV. The results of the robustness check in Table 4 by using different thresholds and adding control variables are shown in Table A8 and Table A9. Our main findings keep robust. Collectively, these results support the notion that the interaction effect plays a crucial role in XRP, in line with the motivated belief hypothesis.

3.3 Subsample Analysis

In this section, we perform a subsample analysis to complement our analysis. We first sort the stocks into two groups by the conventional proxies of the limit of arbitrage, such as Size, IVOL, and institutional holdings. Then, within each group, we decompose the returns. The findings from this subsample analysis are presented in Table 5. The motivated belief effect is more pronounced within small stocks, high-IVOL stocks, and stocks with low institutional holdings. It is worth noting that group thinking can have both positive and negative implications compared to individual thinking. On the one hand, group members may help alleviate cognitive limitations, thereby reducing behavioral biases. On the other hand, group thinking might be more prone to shared heuristics. Our results indicate that the interaction effect is more prominent in stocks with lower institutional holdings, aligning with the explanation in relation to the limit of arbitrage.

To summarize, motivated extrapolative beliefs, characterized by the interaction effect between CGO and extrapolative beliefs, significantly influence asset prices. This effect is both economically and statistically significant. Moreover, the distortion of beliefs is more prominent within stocks exhibiting a higher level of limit of arbitrage.

4 Inspecting the Mechanisms

This section delves into the economic mechanism of motivated extrapolative beliefs. We first employ the aggregate-level survey expectations and cross-sectional order imbalance to assess whether unrealized profits motivate extrapolative beliefs directly. Then we investigate alternative explanations for the pricing pattern. Finally, we investigate who are trading on/against the motivated extrapolative beliefs.

4.1 Evidence from Survey Expectations

Under the hypothesis of motivated belief, investors tend to assign greater importance to optimistic extrapolative beliefs when experiencing losses, resulting in higher expectations. Conversely, investors with positive capital gains are more inclined to prioritize pessimistic extrapolative signals. Thus, the motivated optimistic belief should comove positively with the overall expectations, while the motivated pessimistic belief should be negatively correlated with the overall expectations. We conduct the time-series regressions of survey expectations from the AAI investor sentiment survey on the motivated optimistic and pessimistic beliefs. We use the value-weighted mean and the median value of the CGO and EXTV of individual stocks to construct the market-level CGO and EXTV. The motivated optimistic belief (*Motivated optimism*) equals one if $CGO_t < CGO\ 40^{th}$ percentile and $\mathrm{EXTV_t} >$ EXTV 60^{th} percentile. The motivated pessimistic belief dummy (*Motivated pessimism*) equals one if $CGO_t > CGO\ 60^{th}$ percentile and $\mathrm{EXTV_t} <$ EXTV 40^{th} percentile. The control variables, following (Greenwood & Shleifer, 2014), include the market excess return, the dividend-to-price ratio (DP), the earnings-to-price ratio (EP), risk-free rate (Rf), lagged 12-month market return (R12), and unemployment rate (Unrate). The sample period spans from September 1987 to December 2021.

The results are reported in Table 6. The analysis reveals that the motivated optimistic belief has a significant positive influence on overall expectations. This effect translates into an increase in the bullish-bearish expectation spread, ranging from 4.1% to 5.9%. Furthermore, the magnitude of this increase accounts for approximately 28% to 40% of the standard deviation of the expectation spread, depending on the model specifications used[8]. Conversely, the motivated pessimistic belief demonstrates a negative effect on overall expectations, leading to a decrease ranging from 0.9% to 3.7% (6% to 25% of the standard deviation of survey expectations), albeit with less significance. These findings are consistent with the implications of motivated beliefs. It provides direct evidence of how capital gain overhang motivates extrapolative beliefs. In the Appendix, we also use other thresholds for robustness checks. As shown in Table A10, the results consistently reaffirm the robustness of the main results if

[8] The standard deviation in our sample is 14.7%. Thus, the motivated optimistic belief is associated with a 4.1% increase in expectations, which accounts for 4.1%/14.7% = 28% of the standard deviation in column (2) and a 5.9%/14.7%=40% of the standard deviation in column (3).

the 30% or the 70% thresholds are used.

4.2 Evidence from Order Imbalance

The market-level analysis indicates that investors are inclined to motivate the optimistic extrapolative belief when they experience losses and the pessimistic extrapolative belief when experiencing gains. To provide additional evidence, we employ a cross-sectional approach using order imbalance as a proxy for expectations[9].

We obtain the order imbalance variables, measured for each month-end day, from the Millisecond Intraday Indicators dataset available on the WRDS platform. Subsequently, we conduct Fama-Macbeth regressions to examine the relationship between motivated optimistic and pessimistic beliefs, utilizing the order imbalance data.

The regression results are presented in Table 7. The analysis reveals a significant association between the motivated pessimistic belief and lower order imbalance, indicating a decrease in buying pressure. Additionally, the motivated optimistic belief demonstrates a positive relationship with high order imbalance, suggesting an increase in buying pressure.

Overall, these findings support the hypothesis of motivated beliefs, resonating with the results obtained from the aggregate-level time series and individual-level cross-sectional tests.

4.3 Alternative Explanations

We have shown significant interaction effects of extrapolative beliefs and CGO on stock returns and investor expectations, which is consistent with the motivated belief hypothesis. However, two alternative explanations warrant consideration in relation to this effect.

The first alternative explanation relates to lottery demand. It is posited that investors tend to extrapolate past performance to future returns, resulting in a preference for lottery-like stocks. (Bali et al., 2022) find that more-recent MAX ((Bali et al., 2011)) is stronger than distant MAX. (An et al., 2020) report that investors prefer lottery-like stocks among low-CGO stocks due to their reference-dependent

[9] Although trading behavior may not perfectly align with investors' expectations, the larger sample size and actual trading activities can mitigate measurement errors.

preferences. When investors are experiencing losses, they become risk-seeking and are inclined towards lottery-like stocks. Conversely, when they experience gains, they become risk-averse and avoid such stocks. If EXTV serves as a proxy for lottery demand, it follows that losing investors would prefer high-EXTV stocks, while winning investors would avoid them. It is important to note that the lottery-based explanation may partially account for the motivated optimistic belief effect but fails to explain the observed pricing patterns of extrapolative beliefs among high-CGO stocks.

The second alternative explanation centers around biased risk-return trade-offs driven by reference-dependent preferences. (Wang et al., 2017) find that the negative relationship between risk and return is more pronounced among firms where investors are at a loss. (Atmaz, 2021) proposes a channel that with higher extrapolative returns, the stock prices will be more sensitive to fundamental variance shocks. Consequently, higher (lower) extrapolative beliefs are associated with lower (higher) expected fundamental variance and less (more) volatile returns. Under this mechanism, capital gain investors tend to be more risk-averse and avoid low-EXTV stocks compared to investors without reference-dependent preferences or those at breakeven. Consequently, stocks with high CGO and low EXTV become further underpriced. Similarly, it is unexplained why investors experiencing capital losses demand more high-EXTV stocks. Each alternative explanation can potentially account for one aspect of the observed interaction effect but falls short of explaining the other. However, it remains valuable to examine whether the motivated optimistic belief effect persists after controlling for lottery demand while also exploring the coexistence of the motivated pessimistic belief effect and the interplay between risk-return trade-offs and CGO. It is also possible that both channels work in tandem to elucidate our findings.

We employ formal Fama-Macbeth regressions to discern between the mechanisms underlying the motivated beliefs effect and the effect of reference-dependent preferences on lottery demand and risk-return trade-offs. Two variables, market beta and MAX (maximum daily returns in last month), are introduced into our baseline Fama-Macbeth regressions, as well as their interaction terms with CGO, i.e., $\beta \times CGO$, $IVOL \times CGO$, $MAX \times CGO$, and $SKEW \times CGO$, to proxy the two alternative explanations.

The results are presented in Table 8, demonstrating that even after accounting for the influence of reference-dependent preference effect on risk-return trade-off and lottery demand, the coefficients for *Motivated pessimism*, *Motivated optimism*, and Long-Short remain highly significant. However, the magnitude of the interaction effect diminishes moderately. Upon examining Column (4), it becomes evident that the combined effect of the two alternative channels fails to fully account for the motivated beliefs.

4.4 Additional Robustness Checks

This section discusses a series of additional robustness tests. First, the main variable proxied for extrapolative beliefs is EXTV, which is the weighted average of past returns. We first use convexity ((Gulen & Woeppel, 2022)) as the measure of extrapolative beliefs, which can get very similar results to our findings. Due to space limitations, we do not report the results. To summarize, the equal (value)-weighted XRP strategy earns a significant return of 2.141% (1.734%) for raw returns, 2.371% (2.040%) for Fama-French three-factor alphas, 2.299% (1.961%) for Fama-French five-factor alphas. The interaction effect identified by baseline Fama-Macbeth regressions and Huang et al., (2021)'s decomposition is 1.0% and 0.959%, respectively. A similar XRP constructed by convexity and CGO could explain MOM (6, 2) and MOM (12, 2) at a fraction of 72.3% and 58.7%, respectively. Although the cross-sectional explanatory power is weaker, the similar spanning tests could explain 34 momentum-related anomalies, which is slightly better than the XRP constructed by EXTV and CGO.

Second, we conduct several other robustness tests. We confirm that our findings could not be due to the inclusion of Nasdaq stocks. In column (1) of Table 9, we exclude stocks listed in NASDAQ. Then we ensure that our findings are not driven by extremely illiquid stocks. It is concerned that the mispricing disappears after removing the most illiquid stocks. (See (Bali et al., 2005); (Bali & Cakici, 2008)) Here we follow (An et al., 2020) to exclude the stocks belonging to the top illiquid decile (measured by (Amihud, 2002) illiquidity ratio). Also, the Fama-Macbeth regression is more like the equal-weighted portfolio analysis. We further use two Weighted-Least-Square-based (WLS) Fama-Macbeth regressions to show the robustness. In column (3), we use the gross return weighted Fama-Macbeth regression, and in column (4) we use the value weighted Fama-Macbeth regression. It is shown that all the Long-short differences remain positive and significant. Though in column (6), *Motivated pessimism*'s coefficient is insignificant, the magnitude of *Motivated optimism* increases. Overall, the monthly return spread is from 0.632% to 0.765%, which does not change a lot compared with the 0.695% column (6) in Table 3. These findings confirm that our findings are not driven by the inclusion of NASDAQ stocks, illiquidity, and equal-weighted method.

4.5 Who Are Trading on/against Motivated Extrapolative Beliefs?

The results above indicate that motivated extrapolative beliefs can result in substantial mispricing, and their adjustment occurs in a slow space. A follow-up question is who are trading on or against the XRP bias. To investigate this, we follow (McLean et al., 2022) to examine how XRP relates to investors' holding changes. We utilize the manager classification provided by (Koijen & Yogo, 2019) and incorporate data spanning from 1980 to 2017. Specifically, we merge the manager information with institutional holdings in the Thomson Refinitiv 13F holdings file. The investor holdings are aggregated to stock-quarter-investor type level and are nominated by shares outstanding. The remaining portion is categorized as household holdings. In cases where the sum of institutional holdings exceeds 1, we normalize the holdings to sum up to one following (Koijen & Yogo, 2019). Quarterly EXTV and CGO are measured as the average of monthly EXTV and CGO. We conduct panel regressions to examine the relationship between various types of investors' holding changes and motivated optimistic and pessimistic beliefs.

The results are presented in Table A11. We find that household investors adjust their stock holdings consistent with the direction of distorted beliefs, echoing the "dumb money" argument proposed by (Frazzini & Lamont, 2008). Conversely, institutional investors show an ability to identify overpriced stocks exhibiting motivated optimistic belief, but not the same for stocks with motivated pessimistic belief. Specifically, when examining the XRP effect, investment advisors, possibly hedge funds, tend to be the more informed "smart money." Mutual funds also display a significant ability to avoid overpriced stocks and purchase underpriced stocks, although the significance level is not as strong. Overall, this suggests that active fund management companies possess some capacity to trade against the motivated belief distortion. These findings complement the prior research conducted by (McLean et al., 2022), where they highlight the limitations of institutional investors in trading on market anomalies.

5 Extensions

In this section, we extend our studies to show that XRP can help explain momentum effects. We utilize the Hou and Loh decomposition method to demonstrate the ability of XRP in explaining momentum in the cross section. Furthermore, we perform factor spanning tests, indicating that 30 out of 43 momentum-based testing strategies are inside the span of a two-factor model comprising the market factor and XRP.

5.1 Evidence from Hou and Loh Decomposition

(Grinblatt & Han, 2005) document that the return predictability of past returns becomes insignificant after controlling for CGO and argue that momentum is a noisy proxy for CGO. However, (Novy-Marx, 2012) finds that capital gain overhang cannot explain the momentum. In a similar vein, (Guo et al., 2022) extensively investigate a wide range of candidates, including CGO, to explain momentum, only to find that momentum is largely unexplained by these candidates.

Motivated extrapolative beliefs can be generated when investors face a negative extrapolative signal in the gain domain and a positive extrapolative signal in the loss domain, which amplifies a mean-reversion style belief. This mechanism can generate mid-term momentum. We follow (Hou & Loh, 2016) and (Guo et al., 2022) to decompose momentum's return predictability. The methodology is as follows:

In stage one, we perform a predictive Fama-Macbeth regression on the target momentum strategy:

$$r_{i,t} = a_t + \beta_t MOM_{i,t-1} + \varepsilon_{i,t}, \tag{6}$$

where $r_{i,t}$ is the characteristics-adjusted return (DGTW following (Daniel et al., 1997), but only adjusted by size and book-to-market) of stock *i* in month *t*. We employ MOM (6, 2) and MOM (12, 2) as proxies for momentum. The estimated β_t is called momentum beta.

In stage two, we add the candidate explanatory variable to Equation (7):

$$r_{i,t} = a_t + \beta_t^{\tilde{R}} MOM_{i,t-1} + \beta_t^{\tilde{C}} Candidate_{i,t-1} + \tilde{\varepsilon}_{i,t} \tag{7}$$

This regression is widely used to examine whether the inclusion of candidate variables diminishes the predictive power of focal characteristics. If the candidate variable can encompass the return predictability of the momentum, $\beta_t^{\tilde{R}}$ should be insignificant and smaller in magnitude. Otherwise, the candidate cannot explain the momentum[10].

In stage 3, we regress the momentum strategy on the candidate variable:

$$MOM_{i,t-1} = \mu_{t-1} + \delta_{t-1} Candidate_{i,t-1} + \phi_{i,t-1} \tag{8}$$

Equation (8) examines the relationship between momentum and the candidate explanatory variable. The momentum can be decomposed into two orthogonal components: one related to the candidate $\delta_{t-1} Candidate_{i,t-1}$, and the other unrelated to the candidate $\mu_{t-1} + \phi_{i,t-1}$.

In stage 4, the momentum beta is decomposed into two components: the related candidate momentum beta (β_t^C) and the unrelated beta (β_t^C):

$$\beta_t = \frac{Cov\left[r_{i,t}, MOM_{i,t-1}\right]}{Var\left[MOM_{i,t-1}\right]} = \frac{Cov\left[r_{i,t}, \mu_{t-1} + \delta_{t-1} Candidate_{i,t-1} + \phi_{i,t-1}\right]}{Var\left[MOM_{i,t-1}\right]}$$

$$= \frac{Cov\left[r_{i,t}, \delta_{t-1} Candidate_{i,t-1}\right] + Cov\left[r_{i,t}, \mu_{t-1} + \ \phi_{i,t-1}\right]}{Var\left[MOM_{i,t-1}\right]}$$

$$= \beta_t^C + \beta_t^R \tag{9}$$

The fraction β_t^C / β_t is the portion that can be explained by the candidate variable in month *t*, and β_t^R / β_t^R represents the residual part unexplained by the candidate variable. Then it is shown that:

$$E\left(\frac{\beta_t^C}{\beta_t}\right) \approx \frac{E(\beta_t^C)}{E(\beta_t)}, E\left(\frac{\beta_t^R}{\beta_t}\right) \approx \frac{E(\beta_t^R)}{E(\beta_t)}, \tag{10}$$

[10] Hou and Loh (2016) contend that the $\beta_t^{\tilde{R}}$ in Equation (6) cannot be directly comparable with β_t in Equation (5) because the former is estimated based on the variable in momentum that is independent of the candidate, while the latter is based on the variation of momentum itself. Nevertheless, employing coefficient shrinkage facilitates an intuitive comparison. As a result, we present the results of coefficient shrinkage for reference.

$$Var\left(\frac{\beta_t^C}{\beta_t}\right) \approx \left(\frac{E(\beta_t^C)}{E(\beta_t)}\right) \times \left(\frac{Var(\beta_t^C)}{\left(E(\beta_t^C)\right)^2} + \frac{Var(\beta_t)}{\left(E(\beta_t)\right)^2} - 2\frac{Cov(\beta_t^C, \beta_t)}{E(\beta_t^C)E(\beta_t)}\right)^2 \tag{11}$$

$$Var\left(\frac{\beta_t^R}{\beta_t}\right) \approx \left(\frac{E(\beta_t^R)}{E(\beta_t)}\right) \times \left(\frac{Var(\beta_t^R)}{\left(E(\beta_t^R)\right)^2} + \frac{Var(\beta_t)}{\left(E(\beta_t)\right)^2} - 2\frac{Cov(\beta_t^R, \beta_t)}{E(\beta_t^R)E(\beta_t)}\right)^2 \tag{12}$$

The mean value and variance can be estimated as:

$$\hat{E}\left(\frac{\beta_t^C}{\beta_t}\right) \approx \frac{\overline{\beta_t}^C}{\overline{\beta_t}}, \hat{E}\left(\frac{\beta_t^R}{\beta_t}\right) \approx \frac{\overline{\beta_t}^R}{\overline{\beta_t}}, \tag{13}$$

$$\widehat{Var}\left(\frac{\beta_t^C}{\beta_t}\right) \approx \frac{1}{T}\left(\frac{\overline{\beta_t}^C}{\overline{\beta_t}}\right)^2 \left(\frac{s^2_{\overline{\beta_t}^C}}{\overline{\beta_t}^{C^2}} + \frac{s^2_{\overline{\beta_t}}}{\overline{\beta_t}^2} - 2\frac{\hat{\rho}_{\overline{\beta_t}^C, \overline{\beta_t}} s_{\overline{\beta_t}^C} s_{\overline{\beta_t}}}{\overline{\beta_t}^C \overline{\beta_t}}\right) \tag{14}$$

$$\widehat{Var}\left(\frac{\beta_t^R}{\beta_t}\right) \approx \frac{1}{T}\left(\frac{\overline{\beta_t}^R}{\overline{\beta_t}}\right)^2 \left(\frac{s^2_{\overline{\beta_t}^R}}{\overline{\beta_t}^{R^2}} + \frac{s^2_{\overline{\beta_t}}}{\overline{\beta_t}^2} - 2\frac{\hat{\rho}_{\overline{\beta_t}^R, \overline{\beta_t}} s_{\overline{\beta_t}^R} s_{\overline{\beta_t}}}{\overline{\beta_t}^R \overline{\beta_t}}\right) \tag{15}$$

The decomposition method proposed by Hou and Loh offers a valuable tool for partitioning the return predictability of momentum into two distinct components: one associated with the candidate variable and the other unrelated to it. As acknowledged by Hou and Loh, variables exhibiting a high correlation with momentum do not necessarily elucidate the momentum anomalies. Only those variables linked to the momentum component capable of predicting future returns hold significance.

To begin with, we construct a composite measure of XRP. It is constructed as $Rank\ CGO_{i,t} - Rank\ EXTV_{i,t}$, where $Rank$ is the cross-sectional rank, normalized in [0, 1] uniformly. Such a composition method aids in eliminating outliers. Alternatively, using *z*-score could obtain similar results. Next, we investigate four groups of explanatory candidates: 1. XRP; 2. CGO; 3. EXTV; 4. CGO + EXTV. To account for the influence of size and book-to-market, we use the DGTW returns adjusted by size and book-to-market.

Panel A of Table 10 presents the decomposition results on MOM (6, 2). In stage one, the coefficient of MOM (6, 2) is 0.775 (*t*=3.69), which confirms a significant momentum effect. In stage two, the coefficient shrinks to 0.104 (*t*=0.48) after controlling for XRP, suggesting that the predictive power of MOM (6, 2) is primarily subsumed by XRP. Stage three reveals a significant correlation between MOM (6, 2) and XRP. Nevertheless, the time-series average of the adjusted R-square is only 0.135, indicating a moderate magnitude of correlation between MOM (6, 2) and XRP (0.31 in the whole sample). Thus, the explanatory power primarily derives from the moderate correlation component. Stage four shows that 86.3% of the return predictability of MOM (6, 2) can be explained by XRP, leaving only an insignificant residual part of 13.7%. These findings support that XRP possesses significant explanatory power for MOM (6, 2).

Turning to CGO, in stage two, the coefficient becomes marginally significant after controlling for CGO, aligning with the findings of (Grinblatt & Han, 2005). However, compared to XRP, the magnitude of coefficient shrinkage is smaller. In stage three, the adjusted R-square value is larger than that of XRP, indicating a stronger correlation between CGO and MOM (6, 2). Nevertheless, the explanatory power of CGO is lower overall, suggesting that XRP enhances CGO in explaining MOM (6, 2). In stage four, the explainable fraction accounts for 66.5% of the variation, about 22% lower than that of XRP, while the residual fraction remains significant (*t*=3.05). Concerning EXTV, the results indicate that EXTV does not possess explanatory power for MOM (6, 2). Moreover, when considering candidates with both CGO and EXTV, the explanatory power decreases compared to CGO alone. These findings suggest that XRP demonstrates superior explanatory power for MOM (6, 2)'s return predictability compared to CGO, EXTV, or a combination of both.

Panel B of Table 10 displays the results regarding MOM (12, 2). The explanatory power of XRP diminishes, yet it remains noteworthy. After controlling for XRP, the coefficient of MOM (12, 2) shrinks from 0.669 (*t*=4.30) to 0.243 (*t*=1.49), in comparison to 0.491 (*t*=2.91) for CGO, 0.672 (*t*=4.28) for EXTV, or 0.510 (*t*=2.99) for both candidates. The explainable fraction of MOM (12, 2) attributable to XRP amounts to 69.1%, whereas CGO accounts for 54.2%, EXTV for 2%, and both variables for 52.5%. Though the coefficient on MOM (12, 2) becomes insignificant, the fraction unexplained stands at 30.9% and maintains statistical significance (*t*=2.76).

The aforementioned results demonstrate that XRP possesses explanatory power for momentum anomalies in the cross-section. Despite its imperfections, considering the current candidates and their limited explanatory power compared to XRP, this explanation remains non-trivial.

5.2 Factor Spanning Test

The decomposition tests following (Hou & Loh, 2016) reveal that a substantial portion of the return predictability of momentum can be attributed to the component correlated with XRP. To further evaluate the information ratio of momentum strategies relative to XRP, we perform factor spanning tests. If the alpha of a test strategy on XRP is statistically insignificant, it implies that the test strategy falls within the span of XRP and does not offer any significant additional investment opportunities. We collect 41 momentum-related anomalies from Lu Zhang's *q* library[11]. Additionally, we include two momentum factors: UMD in the Fama-French-Carhart four-factor model and UMD_IND in the Novy-Marx four-factor model.

Table 11 reports the results. The benchmark model is CAPM. However, CAPM fails to explain all 43 test strategies. Consequently, we propose a simple two-factor model, incorporating the market factor and the XRP strategy (CAPM+XRP). This two-factor model demonstrates a capability to explain 30 out of the 43 momentum strategies examined. Notably, the unexplained strategies predominantly consist of customer or supplier momentum strategies, as well as industry lead-lag effect strategies. In contrast, the traditional momentum strategies are all well-explained, displaying small and insignificant alphas. Among the explainable test strategies, the alphas experience an average decrease of 79.6%. On the other hand, the unexplainable strategies witness an average alpha reduction of 29.9%.

Table A12 indicates that neither CGO, EXTV, nor their combination can effectively explain most momentum-related strategies, as they fail to account for 30, 43, and 34 strategies, respectively. Considering other commonly used factor models as benchmarks, it is found that 40 out of 41 momentum anomalies exhibit significant alphas when compared to the Fama-French five-factor model. Moreover, 14 out of 41 momentum anomalies display significant alphas relative to the Hou, Xue, and Zhang Q4 factor model, while only 6 out of 41 anomalies exhibit significance concerning the Hou, Mo, Xue, and

[11] The momentum-related anomalies are of a broader concept than traditional momentum strategies constructed by cumulative returns. Table A13 tabulates the definitions in detail. For more details, please refer to Lu Zhang's website and his joint work: Hou, Xue, and Zhang (2015) and Hou, Mo, Xue, and Zhang (2019, 2021).

Zhang Q5 factor model.

In conclusion, the study reveals that a basic two-factor model consisting of the market factor and the XRP strategy can explain 30 out of the 43 test strategies examined. The simple two-factor model is slightly better than Q4 in explaining momentum, though weaker than Q5. Note that we do not assert XRP as a new common pricing factor, although we look forward to formally testing the property in future research.

In sum, both momentum decomposition and factor spanning tests show that XRP has good explanatory power for the return predictability of momentum.

6 Conclusion

In this study, we present evidence of motivated beliefs in the stock market, observing that investors who are experiencing losses tend to assign greater weight to optimistic extrapolative beliefs, whereas investors who are in a gain position put more emphasis on pessimistic extrapolative beliefs. The interaction between reference prices and extrapolative beliefs contributes to considerable mispricing. We introduce a long-short strategy named XRP, which generates significant returns of 2.284% (t=11.91, equal-weighted) and 1.646% (t=5.97, value-weighted). The motivated optimistic and pessimistic beliefs exhibit co-movement with investors' survey expectations and trading behavior. It is noteworthy that household investors are more susceptible to belief distortion bias, while institutional investors exhibit the ability to avoid overpriced stocks associated with motivated optimistic beliefs. Furthermore, we explore the asset pricing implications of XRP and observe its ability to explain momentum both in cross-sectional and factor-spanning tests. By incorporating the market factor and XRP in a two-factor model, we find that it can account for 30 out of 43 momentum-related test strategies, displaying similar explanatory power to Hou, Xue, and Zhang's Q4 factor model.

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Table A. Variable Definition and Summary Statistics

Panel A. Main Variable Definition.	
Variable Name	Variable Definition
Main Variables	
Asset growth	Total asset growth rate, which is calculated as $AT_T/AT_{T-1} - 1$, following (Cooper et al., 2008). The returns for July of year *T* to June of year *T*+1 are matched with accounting data for all fiscal yearends in calendar year *T*-1. This data merging process is consistent throughout the subsequent analysis.
CGO	At the end of last week *s* in month *t*, the reference price for each stock *i* (omitted) is defined as: $RP_t = \frac{1}{k}\sum_{n=1}^{T}(V_{s-n}\prod_{\tau=1}^{n-1}(1 - V_{s-n+\tau}))P_{s-n}$. Where P_s is the stock price at the end of week *s*; V_s is week *s*'s turnover ratio, calculated as weekly trading volume divided by the number of outstanding shares; *T*=260, i.e., the past five years; and *k* denotes the sum of weights calculated from turnover ratio to make the weights sum to one. $CGO_s = \frac{P_{s-1} - RP_s}{P_{s-1}}$.
DGTW	Characteristics based adjusted returns, following (Daniel et al., 1997). Note we only adjust returns according to size and book-to-market ratio when investigate the momentum effect. To ensure data reliability, two specific requirements are imposed. Firstly, Compustat data must be available for at least 2 years. Secondly, CRSP (Center for Research in Security Prices) data should be available for both the fiscal year end of *T*-1 and June of year *T*. We construct size weights using the market value observed in June, while the book-to-market ratio utilizes the market capitalization at the fiscal year end of year *T*-1. The NYSE (New York Stock Exchange) size breakpoints are utilized to sort stocks into quintiles based on their market value.
EXTV	The value of extrapolative beliefs, which is defined as $EXTV_{i,t} = \sum_{l=1}^{L} w_l R_{i,t-l}$, where $R_{i,t-l}$ is stock *i*'s daily return at day *t-l*, $w_l = \lambda^{l-1}/\sum_{k=0}^{L-1}\lambda^k$, and *t* is the last trading day of a month.
Gross Profitability	Gross profitability is calculated as (REVT-COGS)/AT, following (Novy-Marx, 2013).
IVOL	Idiosyncratic volatility, which is measured as the standard deviation of daily returns' residuals in the Fama-French three-factor model in the month *t*, with at least 15 trading days available, following (Ang et al., 2006).
Kurt	Return kurtosis, which is measured as the kurtosis of daily returns in month *t*.
logBM	Logarithm of book-to-market ratio following (Fama & French, 1992). The book value is measured as stockholders' book equity, plus balance-sheet deferred taxes and investment tax credit (Compustat annual item TXDITC) if available, where Stockholders' equity is the value reported by Compustat (item SEQ), if available. If not, stockholders' equity is the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). minus the book value of preferred stock. The market value is the market capitalization at the end of month *t*.

MOM (12, 2)	Cumulative returns from *t*-12 to *t*-2, following (Jegadeesh & Titman, 1993).
MOM (6, 2)	Cumulative returns from *t*-6 to *t*-2.
Lagged Return	Lagged monthly stock returns.
Size	Logarithm of market capitalization at the end of month *t*.
Skew	Return skewness, which is measured as the skewness of daily returns in month *t*. The skewness is a proxy for lottery demand, see (Barberis & Huang, 2008).
Other Variables	
Expectation	The AAII Sentiment Survey is a weekly survey of its members which asks if they are "Bullish," "Bearish," or "Neutral" on the stock market over the next six months. We calculate the monthly expectations by the average of weekly bullish-bearish spread following (Greenwood & Shleifer, 2014).
Order Imbalance	Order imbalance variables are measured for each month-end day from Millisecond Intraday Indicators by WRDS.
Holding Change	We obtain the manager file from (Koijen & Yogo, 2019) and merge the managers with Thomson/ Refinitiv institutional 13F holdings data. The household holdings are calculated following (Koijen & Yogo, 2019).
Time-series predictors	The market DP (dividend-to-price ratio), EP (earnings-to-price ratio), and risk-free rate are obtained from Goyal's personal website (See (Welch & Goyal, 2008)). The unemployment rate is collected from Federal Reserve Bank of St. Louis.

Table 1. Summary Statistics

This table tabulates the summary statistics of main variables. All the continuous variables but returns are winsorized at 1% and 99% percentile. Panel A presents the summary statistics on the variables used in our baseline models. Panel B reports correlation matrix. Panel C reports the average cross-sectional correlation matrix.

Panel A: Summary Statistics

Variables	Obs.	Mean	Std	P25	Median	P75	Skewness
CGO	1703939	0.001	0.287	-0.100	0.055	0.177	-1.601
EXTV	1840905	0.001	0.009	-0.004	0.001	0.005	0.402
MOM (12, 2)	1839131	0.198	0.501	-0.100	0.111	0.370	1.870
MOM (6, 2)	1839758	0.087	0.292	-0.086	0.051	0.209	1.256
Lagged Return	1840905	0.017	0.118	-0.048	0.009	0.072	0.666
Asset growth	1700937	0.159	0.322	0.011	0.084	0.196	3.238
Size	1840905	12.613	2.003	11.111	12.484	13.951	0.330
Gross Profitability	1705044	0.316	0.257	0.114	0.279	0.459	0.848
logBM	1676345	-0.615	0.798	-1.064	-0.520	-0.064	-0.674
IVOL	1735076	2.081	1.279	1.174	1.749	2.621	1.545

Panel B: Correlation Matrix

	CGO	EXTV	MOM (12, 2)	MOM (6, 2)	Lagged Return	Asset growth	Size	Gross Profitability	logBM	IVOL
CGO	1.000									
EXTV	-0.025	1.000								
MOM (12, 2)	0.490	-0.008	1.000							
MOM (6, 2)	0.456	-0.016	0.637	1.000						
Lagged Return	0.157	0.518	-0.006	-0.007	1.000					
Asset growth	0.089	0.004	0.153	0.053	0.007	1.000				
Size	0.215	0.023	0.019	0.010	0.004	0.027	1.000			
Gross Profitability	0.029	0.004	0.066	0.043	0.018	-0.033	-0.085	1.000		
logBM	-0.311	-0.067	-0.297	-0.214	-0.098	-0.184	-0.398	-0.224	1.000	
IVOL	-0.268	0.103	0.058	0.027	0.128	0.113	-0.340	0.087	-0.055	1.000

Panel C: Correlation Matrix (cross-sectional)

	CGO	EXTV	MOM (12, 2)	MOM (6, 2)	Lagged Return	Asset growth	Size	Gross Profitability	logBM	IVOL
CGO	1.000									
EXTV	-0.001	1.000								
MOM (12, 2)	0.525	0.012	1.000							
MOM (6, 2)	0.479	0.006	0.659	1.000						
Lagged Return	0.308	0.010	0.730	0.014	1.000					
Asset growth	0.176	0.524	0.004	-0.007	0.010	1.000				
Size	0.118	0.007	0.154	0.060	0.151	0.006	1.000			
Gross Profitability	0.207	0.003	0.016	0.010	0.014	0.004	0.042	1.000		
logBM	0.058	0.010	0.072	0.045	0.056	0.017	-0.022	-0.032	1.000	
IVOL	-0.304	-0.062	-0.298	-0.213	-0.212	-0.101	-0.201	-0.313	-0.308	1.000

Table 2. Independent Double Sorts on CGO and EXTV

This table presents characteristics and performance of portfolios double-sorted by *CGO* (capital gain overhang) and *EXTV* (the value of extrapolative beliefs). At the end of each month *t*-1, stocks are independently sorted into five groups according to their *CGO* and *EXTV* levels, respectively. Then we construct 25 portfolios interacted by the *CGO*- and *EXTV*-sorted groups. Each portfolio is held for one month. Panel A reports the time-series average of equal-weighted characteristics of each group, which include the fraction of stocks in the cross section, *EXTV*, *CGO*, and (logarithmic) market capitalization. Panel B reports the equal-weighted performance of each group. Panel C presents the value-weighted performance of each group. We tabulate the excess returns (Excess ret), alphas adjusted by CAPM, Fama-French three-factor model (FF 3), and Fama-French five-factor model (FF 5). At the bottom of each block, we report the performance of *XRP* strategy, which longs stocks within the highest *CGO* quintile and the lowest *EXTV* quintile, and shorts stocks within the lowest *CGO* quintile and the highest *EXTV* quintile. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Distribution and Characteristics of Double-sorted Portfolios

		Low	2	3	4	High			Low	2	3	4	High
Fraction		*EXTV*					*Size*		*EXTV*				
	CGO							*CGO*					
	Low	4.90%	3.70%	3.30%	3.40%	4.70%		Low	12.88	13.26	13.31	13.27	12.91
	2	4.00%	4.10%	4.00%	4.00%	3.80%		2	13.66	14.13	14.18	14.12	13.73
	3	3.60%	4.20%	4.40%	4.30%	3.60%		3	13.92	14.43	14.50	14.45	13.99
	4	3.50%	4.20%	4.40%	4.30%	3.60%		4	14.03	14.53	14.66	14.61	14.09
	High	3.70%	4.00%	4.10%	4.20%	4.10%		High	13.76	14.19	14.37	14.32	13.81
		Low	2	3	4	High			Low	2	3	4	High
CGO		*EXTV*					*EXTV*		*EXTV*				
	CGO							*CGO*					
	Low	-0.45	-0.41	-0.40	-0.41	-0.46		Low	-0.011	-0.003	0.000	0.004	0.015
	2	-0.10	-0.10	-0.09	-0.09	-0.10		2	-0.01	-0.003	0.000	0.004	0.013
	3	0.03	0.03	0.03	0.03	0.03		3	-0.01	-0.003	0.000	0.004	0.012
	4	0.13	0.13	0.13	0.13	0.13		4	-0.01	-0.003	0.000	0.004	0.012
	High	0.28	0.27	0.27	0.28	0.28		High	-0.01	-0.003	0.000	0.004	0.013

Panel B: Performance of Double-Sorted Portfolios (Independent Sorting, Equal Weighted)

		(1) Low	(3) Mid	(5) High	(6) Low - (3)	(7) (3) - High	(7) - (6)	XRP
		EXTV						
	CGO							
Excess ret	Low	1.341	0.994	-0.049	0.347	1.043	0.695	
		(4.39)	(3.72)	(-0.18)	(3.08)	(7.62)	(4.32)	
	2	1.406	1.143	0.492	0.264	0.651	0.387	
		(5.25)	(5.47)	(2.02)	(2.52)	(5.65)	(2.22)	
	3	1.434	1.181	0.729	0.253	0.452	0.198	
		(5.89)	(6.22)	(3.33)	(2.42)	(4.49)	(1.21)	
	4	1.659	1.260	0.881	0.399	0.380	-0.019	
		(6.85)	(6.53)	(3.80)	(4.04)	(3.55)	(-0.12)	
	High	2.234	1.526	1.295	0.708	0.231	-0.477	
		(9.19)	(7.45)	(5.54)	(7.31)	(2.44)	(-3.05)	
High-Low					0.361***	-0.812***	-1.173***	2.284***
					(2.93)	(-5.15)	(-6.03)	(11.91)
CAPM	Low	0.185	-0.034	-1.094	0.219	1.059	0.840	
		(1.01)	(-0.23)	(-6.39)	(1.84)	(7.62)	(5.08)	
	2	0.304	0.203	-0.496	0.101	0.699	0.598	
		(1.96)	(1.68)	(-3.78)	(0.99)	(6.26)	(3.82)	
	3	0.377	0.287	-0.234	0.090	0.521	0.431	
		(2.77)	(2.66)	(-2.17)	(0.86)	(5.52)	(2.91)	
	4	0.623	0.379	-0.084	0.245	0.463	0.219	
		(4.50)	(3.55)	(-0.67)	(2.40)	(4.63)	(1.45)	
	High	1.228	0.634	0.356	0.594	0.278	-0.316	
		(8.27)	(5.97)	(2.83)	(5.93)	(3.04)	(-2.08)	
High-Low					0.375***	-0.781***	-1.156***	2.322***
					(3.03)	(-4.88)	(-5.95)	(12.78)

		(1) Low	(3) Mid	(5) High	(6) Low - (3)	(7) (3) - High	(7) - (6)	XRP
		EXTV						
	CGO							
FF 3	Low	-0.057	-0.287	-1.293	0.230	1.006	0.776	
		(-0.46)	(-3.11)	(-11.04)	(1.94)	(7.80)	(5.34)	
	2	0.103	-0.014	-0.668	0.117	0.654	0.537	
		(1.06)	(-0.20)	(-8.18)	(1.26)	(6.21)	(3.99)	
	3	0.208	0.11	-0.378	0.098	0.489	0.390	
		(2.28)	(1.70)	(-5.42)	(0.98)	(5.36)	(2.89)	
	4	0.495	0.24	-0.191	0.255	0.431	0.176	
		(5.13)	(3.42)	(-2.24)	(2.48)	(4.05)	(1.13)	
	High	1.152	0.547	0.293	0.605	0.254	-0.351	
		(11.44)	(7.29)	(3.10)	(6.59)	(2.49)	(-2.28)	
High-Low					0.376***	-0.752***	-1.128***	2.445***
					(2.94)	(-4.62)	(-5.56)	(12.51)
FF 5	Low	0.106	-0.225	-1.208	0.331	0.983	0.652	
		(0.67)	(-1.79)	(-8.76)	(2.82)	(7.46)	(4.42)	
	2	0.159	-0.068	-0.674	0.227	0.606	0.379	
		(1.47)	(-0.88)	(-7.34)	(2.44)	(5.79)	(2.97)	
	3	0.269	0.008	-0.404	0.261	0.413	0.152	
		(2.85)	(0.12)	(-5.66)	(2.61)	(4.63)	(1.15)	
	4	0.486	0.13	-0.231	0.355	0.362	0.006	
		(5.51)	(1.93)	(-2.48)	(3.33)	(3.26)	(0.04)	
	High	1.176	0.459	0.265	0.718	0.194	-0.524	
		(9.85)	(5.79)	(2.13)	(6.55)	(1.73)	(-2.93)	
High-Low					0.387***	-0.789***	-1.176***	2.388***
					(2.87)	(-4.59)	(-5.19)	(10.13)

Panel C: Performance of Double-Sorted Portfolios (Independent Sorting, Value Weighted)

		(1) Low	(3) Mid	(5) High	(6) Low - (3)	(7) (3) - High	(7) - (6)	XRP		(1) Low	(3) Mid	(5) High	(6) Low - (3)	(7) (3) - High	(7) - (6)	XRP
		EXTV								*EXTV*						
	CGO															
Excess ret	Low	1.227	0.991	-0.091	0.236	1.082	0.846		FF 3	-0.117	-0.18	-1.304	0.063	1.124	1.060	
		(4.02)	(3.69)	(-0.30)	(1.33)	(5.14)	(2.69)			(-0.69)	(-1.12)	(-7.09)	(0.34)	(5.51)	(3.50)	
	2	1.296	1.004	0.576	0.292	0.428	0.136			0.072	-0.059	-0.474	0.131	0.416	0.285	
		(5.02)	(5.08)	(2.64)	(2.11)	(2.49)	(0.56)			(0.48)	(-0.54)	(-3.77)	(0.87)	(2.26)	(1.13)	
	3	1.227	1.048	0.663	0.179	0.385	0.206			0.153	0.06	-0.307	0.094	0.367	0.273	
		(5.43)	(6.03)	(3.42)	(1.37)	(2.70)	(0.93)			(1.30)	(0.80)	(-2.69)	(0.73)	(2.66)	(1.39)	
	4	1.421	1.048	0.6	0.373	0.448	0.075			0.389	0.148	-0.301	0.240	0.449	0.209	
		(6.47)	(6.24)	(2.98)	(2.82)	(4.19)	(0.38)			(3.69)	(1.77)	(-3.03)	(1.86)	(4.30)	(1.11)	
	High	1.543	1.149	0.868	0.394	0.281	-0.113			0.637	0.329	0.008	0.308	0.321	0.013	
		(7.14)	(5.92)	(3.94)	(2.97)	(1.85)	(-0.47)			(5.41)	(3.43)	(0.07)	(2.25)	(1.99)	(0.05)	
High-Low					0.158	-0.801***	-0.959***	1.646***					0.244	-0.802***	-1.047***	1.941***
					(0.87)	(-3.35)	(-2.77)	(5.97)					(1.27)	(-3.29)	(-2.98)	(7.38)
CAPM	Low	0.055	-0.033	-1.187	0.088	1.154	1.066		FF 5	0.102	-0.042	-1.231	0.144	1.189	1.044	
		(0.30)	(-0.20)	(-6.44)	(0.49)	(5.54)	(3.48)			(0.47)	(-0.22)	(-5.79)	(0.78)	(5.34)	(3.42)	
	2	0.206	0.061	-0.400	0.145	0.461	0.317			0.216	-0.066	-0.475	0.283	0.408	0.125	
		(1.33)	(0.55)	(-3.22)	(0.98)	(2.62)	(1.27)			(1.29)	(-0.53)	(-3.49)	(2.02)	(2.24)	(0.53)	
	3	0.213	0.155	-0.259	0.058	0.414	0.355			0.248	-0.056	-0.356	0.304	0.300	-0.004	
		(1.84)	(1.85)	(-2.48)	(0.44)	(2.77)	(1.59)			(1.81)	(-0.77)	(-2.82)	(2.15)	(2.12)	(-0.02)	
	4	0.435	0.17	-0.305	0.265	0.475	0.210			0.339	0.03	-0.399	0.309	0.429	0.120	
		(3.96)	(2.08)	(-3.09)	(2.02)	(4.62)	(1.12)			(3.26)	(0.37)	(-3.63)	(2.34)	(4.21)	(0.64)	
	High	0.589	0.26	-0.049	0.328	0.309	-0.019			0.609	0.239	-0.021	0.371	0.260	-0.111	
		(4.87)	(2.53)	(-0.40)	(2.43)	(2.00)	(-0.08)			(5.31)	(2.50)	(-0.13)	(2.67)	(1.59)	(-0.45)	
High-Low					0.241	-0.844***	-1.085***	1.775***					0.226	-0.929***	-1.155***	1.848***
					(1.29)	(-3.53)	(-3.13)	(6.66)					(1.18)	(-3.59)	(-3.26)	(6.66)

Table 3. Fama-Macbeth Regressions

This table presents the results for predictive Fama-Macbeth (1973) regressions. The dependent variable is the monthly return in month *t*. *Motivated optimism* is an indicator variable which equals one if the stock belongs to the highest-*CGO* quintile and lowest-*EXTV* quintile. *Motivated pessimism* equals one if the stock belongs to the lowest-*CGO* quintile and highest-*EXTV* quintile. The control variables include *Size* (logarithmic market capitalization), *logBM* (logarithmic book-to-market ratio), *Gross Profitability*, *Asset growth* (growth rate of total asset), *MOM (12,2)* (cumulative returns from *t*-12 to *t*-2), *IVOL* (idiosyncratic volatility in month *t*-1), *Skew* (skewness in month *t*-1), and *Kurt* (kurtosis in month *t*-1). Columns (4) to (6) control for the cross-sectional rank of *CGO* and *EXTV*, which are normalized into [0, 1] uniformly. *Long-Short* represents the difference between the coefficients of *Motivated pessimism* and *Motivated optimism*. The independent variables are collected at the end of month *t*-1. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var =	Return					
Motivated pessimism	1.062***	1.166***	0.902***	0.399***	0.392***	0.352***
	(9.77)	(12.67)	(12.13)	(4.56)	(4.94)	(5.03)
Motivated optimism	-1.220***	-1.316***	-0.930***	-0.522***	-0.477***	-0.343***
	(-8.83)	(-10.41)	(-8.57)	(-5.16)	(-5.80)	(-4.27)
Rank CGO				0.744***	0.928***	0.258*
				(4.30)	(5.65)	(1.79)
Rank EXTV				-0.945***	-1.155***	-1.156***
				(-7.07)	(-8.67)	(-8.82)
Size		0.003	-0.047		0.002	-0.034
		(0.07)	(-1.47)		(0.04)	(-1.04)
logBM		0.580***	0.637***		0.618***	0.597***
		(6.17)	(8.37)		(6.85)	(8.00)
Gross Profitability		1.164***	1.167***		1.152***	1.151***
		(7.03)	(7.46)		(7.17)	(7.47)
Asset growth		0.641***	0.584***		0.583***	0.595***
		(6.01)	(6.40)		(5.70)	(6.54)
MOM (12, 2)			0.718***			0.728***
			(5.02)			(4.90)
IVOL			-0.241***			-0.229***
			(-5.61)			(-5.57)
Skew			-0.050**			-0.011
			(-2.25)			(-0.57)
Kurt			-0.015			-0.021**
			(-1.62)			(-2.26)
Adj-Rsquare	0.005	0.038	0.056	0.020	0.051	0.064
Observations	1701469	1545554	1544045	1701469	1545554	1544045
Long-Short	2.282***	2.482***	1.832***	0.920***	0.870***	0.695***
	(11.93)	(13.72)	(12.66)	(8.40)	(8.11)	(6.89)

Table 4. Return Decomposition

This table presents the results of return decomposition. We first sort stocks into 5×5 portfolios according to their *CGO* and *EXTV*. The returns are subsequently decomposed into the benchmark return, the pure *CGO* effect ($A_h - A_l$), the pure *EXTV* effect ($E_{gg} - E_{bb}$), and the interaction effect ($I_{bb,l} - I_{gg,h}$). Panel A reports the return decomposition including the interaction effect. Panel B presents the results excluding the interaction effect. We tabulate the excess returns, CAPM alphas, Fama-French three-factor model alphas, and Fama-French five-factor model alphas of the pure *CGO* effect, the pure *EXTV* effect, and the interaction effect. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Interaction Effect Included					
model	Pure CGO	Pure EXTV	Interaction	$I_{bb,l}$	$I_{gg,h}$
Excess Ret	0.521***	-0.571***	1.181***	0.374***	-0.807***
	(3.71)	(-4.34)	(6.30)	(3.10)	(-5.31)
CAPM	0.652***	-0.491***	1.169***		
	(5.10)	(-3.58)	(6.22)		
FF 3	0.817***	-0.478***	1.140***		
	(7.02)	(-3.28)	(5.83)		
FF 5	0.681***	-0.523***	1.171***		
	(3.99)	(-3.32)	(5.40)		
Panel B: Interaction Effect Excluded					
Excess Ret	0.798***	-0.971***			
	(5.60)	(-8.79)			
CAPM	0.920***	-0.881***			
	(7.03)	(-7.40)			
FF 3	1.077***	-0.852***			
	(8.40)	(-7.04)			
FF 5	0.951***	-0.917***			
	(4.90)	(-7.27)			

Table 5. Subsample Analysis

This table presents the results of return decomposition in subsamples. At the end of month *t*-1, we first sort the stocks into two groups according to their *IVOL* (in the month *t*-1, Panel A), *Size* (at the end of month *t*-1, Panel B), and institutional holding ratios (the same quarter, Panel C). Then stocks are sorted by their CGO and EXTV into 5×5 portfolios, independently within each group. We tabulate the excess returns, CAPM alphas, Fama-French three-factor model alphas, and Fama-French five-factor model alphas of the pure *CGO* effect, the pure *EXTV* effect, and the interaction effect. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	Pure CGO	Pure EXTV	Interaction	Pure CGO	Pure EXTV	Interaction
Panel A: Subsamples Sorted by IVOL						
	Low IVOL			High IVOL		
Excess Ret	0.117	-0.612***	0.497***	0.964***	-1.223***	0.847***
	(0.93)	(-5.83)	(2.94)	(5.54)	(-6.72)	(3.47)
CAPM	0.173	-0.529***	0.515***	1.059***	-1.113***	0.870***
	(1.40)	(-5.20)	(3.07)	(6.64)	(-5.61)	(3.58)
FF 3	0.334***	-0.511***	0.516***	1.213***	-1.102***	0.826***
	(3.10)	(-4.96)	(3.05)	(7.34)	(-5.45)	(3.38)
FF 5	0.267**	-0.523***	0.499***	1.099***	-1.279***	0.761***
	(2.16)	(-4.69)	(2.82)	(4.70)	(-6.08)	(3.11)
Panel B: Subsamples Sorted by Size						
	Pure CGO	Pure EXTV	Interaction	Pure CGO	Pure EXTV	Interaction
	Small			Big		
Excess Ret	0.837***	-0.641***	1.128***	0.324*	-0.679***	0.671***
	(5.45)	(-3.36)	(4.82)	(1.91)	(-4.86)	(2.90)
CAPM	0.963***	-0.592***	1.081***	0.441***	-0.559***	0.758***
	(6.95)	(-3.05)	(4.75)	(2.64)	(-3.91)	(3.29)
FF 3	1.065***	-0.555***	1.106***	0.622***	-0.568***	0.696***
	(7.13)	(-2.88)	(4.91)	(4.10)	(-3.85)	(3.11)
FF 5	0.927***	-0.640***	1.108***	0.520**	-0.691***	0.590**
	(5.14)	(-3.20)	(4.60)	(2.42)	(-3.85)	(2.40)
Panel C: Subsamples Sorted by Institutional Holdings						
	Pure CGO	Pure EXTV	Interaction	Pure CGO	Pure EXTV	Interaction
	Low Institutional Holdings			High Institutional Holdings		
Excess Ret	0.984***	-0.192	1.353***	0.355*	-1.025***	0.465*
	(5.77)	(-1.20)	(5.02)	(1.74)	(-5.80)	(1.76)
CAPM	1.064***	-0.086	1.427***	0.506***	-0.934***	0.461*
	(6.22)	(-0.53)	(5.16)	(2.60)	(-5.34)	(1.81)
FF 3	1.154***	-0.122	1.406***	0.682***	-0.915***	0.489*
	(6.64)	(-0.72)	(4.89)	(3.49)	(-4.98)	(1.87)
FF 5	0.988***	-0.235	1.334***	0.557*	-1.053***	0.377
	(4.11)	(-1.23)	(4.35)	(1.93)	(-4.80)	(1.36)

Table 6. Motivated Extrapolative Beliefs and Survey Expectations

This table presents the results associated with regressions of survey expectations of future stock market returns on motivated extrapolative beliefs as follows:

$$Expectation_t = a + b \times Motivated\ Optimism_t + c \times Motivated\ Pessimism_t + d \times Controls_t + u_t,$$

where $Expectation_t$ represents the monthly AAI survey expectations in month *t*, which is calculated as the average of weekly bullish-bear spreads. The aggregate levels CGO and EXTV are calculated as the median value or the value weighted average of stock-level CGO and EXTV. *Motivated optimism* is an indicator variable, which equals one if $CGO_t < CGO\ 40^{th}$percentile and $EXTV_t > EXTV\ 60^{th}$ percentile . *Motivated pessimism* equals one if $CGO_t > CGO\ 60^{th}$percentile and $EXTV_t < EXTV\ 40^{th}$ percentile. The control variables include the market excess return in month *t* (*MKT*), the dividend-to-price ratio (*DP*), the earnings-to-price ratio (*EP*), the risk-free rate (*Rf*), the lagged 12-month market return (*R12*), and the unemployment rate (*Unrate*). The sample period spans from September 1987 to December 2021. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var =	Expectation			
Aggregation Method:	Median	Mean	Median	Mean
Motivated optimism	0.057**	0.041**	0.059***	0.050***
	(2.28)	(2.06)	(3.11)	(2.76)
Motivated pessimism	-0.037**	-0.009	-0.028*	-0.010
	(-2.09)	(-0.27)	(-1.75)	(-0.32)
EXTV	8.145***	7.001***	8.683***	7.612***
	(2.75)	(3.25)	(3.73)	(3.28)
CGO	0.917***	0.734***	0.449*	0.521***
	(5.40)	(4.92)	(1.93)	(2.91)
MKT			0.009***	0.009***
			(4.78)	(4.78)
Dp			-0.006***	-0.006***
			(-3.32)	(-3.57)
Ep			0.000	0.000
			(0.40)	(0.55)
Rf			-31.829***	-39.700***
			(-4.68)	(-4.62)
R12			0.252***	0.180*
			(3.42)	(1.89)
Unrate			-0.038***	-0.039***
			(-5.18)	(-5.45)
t-stat:				
(Motivated optimism- Motivated pessimism = 0)	3.41***	3.04***	3.41***	3.04***
Adj-Rsquare	0.191	0.158	0.394	0.383
Observations	412	412	412	412

Table 7. Motivated Extrapolative Beliefs and Order Imbalance

This table presents the results of Fama-Macbeth regressions of order imbalance on motivated extrapolative beliefs:

$$Order\ Imbalance_{i,t} = a + b \times Motivated\ pessimism_{i,t} + c \times Motivated\ optimism_{i,t} + d \times Controls + u_{i,t},$$

where *Volume imbalance* is calculated by the difference of number of shares of buys and sells divided by the sum of them. *Dollar imbalance* is the difference in dollar value of buys and dollar value of sells divided by the total of them. *Trade imbalance* is the difference of the number of buys and sells divided by the total of them. *Order imbalance* variables are measured for each month-end day. *Motivated optimism* is an indicator variable, which equals one if $CGO_{i,t} < CGO_t\ 20^{th}$ percentile $and\ EXTV_{i,t} > EXTV_t\ 80^{th}$ percentile . *Motivated pessimism* equals one if $CGO_{i,t} > CGO_t\ 80^{th}$percentile $and\ EXTV_{i,t} < EXTV_t\ 20^{th}$ percentile. The control variables include *CGO* and *EXTV*, logarithm of market capitalization (*Size*), logarithm of book-to-market ratio (*logBM*), *Gross Profitability*, *Asset Growth*, positive MOM (12, 2) (*MOM12p*, equals $MOM(12,2) \times I_{MOM(12,2)>0}$), negative MOM (12, 2) (*MOM12n*, equals $MOM\ (12,2) \times I_{MOM(12,2)<0}$), idiosyncratic risk (*IVOL*), return skewness (*Skew*), and return kurtosis (*Kurt*). The *t*-statistics are adjusted by Newey-West HAC method. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var=	Volume imbalance			Dollar imbalance			Trade imbalance		
Motivated pessimism	-0.022***	-0.024***	-0.017***	-0.022***	-0.024***	-0.016***	-0.014***	-0.018***	-0.011***
	(-5.53)	(-6.30)	(-4.76)	(-5.45)	(-6.27)	(-4.70)	(-3.76)	(-5.08)	(-3.83)
Motivated optimism	0.013***	0.020***	0.009***	0.014***	0.020***	0.009***	0.010***	0.016***	0.007***
	(5.66)	(9.58)	(3.44)	(5.98)	(9.61)	(3.46)	(4.65)	(8.79)	(3.05)
CGO			0.036***			0.036***			0.038***
			(6.87)			(6.88)			(8.41)
EXTV			1.524***			1.528***			1.401***
			(13.50)			(13.52)			(12.25)
Size		0.004***	0.004***		0.004***	0.003***		0.003***	0.002**
		(4.11)	(3.60)		(3.72)	(3.20)		(2.61)	(2.26)
logBM		-0.006***	-0.004***		-0.006***	-0.004***		-0.005***	-0.003***
		(-8.18)	(-6.00)		(-8.23)	(-6.04)		(-6.33)	(-4.39)
Gross Profitability		0.006*	0.005		0.006*	0.004		0.005	0.005
		(1.86)	(1.46)		(1.75)	(1.37)		(1.49)	(1.43)
Asset Growth		0.004***	0.004***		0.004***	0.004***		0.001	0.001
		(3.75)	(3.91)		(3.71)	(3.88)		(1.15)	(1.41)
MOM12p		0.005***	0.001		0.005***	0		0.008***	0.003*
		(2.87)	(0.34)		(2.77)	(0.25)		(4.68)	(1.66)
MOM12n		0.009**	-0.012**		0.010**	-0.011**		0.017***	-0.006
		(2.03)	(-2.52)		(2.27)	(-2.28)		(3.92)	(-1.42)
IVOL		0.002*	0.002**		0.002*	0.002***		0.001	0.002**
		(1.76)	(2.41)		(1.97)	(2.64)		(1.34)	(2.21)
Skew		0.002***	-0.001*		0.002***	-0.001*		0.002***	-0.001
		(4.62)	(-1.97)		(4.70)	(-1.89)		(4.16)	(-1.45)
Kurt		0.000	0.000		0.000	0.000		0.000	0.000
		(-0.91)	(-0.76)		(-1.04)	(-0.90)		(1.01)	(1.09)
Adj-Rsquare	0.001	0.010	0.014	0.001	0.010	0.013	0.001	0.013	0.017
Start	200702	200702	200702	200702	200702	200702	200702	200702	200702
End	202112	202112	202112	202112	202112	202112	202112	202112	202112
Observations	465487	437525	417384	465487	437525	417384	465487	437525	417384

Table 8. Controlling the Interaction between Volatility and Lottery with CGO

This table presents the results for predictive Fama-Macbeth (1973) regressions. The dependent variable is the monthly return in month *t*. *Motivated optimism* is an indicator variable, which equals one if the stock belongs to the highest *CGO* quintile and lowest *EXTV* quintile. *Motivated pessimism* equals one if the stock belongs to the lowest *CGO* quintile and highest *EXTV* quintile. The control variables include market beta (*BETA*, which is estimated using past 52-week weekly returns), *MAX* (the maximum daily returns in month *t*-1), *Size* (logarithmic market capitalization), *logBM* (logarithmic book-to-market ratio), *Gross Profitability*, *Asset growth* (growth rate of total assets), *MOM(12, 2)* (cumulative returns from *t*-12 to *t*-2), *IVOL* (idiosyncratic volatility in month *t*-1), *Skew* (skewness in month *t*-1), and *Kurt* (kurtosis in month *t*-1). All the dependent variables are collected at the end of month *t*-1. *Long-Short* is the difference between the coefficients of *Motivated pessimism* and *Motivated optimism*. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var =		Return		
Motivated pessimism	0.382***	0.362***	0.390***	0.377***
	(5.26)	(5.04)	(5.29)	(5.20)
Motivated optimism	-0.333***	-0.263***	-0.234***	-0.221***
	(-4.16)	(-3.51)	(-3.11)	(-2.99)
CGO	0.479***	-0.287	-0.161	-0.19
	(3.40)	(-1.05)	(-0.79)	(-0.69)
Rank EXTV	-1.058***	-1.073***	-1.084***	-1.085***
	(-8.07)	(-8.15)	(-8.20)	(-8.17)
CGO × IVOL		0.286***		0.007
		(4.37)		(0.05)
CGO × BETA		-0.031		-0.066
		(-0.30)		(-0.61)
CGO × MAX			9.464***	10.056**
			(4.59)	(2.24)
CGO × SKEW			0.039	0.028
			(0.51)	(0.37)
MAX	-7.341***	-7.146***	-5.813***	-5.399***
	(-5.40)	(-5.32)	(-4.67)	(-4.35)
BETA	0.174**	0.128	0.161*	0.118
	(1.99)	(1.39)	(1.88)	(1.30)
Size	-0.041	-0.033	-0.036	-0.035
	(-1.24)	(-0.99)	(-1.07)	(-1.03)
logBM	0.579***	0.574***	0.571***	0.573***
	(8.10)	(8.02)	(7.99)	(8.03)
Gross Profitability	1.120***	1.116***	1.114***	1.113***
	(7.33)	(7.28)	(7.28)	(7.28)
Asset growth	0.566***	0.565***	0.559***	0.560***
	(6.97)	(6.89)	(6.85)	(6.85)
MOM (12, 2)	0.720***	0.727***	0.718***	0.721***
	(5.07)	(5.19)	(5.14)	(5.19)
IVOL	-0.059	-0.044	-0.089**	-0.096**
	(-1.29)	(-0.89)	(-2.01)	(-2.02)
Skew	0.105***	0.098***	0.099***	0.094***
	(4.14)	(3.88)	(3.85)	(3.62)
Kurt	0.004	0.004	0.001	0.001
	(0.51)	(0.51)	(0.16)	(0.17)
Adj-Rsquare	0.077	0.080	0.079	0.081
Observations	1543593	1543593	1543593	1543593
Long-Short	0.715***	0.626***	0.624***	0.598***
	(6.78)	(6.33)	(6.24)	(6.13)

Table 9. Additional Robustness Checks on Baseline Model

This table presents the results of predictive Fama-Macbeth (1973) regressions. The dependent variable is the monthly return in month *t*. *Motivated pessimism* is an indicator variable, which equals to one if the stock belongs to the highest *CGO* quintile and lowest *EXTV* quintile. *Motivated optimism* equals one if the stock belongs to the lowest *CGO* quintile and highest *EXTV* quintile. The control variables include *Size*, *logBM*, *Gross profitability*, *Asset growth*, *MOM (12, 2)*, *IVOL*, *Skew*, and *Kurt*. *Long-short* is the spread of *Motivated pessimism* and *Motivated optimism*. Column (1) reports the results excluding NASDAQ stocks, Column (2) presents the results excluding cross-sectional top 10% illiquid stocks. Columns (3) and (4) tabulate the WLS Fama-Macbeth regressions weighted by gross returns and market capitalization at the end of month *t*-1, respectively. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var =	Return			
	Exclude NASDAQ Stocks	Exclude Illiquid Stocks	WLS: Gross Return	WLS: value-weighted
Motivated pessimism	0.303***	0.357***	0.349***	0.158
	(3.83)	(4.83)	(4.90)	(1.46)
Motivated optimism	-0.439***	-0.408***	-0.360***	-0.474***
	(-5.24)	(-5.29)	(-4.42)	(-3.32)
Rank CGO	-0.044	0.191	0.301**	-0.306
	(-0.33)	(1.33)	(2.10)	(-1.58)
Rank EXTV	-1.058***	-1.191***	-1.144***	-1.149***
	(-7.42)	(-8.71)	(-8.79)	(-8.33)
Size	-0.031	-0.03	-0.031	-0.045
	(-0.95)	(-0.95)	(-0.96)	(-1.53)
logBM	0.537***	0.561***	0.597***	0.350***
	(8.18)	(7.42)	(7.97)	(4.37)
Gross Profitability	1.038***	1.108***	1.147***	1.089***
	(6.54)	(7.25)	(7.35)	(6.53)
Asset growth	0.461***	0.550***	0.604***	0.443***
	(4.82)	(6.01)	(6.49)	(3.23)
MOM (12, 2)	0.743***	0.718***	0.750***	0.961***
	(4.36)	(4.64)	(4.99)	(4.60)
IVOL	-0.239***	-0.225***	-0.227***	-0.202***
	(-4.71)	(-4.62)	(-5.41)	(-3.18)
Skew	-0.012	0.007	-0.008	0.097***
	(-0.63)	(0.37)	(-0.39)	(3.11)
Kurt	-0.023**	-0.022**	-0.018*	-0.021**
	(-2.33)	(-2.25)	(-1.91)	(-2.12)
Adj-Rsquare	0.071	0.070	0.065	0.147
Observations	929333	1400649	1544045	1544045
Long-Short	0.742***	0.765***	0.709***	0.632***
	(6.52)	(7.13)	(6.80)	(3.31)

Table 10.Decomposing Momentum in the Cross Section

This table presents the results of return predictability decomposition of momentum. Stocks with non-missing momentums, *EXTV*, *CGO*, and Rank-*XRP* are required in this test. Stage 1 runs the regression model: $r_{i,t} = \alpha_t + \beta_t MOM(t-h, t-l)_{\,i,t-1} + \varepsilon_{i,t}$. In stage 2, the candidate variable is added to the regression model: $r_{i,t} = \alpha_t + \widetilde{\beta_t^R} MOM(t-h, t-l)_{\,i,t-1} + \widetilde{\beta_t^C} Candidate_{i,t} + \varepsilon_{i,t}$. In stage 3, regressions of the momentum on candidate variable(s) are conducted: $MOM(t-h, t-l)_{i,t-1} = \mu_{t-1} + \delta_{t-1} Candidate_{i,t-1} + \phi_{i,t-1}$. It decomposes momentum into two components: $\delta_{t-1} Candidate_{i,t-1}$ and $\mu_{t-1} + \phi_{i,t-1}$. In stage 4, the coefficient of momentum beta β_t is decomposed as $\beta_t = \frac{Cov[r_{it}, MOM(t-h,t-l)_{i,t-1}]}{Var[MOM(t-h,t-l)_{i,t-1}]} = \frac{Cov[r_{it}, \delta_{t-1}\, candidate\ _{it-1}]}{Var[MOM(t-h,t-l)_{i,t-1}]} + \frac{Cov([r_{it}(\mu_{t-1} + \varphi_{it-1})]}{Var[MOM(t-h,t-l)_{i,t-1}]} = \beta_t^C + \beta_t^R$, where β_t^C is the *Candidate Beta* and β_t^R is the *Residual Beta*. The fraction that can be explained is defined as the time-series average of β_t^C divided by time-series average of β_t, namely *Fraction of Candidate.* The unexplained component is referred to as *Fraction of Residual*. Standard errors of the fraction are based on multivariate delta method. We use DGTW-adjusted returns (adjusted by *Size* and *Book-to-Market* ratio) to adjust characteristics. Panel A presents the results on *MOM* (6, 2) and Panel B presents the results on *MOM* (12, 2). Time-series averages of estimated coefficients ($\times$ 100) are reported with *t*-statistics in parentheses. The candidates include Rank-*XRP*, *CGO*, *EXTV*, and both *CGO* and *EXTV*. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Decomposition of MOM (6, 2)

Stage	Description	Var	Rank-XRP	T	CGO	T	EXTV	T
1	DTGW on *MOM*	*MOM (6, 2)*	0.775***	(3.69)	0.775***	(3.69)	0.775***	(3.69)
		Adj-Rsquare	0.011		0.011		0.011	
2	Add Candidate	*MOM (6, 2)*	0.104	(0.48)	0.349	(1.64)	0.773***	(3.67)
		Candidate	1.022***	(10.98)	1.070***	(7.02)	-43.235***	(-9.29)
		Adj-Rsquare	0.017		0.018		0.017	
3	*MOM* on Candidate	*Candidate*	0.210***	(32.60)	0.500***	(22.34)	0.263**	(2.52)
		Adj-Rsquare	0.135		0.24		0.011	
4	Decompose	*Candidate Beta*	0.668		0.515		0.005	
	MOM coef.	*Fraction of Candidate*	0.863	(4.59)	0.665	(6.05)	0.007	(0.22)
	In Stage 1	*Residual Beta*	0.106		0.26		0.769	
		Fraction of Residual	0.137	(0.73)	0.335	(3.05)	0.993	(33.09)
		Start	196502		196502		196502	
		End	202112		202112		202112	
		Observations	1564026		1564026		1564026	

Panel B: Decomposition of MOM (12, 2)

Stage	Description	Var	Rank-XRP	T	CGO	T	EXTV	T
1	DTGW on *MOM*	*MOM (12, 2)*	0.669***	(4.30)	0.669***	(4.30)	0.669***	(4.30)
		Adj-Rsquare	0.014		0.014		0.014	
2	Add Candidate	*MOM (12, 2)*	0.243	(1.49)	0.491***	(2.91)	0.672***	(4.28)
		Candidate	0.946***	(10.42)	0.837***	(5.22)	-44.136***	(-9.33)
		Adj-Rsquare	0.019		0.021		0.019	
3	*MOM* on Candidate	*Candidate*	0.386***	(29.53)	0.917***	(26.05)	0.682***	(3.48)
		Adj-Rsquare	0.16		0.292		0.013	
4	Decompose	*Candidate Beta*	0.462		0.363		0.002	
	MOM coef.	*Fraction of Candidate*	0.691	(6.15)	0.542	(6.83)	0.002	(0.11)
	In Stage 1	*Residual Beta*	0.207		0.306		0.667	
		Fraction of Residual	0.309	(2.76)	0.458	(5.76)	0.998	(45.68)
		Start	196502		196502		196502	
		End	202112		202112		202112	
		Observations	1564026		1564026		1564026	

Panel C: Decomposition of Momentum Strategies by EXTV + CGO						
			MOM (6, 2)		MOM (12, 2)	
Stage	Description	Var	Est.	T	Est.	T
1	DTGW on *MOM*	*MOM*	0.775***	(3.69)	0.669***	(4.30)
		Adj-Rsquare	0.011		0.014	
2	Add Candidate	*MOM*	0.367*	(1.74)	0.510***	(2.99)
		EXTV	-44.622***	(-9.44)	-45.295***	(-9.48)
		CGO	1.045***	(6.79)	0.811***	(4.97)
		Adj-Rsquare	0.023		0.026	
3	*MOM* on Candidate	*EXTV*	0.258***	(3.17)	0.665***	(4.13)
		CGO	0.497***	(22.37)	0.913***	(26.21)
		Adj-Rsquare	0.246		0.3	
4	Decompose *MOM* coef. In Stage 1	*Candidate Beta*	0.498		0.351	
		Fraction of Candidate	0.643	(6.30)	0.525	(7.07)
		Residual Beta	0.277		0.318	
		Fraction of Residual	0.357	(3.50)	0.475	(6.41)
		Start	196502		196502	
		End	202112		202112	
		Observations	1564026		1564026	

Table 11.Factor Spanning Test on Various Momentum Strategies

This table presents factor spanning tests on various momentum-related strategies. The dependent variables include 41 testing portfolios in momentum category from *q-data library*, and two factors: *UMD* from Kenneth French's website and industry-adjusted *UMD** from Novy-Marx's website. We utilize the CAPM as the baseline model, and compare it with a candidate model that includes both the market factor and the *XRP* factor. The *XRP* factor represents the long-short spread between stocks classified in the highest *CGO* quintile but lowest *EXTV* quintile, and stocks in the lowest *CGO* quintile but highest *EXTV* quintile. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. The unexplained strategies are highlighted in red. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Model		abr_1	abr_6	abr_12	cim_1	cim_6	cim_12	cm_1	cm_12	def_1	def_6	def_12
CAPM	*Alpha*	**0.773*** **	**0.361*** **	**0.234*** **	**0.903*** **	**0.395*** **	**0.349*** **	**0.805*** **	**0.138** **	**1.024*** **	**0.587*** **	**0.331*** **
		(6.07)	(4.17)	(3.05)	(4.04)	(3.43)	(3.93)	(4.24)	(2.57)	(5.26)	(3.54)	(2.60)
	β_{mkt}	-0.078**	-0.013	0.024	-0.1	-0.101**	-0.058*	-0.07	0.007	-0.1	-0.027	-0.045
		(-2.25)	(-0.45)	(0.79)	(-1.43)	(-2.39)	(-1.73)	(-0.81)	(0.21)	(-1.50)	(-0.48)	(-0.84)
CAPM +XRP	*Alpha*	**0.588*** **	**0.200** **	0.092	**0.878*** **	0.175	**0.181** **	**0.779*** **	0.057	**0.679*** **	0.224	0.049
		(4.28)	(2.22)	(1.21)	(3.74)	(1.55)	(2.01)	(3.42)	(1.00)	(3.25)	(1.29)	(0.39)
	β_{mkt}	-0.054	0.008	0.042	-0.097	-0.072*	-0.036	-0.067	0.017	-0.061	0.013	-0.013
		(-1.60)	(0.30)	(1.50)	(-1.35)	(-1.84)	(-1.12)	(-0.76)	(0.56)	(-1.06)	(0.29)	(-0.29)
	β_{XRP}	0.110***	0.095***	0.084***	0.014	0.122***	0.093***	0.016	0.049***	0.206***	0.217***	0.169***
		(3.64)	(5.17)	(6.59)	(0.28)	(5.79)	(5.17)	(0.31)	(3.56)	(4.50)	(5.76)	(5.51)

Model		ile_1	ilr_1	ilr_6	ilr_12	im_1	im_6	im_12	nei_1	p52w_6	p52w_12	r6_1
CAPM	*Alpha*	**0.565*** **	**0.765*** **	**0.441*** **	**0.399*** **	**0.878*** **	**0.717*** **	**0.655*** **	**0.324*** **	**0.975*** **	**0.777*** **	**0.846*** **
		(3.69)	(4.09)	(4.70)	(5.38)	(4.10)	(4.04)	(3.96)	(3.21)	(4.37)	(3.98)	(3.49)
	β_{mkt}	-0.079	-0.194***	-0.125***	-0.070**	-0.252***	-0.132	-0.066	-0.052	-0.764***	-0.649***	-0.323***
		(-1.47)	(-3.13)	(-2.92)	(-2.03)	(-2.60)	(-1.64)	(-0.87)	(-1.21)	(-7.54)	(-7.88)	(-3.11)
CAPM +XRP	*Alpha*	**0.311** **	**0.631*** **	0.143	**0.148* **	0.197	0.095	0.162	0.092	0.223	0.169	-0.112
		(2.20)	(3.64)	(1.31)	(1.81)	(0.79)	(0.49)	(1.11)	(0.94)	(0.96)	(0.86)	(-0.42)
	β_{mkt}	-0.046	-0.177***	-0.087**	-0.038	-0.163*	-0.051	-0.001	-0.019	-0.666***	-0.569***	-0.198**
		(-0.98)	(-3.05)	(-2.35)	(-1.28)	(-1.89)	(-0.73)	(-0.02)	(-0.47)	(-7.47)	(-8.12)	(-2.42)
	β_{XRP}	0.141***	0.074	0.165***	0.139***	0.377***	0.345***	0.273***	0.131***	0.417***	0.337***	0.531***
		(4.03)	(1.42)	(9.03)	(8.27)	(7.90)	(7.54)	(6.59)	(5.32)	(9.99)	(7.27)	(9.81)

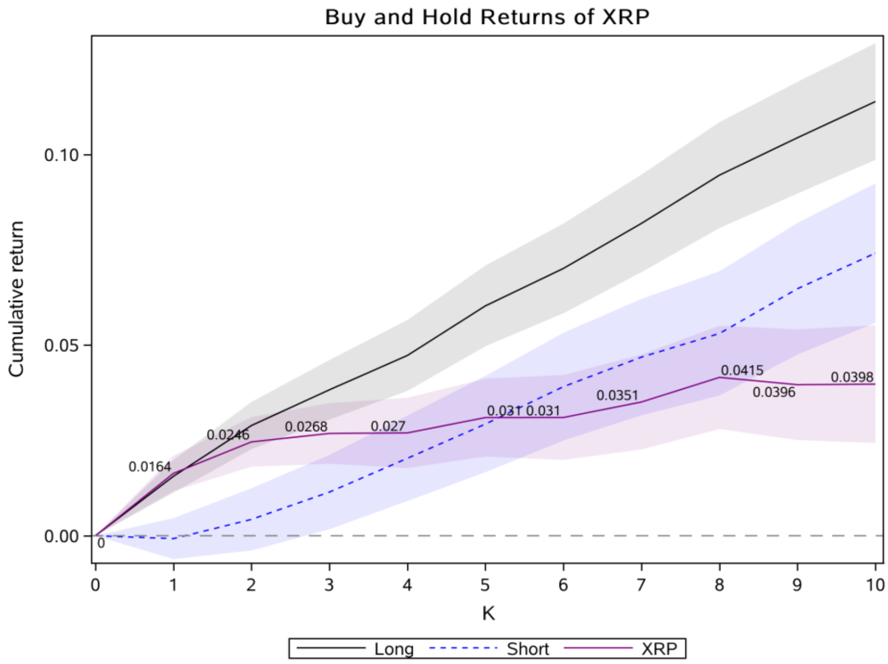
Model		r6_6	r6_12	r11_1	r11_6	r11_12	re_1	re_6	resid6_6	resid6_12	resid11_1	resid11_6
CAPM	*Alpha*	**0.886*** **	**0.547*** **	**1.250*** **	**0.839*** **	**0.455** **	**1.007*** **	**0.605*** **	**0.402*** **	**0.326*** **	**0.557*** **	**0.451*** **
		(4.30)	(3.13)	(5.09)	(3.63)	(2.04)	(4.99)	(3.42)	(3.61)	(3.89)	(3.68)	(3.76)
	β_{mkt}	-0.205**	-0.107	-0.328***	-0.213*	-0.129	-0.322***	-0.260***	-0.052	-0.044	-0.02	-0.033
		(-2.14)	(-1.27)	(-2.58)	(-1.85)	(-1.27)	(-4.04)	(-3.62)	(-1.18)	(-1.13)	(-0.31)	(-0.62)
CAPM +XRP	*Alpha*	0.178	-0.017	0.303	0.063	-0.167	**0.553** **	0.168	0.153	0.081	0.21	0.143
		(0.89)	(-0.10)	(1.23)	(0.27)	(-0.76)	(2.36)	(0.91)	(1.40)	(0.98)	(1.43)	(1.15)
	β_{mkt}	-0.112	-0.034	-0.204*	-0.112	-0.048	-0.273***	-0.213***	-0.02	-0.012	0.025	0.007
		(-1.35)	(-0.47)	(-1.87)	(-1.11)	(-0.55)	(-3.80)	(-3.32)	(-0.46)	(-0.33)	(0.44)	(0.14)
	β_{XRP}	0.392***	0.313***	0.525***	0.430***	0.345***	0.271***	0.261***	0.138***	0.136***	0.192***	0.171***
		(9.09)	(8.10)	(10.02)	(8.62)	(7.20)	(4.08)	(5.22)	(6.47)	(6.29)	(6.88)	(5.58)

Model		resid11_1	rs_1	sim_1	sim_12	sm_1	sm_12	sue_1	sue_6	UMD	UMD*	(#) Sig,
CAPM	*Alpha*	**0.289*** **	**0.433*** **	**0.822*** **	**0.151** **	**0.512** **	**0.167** **	**0.537*** **	**0.230** **	**0.716*** **	**0.665*** **	43
		(2.72)	(3.11)	(3.61)	(1.99)	(2.09)	(2.29)	(4.60)	(2.38)	(4.88)	(6.37)	
	β_{mkt}	-0.03	-0.065	-0.062	-0.001	-0.071	-0.011	-0.131***	-0.069	-0.152*	-0.109*	
		(-0.74)	(-1.17)	(-1.12)	(-0.02)	(-1.42)	(-0.40)	(-2.60)	(-1.52)	(-1.82)	(-1.76)	
CAPM +XRP	*Alpha*	0.01	0.23	**0.720*** **	-0.003	**0.518** **	0.038	**0.264** **	-0.034	0.128	0.152	13
		(0.08)	(1.44)	(3.16)	(-0.03)	(2.23)	(0.49)	(2.14)	(-0.35)	(0.85)	(1.29)	
	β_{mkt}	0.006	-0.038	-0.048	0.019	-0.071	0.003	-0.095*	-0.034	-0.078	-0.055	
		(0.16)	(-0.68)	(-0.84)	(0.61)	(-1.41)	(0.12)	(-1.91)	(-0.76)	(-1.08)	(-1.12)	
	β_{XRP}	0.155***	0.113***	0.056	0.085***	-0.004	0.076***	0.151***	0.146***	0.331***	0.235***	
		(5.09)	(3.48)	(1.01)	(3.87)	(-0.07)	(5.08)	(4.32)	(4.39)	(10.27)	(10.08)	

Figure 1. Buy-and Hold Cumulative Returns of XRP Strategy

This figure illustrates the buy-and-hold cumulative returns of the *XRP* Strategy, which longs the stocks within the highest quintile of *CGO* and the lowest quintile of *EXTV*, and shorts the stocks within the lowest quintile *CGO* and the highest quintile of *EXTV*. At the end of each month *t*-1, the value-weighted portfolios are constructed and held for the subsequent ten months. The figure exhibits the average cumulative returns over time for varying holding periods, accompanied by 95% confidence intervals. The backtesting period spans from February 1965 to December 2021. Panel A presents the performance in raw returns. Panel B displays the performance using DGTW returns (adjusted by size, book-to-market, and momentum).

Panel A: *The Buy-and-Hold Cumulative Returns in Raw Returns*



Panel B: *The Buy-and-Hold Cumulative Returns in DGTW Returns*

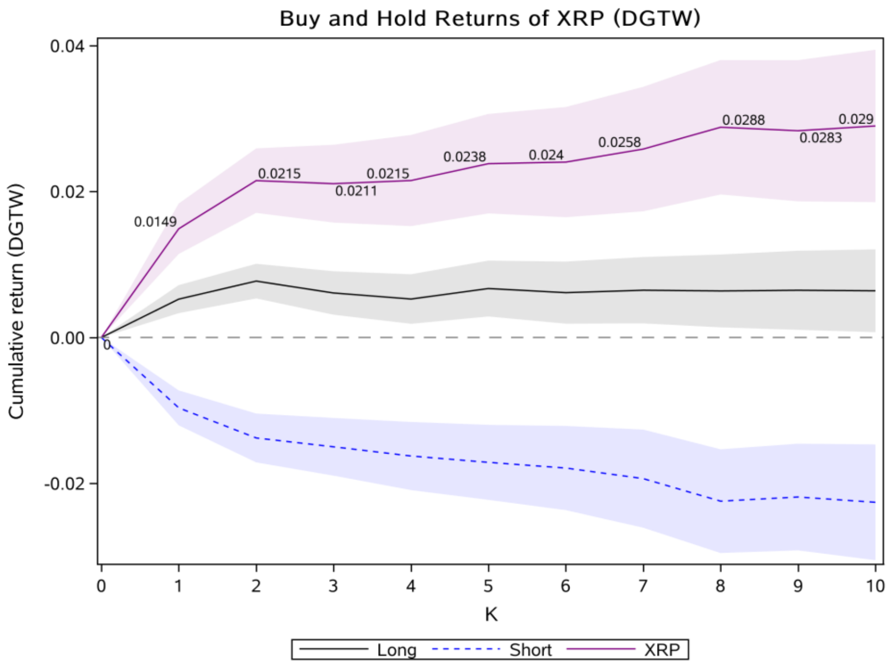
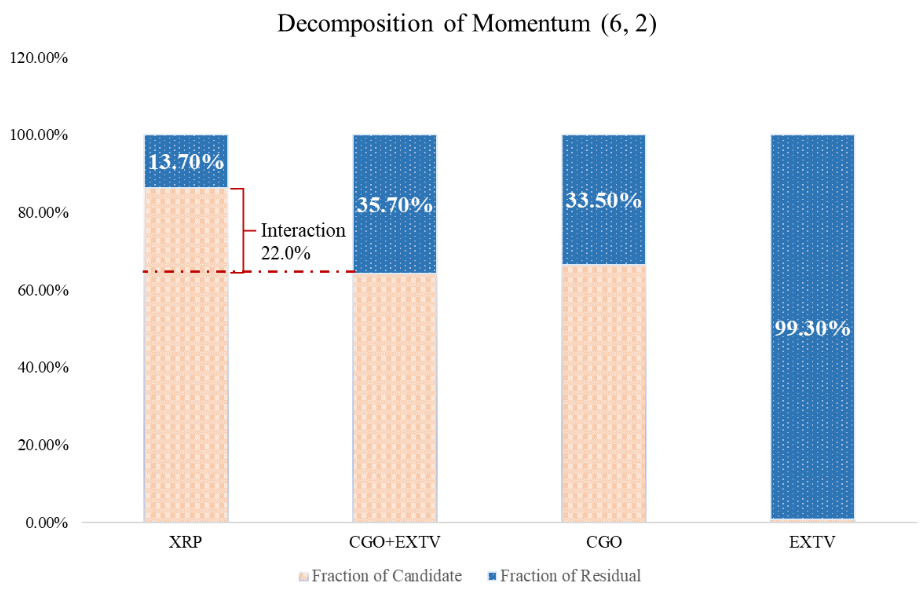


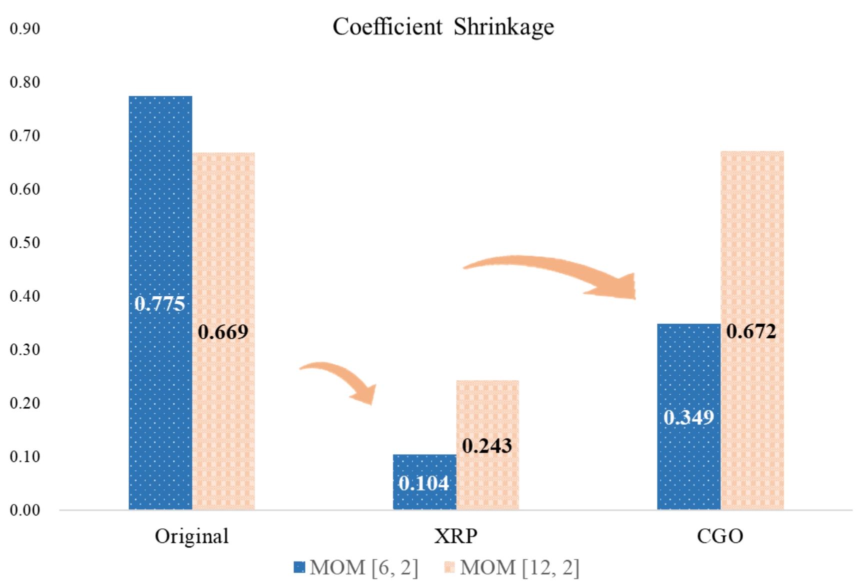
Figure 2. Decomposition of Momentum Strategies

This figure illustrates the results of decomposition of momentum strategies with *XRP*, *CGO*, *EXTV*, and *CGO & EXTV*. Panel A presents the figure of decomposition of *MOM* (6, 2) return predictability using the method proposed by Hou and Loh (2016). Panel B displays the figure depicting the coefficient shrinkage of momentum strategies, presenting the coefficients obtained from Fama-Macbeth regressions before and after accounting for the candidate variables.

Panel A: *The Decomposition of* MOM (6, 2)



Panel B: *Coefficient Shrinkage of Momentum Strategies*



Internet Appendix

Motivated Extrapolative Beliefs

This Internet Appendix provides supplementary materials to our primary analysis. This section employs data on retail investors to provide further evidence on motivated extrapolative beliefs. We first discuss the validation of CGO to proxy the unrealized profits in the cross section. We then discuss the motivated extrapolative beliefs using actual transaction data. Below we provide more information about these two tests.

A. Transaction Data from a Large Discount Broker

We use real transaction data from retail investors, as used by (Barber & Odean, 2000), (Barber & Odean, 2001), and (Barber & Odean, 2002). The dataset is obtained from a large discount broker (referred to as "LDB"), which includes stock transactions from 77,037 individual accounts from January 1990 through December 1996. We follow (Ben-David & Hirshleifer, 2012) and An (2016) to clean the data and construct a holding sample containing the observations of each investor-stock-day.

First, we retain only securities that are common shares. For each investor, a position in a stock is built up through their transaction history. Any investor-stocks wherein any position observations become negative or open before 1991 are eliminated. Additionally, we remove any investor-stocks where commission values are negative in any of the entries. We restrict our focus to stocks listed on NYSE, AMEX, and NASDAQ and align the stocks traded through the LDB with the CRSP database using their 8-digit CUSIP. We exclude the initial purchase day from the sample.

In instances of multiple acquisitions, purchase prices are determined based on the weighted average price. A gain is attributed when the end-of-day price obtained from the CRSP database for an investor-stock-day is strictly higher than the purchase price. Conversely, a loss indicator registers as one if the current price falls strictly below the weighted average purchase price and as zero otherwise. In this section, we continue to use CGO to represent the capital gain overhang, where CGO_{LDB} refers to the actual capital gain overhang in LDB and CGO_{GH} denotes the capital gain overhang constructed following (Grinblatt & Han, 2005). The EXTV is constructed by the same method.

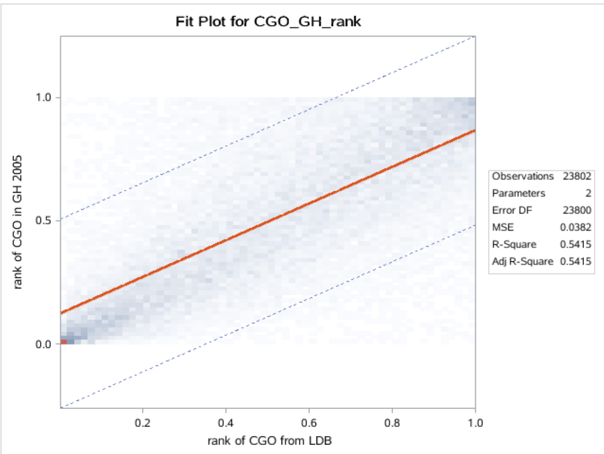
B. The Validation of CGO to Proxy the Unrealized Profits

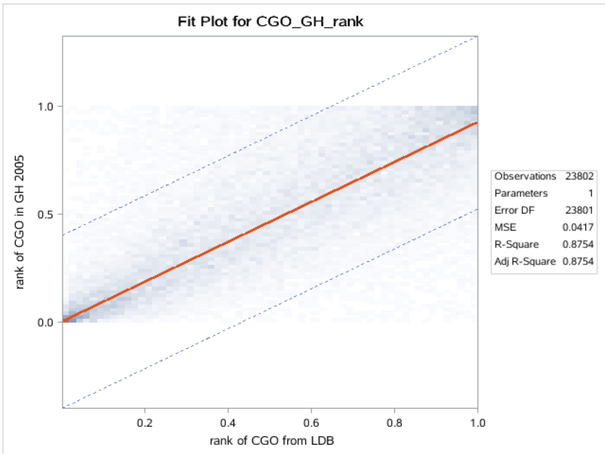
CGO, as proposed by (Grinblatt & Han, 2005), has been implicated as a proxy for average unrealized capital gains in prior studies, see (Wang et al., 2017), (An et al., 2020). This metric employs the turnover ratio to update the reference price and consistently yields compelling empirical conclusions. However, there remains a degree of uncertainty surrounding its validity as a proxy for the average capital gain overhang. In this section, we aim to validate the CGO variable by juxtaposing it with investors' actual capital gain overhang, as reflected in the data from the Large Discount Broker (LDB).

We aggregate capital gain overhang at the stock level according to the position-weighted average unrealized profits, requiring that at least 24 investors (the 90th percentile) were holding the stock. We compare the last observations of a month of CGO_{LDB} and CGO_{GH}. It is noteworthy to mention that the average capital gain overhang may exhibit unexpected volatility due to the limited number of investors. For comparison and alignment with our primary analyses, we utilize the cross-sectional rank of CGO_{LDB} and CGO_{GH}. We conduct a simple univariate regression:

$$Rank\ CGO_{GH} = (Intercept) + \beta \times Rank\ CGO_{LDB} + \epsilon,$$

where we implement two specifications, one incorporating an intercept and one without. The results are tabulated as follows:





$$RankCGO_{GH2005} = 0.121 + 0.744 \times RankCGO_{LDB} + \varepsilon$$
$$(t = 167.65)$$

$$RankCGO_{GH2005} = 0.925 \times RankCGO_{LDB} + \varepsilon$$
$$(t = 408.88)$$

It can be observed that both models showcase a significant and positive correlation between the two capital gain overhang variables. In the model excluding the intercept, the coefficient registers at 0.925, which is proximate to the value of one, suggesting a one-to-one relationship, combined with an R-square value of 87.5%. Even though the sample period and investor coverage in the Large Discount Broker (LDB) data represent only a subsample in relation to our primary testing sample, the comparison nonetheless offers supporting evidence that CGO_{GH} can effectively function as a proxy for real capital gain overhang. This bolsters our confidence in utilizing the rank of CGO_{GH} in our main analysis.

C. Motivated Extrapolative Beliefs and Real Transaction Records

Our main text uses the time-series survey expectations and order imbalance to scrutinize the mechanism behind motivated extrapolative beliefs. It is also demonstrated that CGO can serve as a proxy for unrealized capital gain. We delve further into the correlation between motivated extrapolative beliefs and actual transactions of retail investors. As demonstrated in Table A13, household investors potentially succumb to such belief distortion. Therefore, this section supplements the findings presented in Table A13. Because the recent price path relates to investors' attention. For example, stocks with extreme extrapolative beliefs can absorb investors' attention, thereby triggering transactions. To attenuate the effects of attention, we scrutinize active transactions specifically. Instead of considering a holding period to originate from initial purchases based on chronological intervals, we singularly identify each transaction as a 'fresh' commencement of a holding period and concentrate solely on holding periods within a 20-day timeframe. This approach allows us to focus on active trading transactions and circumvent computational capacity limitations. It is also worth noting that we observe the well-documented investor behavior, such as the ("V-shape") disposition effect, primarily in this subsample. The main independent variables of interest, *Motivated pessimism* and *Motivated optimism*, are constructed by the same method as those in the main text. The dependent variables are dummy variables that indicate a selling or buying decision.

The results are presented in Table A14. As represented in column (1), the coefficient of *motivated pessimism* is negative and statistically significant at the 1% level, thereby suggesting a correlation between motivated pessimistic extrapolative beliefs and an increased propensity to sell stocks. In column (3), an association is observed between *Motivated pessimism* and a diminished inclination to purchase additional stocks, while *Motivated optimism* elevates the likelihood of stock acquisitions. Conversely, *Motivated optimism* increases the propensity of buying additional stocks. These findings are coherent with the results concerning order imbalance and survey expectations. Moreover, (Ben-David & Hirshleifer, 2012) and An (2016) document that "V-shape" selling and buying schedules better fit the truncation data. We subsequently dichotomize the rank of capital gain overhang into two components based on whether the value of CGO_{LDB} is positive or negative in columns (2) and (4). Consistent with the "V-shape" selling and buying pattern, the coefficients on *Rank* CGO_{LDB} $\times I(CGO_{LDB} > 0)$ are positive while the coefficients of *Rank* CGO_{LDB} $\times I(CGO_{LDB} < 0)$ yield negative values. Notably, even when the 'V-shape' trading pattern is controlled for, the results pertaining to motivated extrapolative beliefs retain their robustness.

These findings lend additional substantiation to the mechanism underlying motivated extrapolative beliefs and bolster the utilization of CGO_{GH} as a proxy for capital gain overhang at the individual stock level.

Table A1. Single Sorts on CGO and EXTV

This table presents the performance of single-sorted portfolios based on *CGO* and *EXTV*. At the end of each month *t*-1, stocks are sorted into ten groups based on their *CGO* and *EXTV* values, respectively. The returns are calculated using a value-weighted methodology. The characteristics, i.e., *Size*, *CGO*, and *EXTV*, are equal-weighed within each portfolio at the end of each month, and then averaged across the time series. The value of *EXTV* is scaled by a factor of 100 for ease of interpretation. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Single Sorting on EXTV											
EXTV	Low	2	3	4	5	6	7	8	9	High	High-Low
Excess Ret	1.312	1.248	1.188	1.082	1.046	0.915	0.795	0.759	0.712	0.493	-0.818***
	(6.23)	(6.38)	(6.49)	(6.61)	(6.30)	(5.24)	(4.32)	(4.06)	(3.67)	(2.24)	(-5.14)
CAPM	0.222	0.254	0.246	0.164	0.163	0.028	-0.086	-0.13	-0.2	-0.479	-0.701***
	(1.79)	(3.44)	(4.52)	(2.66)	(2.72)	(0.49)	(-1.67)	(-2.26)	(-3.09)	(-4.42)	(-4.04)
FF 3	0.174	0.226	0.223	0.134	0.145	0.018	-0.09	-0.128	-0.199	-0.474	-0.648***
	(1.43)	(3.08)	(3.97)	(2.43)	(2.28)	(0.29)	(-1.79)	(-2.22)	(-2.96)	(-4.24)	(-3.55)
FF 5	0.314	0.288	0.207	0.087	0.107	-0.045	-0.125	-0.177	-0.228	-0.457	-0.771***
	(2.17)	(3.65)	(3.68)	(1.68)	(1.79)	(-0.80)	(-2.19)	(-2.89)	(-3.11)	(-3.70)	(-3.81)
Size	14.27	14.85	15.04	15.13	15.14	15.16	15.10	15.04	14.85	14.29	
EXTV	-1.425	-0.647	-0.377	-0.191	-0.036	0.115	0.280	0.485	0.801	1.873	
CGO	-0.08	-0.03	-0.01	0.00	0.01	0.01	0.01	0.00	-0.01	-0.08	
Panel B: Single Sorting on CGO											
CGO	Low	2	3	4	5	6	7	8	9	High	High-Low
Excess Ret	0.545	0.761	0.914	0.873	0.968	0.913	0.851	1.055	1.033	1.252	0.707***
	(1.80)	(3.10)	(4.31)	(4.99)	(5.56)	(5.27)	(4.76)	(6.03)	(5.63)	(6.15)	(2.99)
CAPM	-0.653	-0.276	-0.091	-0.078	0.054	0.012	-0.052	0.162	0.137	0.33	0.983***
	(-3.62)	(-2.06)	(-0.97)	(-1.00)	(0.77)	(0.21)	(-0.80)	(2.52)	(1.92)	(3.66)	(4.36)
FF 3	-0.813	-0.435	-0.215	-0.164	-0.018	-0.051	-0.082	0.156	0.19	0.404	1.217***
	(-5.22)	(-3.71)	(-2.53)	(-2.41)	(-0.25)	(-0.94)	(-1.22)	(2.58)	(2.99)	(5.10)	(6.27)
FF 5	-0.576	-0.332	-0.164	-0.157	-0.065	-0.107	-0.19	0.013	0.094	0.324	0.900***
	(-2.67)	(-2.10)	(-1.38)	(-1.69)	(-0.95)	(-1.65)	(-2.79)	(0.20)	(1.27)	(3.13)	(3.11)
Size	13.48	14.43	14.76	14.96	15.09	15.18	15.29	15.31	15.23	14.96	
EXTV	0.143	0.077	0.073	0.067	0.073	0.073	0.074	0.084	0.089	0.111	
CGO	-0.611	-0.251	-0.134	-0.057	0.003	0.055	0.104	0.156	0.219	0.336	

Table A2. Dependent Double Sorts on CGO and EXTV

This table presents the performance of portfolios double-sorted by *CGO* (capital gain overhang) and *EXTV* (the value of extrapolative beliefs). At the end of each month *t*-1, stocks are firstly sorted into five groups according to their *CGO* levels, and then sorted into five portfolios based on their *EXTV* within each group. Each portfolio is held for one month. We tabulate the excess returns (Excess ret), alphas adjusted by CAPM, Fama-French three-factor model (FF 3), and Fama-French five-factor model (FF 5). At the bottom of each block, we report the performance of *XRP* strategy, which longs stocks within the highest *CGO* quintile and the lowest *EXTV* quintile, and shorts stocks within the lowest *CGO* quintile and the highest *EXTV* quintile. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Dependent Sorting on CGO and EXTV (equal-weighted)

		(1) Low	(3) Mid	(5) High	(6) Low-(3)	(7) (3)-High	(7) - (6)	XRP
		EXTV						
Excess ret	Low	1.318	0.967	-0.116	0.351	1.083	0.732	
		(4.56)	(3.98)	(-0.40)	(2.94)	(7.38)	(4.32)	
	2	1.417	1.123	0.497	0.294	0.626	0.332	
		(5.62)	(5.85)	(2.02)	(2.87)	(5.48)	(1.96)	
	CGO	1.443	1.165	0.748	0.278	0.417	0.138	
		(6.41)	(6.53)	(3.52)	(2.80)	(4.44)	(0.90)	
	4	1.648	1.307	0.870	0.340	0.438	0.098	
		(7.06)	(6.90)	(3.92)	(3.62)	(4.66)	(0.67)	
	High	2.167	1.531	1.223	0.636	0.308	-0.328	
		(9.08)	(7.66)	(5.36)	(7.03)	(3.23)	(-2.24)	
	High-Low				0.285**	-0.774***	-1.059***	2.283***
					(2.14)	(-4.69)	(-5.24)	(11.65)
CAPM	Low	0.156	-0.052	-1.161	0.208	1.109	0.901	
		(0.74)	(-0.34)	(-5.70)	(1.64)	(7.57)	(5.38)	
	2	0.320	0.181	-0.494	0.138	0.675	0.536	
		(1.83)	(1.36)	(-3.30)	(1.41)	(6.11)	(3.60)	
	CGO	0.395	0.271	-0.211	0.125	0.481	0.357	
		(2.66)	(2.28)	(-1.78)	(1.25)	(5.46)	(2.57)	
	4	0.620	0.430	-0.088	0.189	0.519	0.329	
		(4.03)	(3.72)	(-0.68)	(1.93)	(5.85)	(2.38)	
	High	1.165	0.645	0.289	0.520	0.356	-0.164	
		(7.35)	(5.65)	(2.21)	(5.68)	(3.88)	(-1.18)	
	High-Low				0.312**	-0.753***	-1.066***	2.326***
					(2.35)	(-4.52)	(-5.42)	(12.51)

		(1) Low	(3) Mid	(5) High	(6) Low-(3)	(7) (3)-High	(7) - (6)	XRP
		EXTV						
FF 3	Low	-0.084	-0.299	-1.354	0.215	1.055	0.840	
		(-0.62)	(-3.70)	(-9.45)	(1.65)	(7.80)	(5.61)	
	2	0.110	-0.034	-0.666	0.144	0.632	0.488	
		(1.09)	(-0.50)	(-7.16)	(1.57)	(6.19)	(3.85)	
	CGO	0.217	0.090	-0.353	0.127	0.444	0.317	
		(2.45)	(1.42)	(-4.80)	(1.31)	(5.32)	(2.51)	
	4	0.485	0.290	-0.198	0.194	0.489	0.294	
		(4.97)	(4.00)	(-2.42)	(1.96)	(5.17)	(2.06)	
	High	1.092	0.558	0.230	0.534	0.329	-0.205	
		(10.40)	(7.66)	(2.18)	(6.12)	(3.21)	(-1.40)	
	High-Low				0.319**	-0.726***	-1.046***	2.446***
					(2.34)	(-4.32)	(-5.12)	(12.19)
FF 5	Low	0.111	-0.227	-1.265	0.337	1.039	0.701	
		(0.60)	(-1.95)	(-7.89)	(2.45)	(7.52)	(4.34)	
	2	0.157	-0.071	-0.671	0.228	0.600	0.372	
		(1.32)	(-0.95)	(-6.34)	(2.37)	(5.82)	(2.98)	
	CGO	0.250	-0.007	-0.391	0.256	0.384	0.128	
		(2.76)	(-0.10)	(-5.05)	(2.62)	(4.64)	(1.00)	
	4	0.465	0.167	-0.254	0.298	0.422	0.123	
		(5.66)	(2.39)	(-2.83)	(3.00)	(4.37)	(0.85)	
	High	1.111	0.469	0.199	0.642	0.270	-0.373	
		(9.22)	(6.05)	(1.48)	(6.16)	(2.50)	(-2.22)	
	High-Low				0.305**	-0.769***	-1.074***	2.380***
					(2.06)	(-4.36)	(-4.65)	(10.04)

Panel B: Dependent Sorting on CGO and EXTV (value-weighted)

		(1) Low	(3) Mid	(5) High	(6) Low-(3)	(7) (3)-High	(7) - (6)	XRP		(1) Low	(3) Mid	(5) High	(6) Low-(3)	(7) (3)-High	(7) - (6)	XRP
		EXTV								*EXTV*						
Excess ret	Low	1.231	0.975	-0.183	0.255	1.158	0.903		FF 3	-0.119	-0.185	-1.405	0.066	1.220	1.153	
		(4.15)	(4.16)	(-0.56)	(1.51)	(5.21)	(2.92)			(-0.70)	(-1.36)	(-6.77)	(0.40)	(5.80)	(4.16)	
	2	1.341	0.968	0.607	0.373	0.360	-0.013			0.147	-0.09	-0.449	0.237	0.359	0.122	
		(5.86)	(5.15)	(2.72)	(2.64)	(2.12)	(-0.05)			(1.12)	(-0.89)	(-3.35)	(1.77)	(2.00)	(0.48)	
	CGO	1.265	1.013	0.679	0.252	0.334	0.082			0.179	0.03	-0.287	0.149	0.316	0.167	
		(6.23)	(6.21)	(3.52)	(2.24)	(2.80)	(0.45)			(1.91)	(0.38)	(-2.83)	(1.32)	(2.70)	(0.97)	
	4	1.433	1.075	0.647	0.358	0.428	0.070			0.403	0.178	-0.259	0.225	0.437	0.212	
		(7.18)	(6.12)	(3.20)	(2.96)	(4.24)	(0.38)			(4.18)	(2.10)	(-2.85)	(1.91)	(4.25)	(1.19)	
	High	1.602	1.122	0.786	0.480	0.336	-0.143			0.692	0.296	-0.069	0.396	0.365	-0.030	
		(7.49)	(5.87)	(3.75)	(4.30)	(2.70)	(-0.72)			(5.99)	(3.87)	(-0.65)	(3.46)	(2.88)	(-0.15)	
	High-Low				0.224	-0.822***	-1.046***	1.792***					0.329*	-0.854***	-1.184***	1.941***
					(1.32)	(-3.40)	(-3.10)	(6.22)					(1.93)	(-3.52)	(-3.66)	(7.38)
CAPM	Low	0.048	-0.035	-1.282	0.083	1.247	1.164		FF 5	0.094	-0.093	-1.341	0.187	1.248	1.060	
		(0.24)	(-0.24)	(-5.98)	(0.50)	(5.72)	(4.03)			(0.41)	(-0.55)	(-5.76)	(1.04)	(5.51)	(3.64)	
	2	0.27	0.029	-0.37	0.240	0.399	0.159			0.262	-0.064	-0.45	0.326	0.387	0.061	
		(1.83)	(0.28)	(-2.81)	(1.69)	(2.31)	(0.63)			(1.59)	(-0.51)	(-3.19)	(2.40)	(2.20)	(0.25)	
	CGO	0.258	0.13	-0.241	0.128	0.371	0.243			0.227	-0.065	-0.343	0.292	0.278	-0.014	
		(2.59)	(1.68)	(-2.56)	(1.16)	(3.00)	(1.37)			(1.84)	(-0.84)	(-2.90)	(2.12)	(2.27)	(-0.07)	
	4	0.458	0.2	-0.26	0.257	0.460	0.203			0.326	0.067	-0.377	0.259	0.444	0.185	
		(4.43)	(2.42)	(-2.87)	(2.13)	(4.60)	(1.15)			(3.58)	(0.82)	(-3.62)	(2.16)	(4.28)	(1.03)	
	High	0.641	0.233	-0.133	0.408	0.366	-0.042			0.667	0.213	-0.119	0.454	0.332	-0.121	
		(5.48)	(2.61)	(-1.24)	(3.69)	(2.88)	(-0.22)			(6.58)	(2.35)	(-0.84)	(3.97)	(2.53)	(-0.64)	
	High-Low				0.325*	-0.881***	-1.206***	1.923***					0.266	-0.915***	-1.182***	2.017***
					(1.95)	(-3.67)	(-3.74)	(6.89)					(1.55)	(-3.62)	(-3.63)	(7.05)

Table A3. Factor Spanning Tests on XRP Using Alternative Factor Models

This table presents the results of factor spanning tests on the *XRP* strategy. The factor models include Novy-Marx four factor model (Novy-Marx, 4), Hou, Xue, and Zhang Q5 factor model (HXZ, Q5), Stambaugh, Yuan four factor model (SY, M4), and Daniel, Hirshleifer, and Sun three factor model (DHS). *T*-statistics based on standard errors adjusted by Newey-West HAC are shown in the parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

XRP	DHS	SY, M4	Novy-Marx, 4	HXZ, Q5
VW	1.159***	1.660***	1.671***	1.281***
	(3.38)	(6.62)	(5.42)	(4.11)
EW	1.796***	2.096***	2.121***	1.893***
	(8.55)	(11.94)	(8.88)	(8.99)
Start	1965.2	1965.2	1965.2	1965.2
End	2012.12	2021.12	2016.12	2018.12

Table A4. Double Sorts on CGO and EXTV, Excluding January

This table presents the performance of portfolios double-sorted by *CGO* and *EXTV*. At the end of each month *t*-1, stocks are independently sorted into five groups by *CGO* and *EXTV*, respectively. Then we construct 25 portfolios interacted by the *CGO*- and *EXTV*-sorted groups. Each portfolio is to be held for one month. Panel A reports the equal-weighted performance of each group. Panel B presents the value-weighted performance of each group. We tabulate the excess returns, alphas adjusted by CAPM, Fama-French three model (FF 3), and Fama-French five-factor model (FF 5). At the bottom of each block, we report the performance of the *XRP* strategy, which longs the stocks within the highest *CGO* quintile and the lowest *EXTV* quintile, and shorts the stocks within the lowest *CGO* quintile and the highest *EXTV* quintile. *T*-statistics based on standard errors adjusted by Newey-West HAC with 13 lags are shown in the parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Independent Sorting on CGO and EXTV (equal-weighted)

		(1) Low	(3) Mid	(5) High	(6) Low-(3)	(7) (3)-High	(7) - (6)	XRP
		EXTV						
Excess ret	Low	0.844	0.611	-0.346	0.232	0.957	0.725	
		(2.90)	(2.35)	(-1.23)	(2.06)	(6.77)	(4.44)	
	2	1.098	0.918	0.324	0.179	0.595	0.415	
		(4.26)	(4.50)	(1.31)	(1.72)	(5.21)	(2.37)	
	CGO	1.205	1.080	0.687	0.125	0.393	0.268	
		(4.99)	(5.61)	(3.06)	(1.17)	(3.91)	(1.64)	
	4	1.498	1.217	0.900	0.281	0.317	0.036	
		(6.12)	(6.14)	(3.84)	(2.65)	(2.96)	(0.23)	
	High	2.186	1.550	1.350	0.636	0.200	-0.436	
		(8.75)	(7.37)	(5.70)	(6.31)	(2.04)	(-2.64)	
	High-Low				0.403***	-0.757***	-1.160***	2.532***
					(3.21)	(-4.67)	(-5.69)	(12.03)
CAPM	Low	-0.266	-0.360	-1.343	0.094	0.983	0.889	
		(-1.57)	(-2.55)	(-7.49)	(0.75)	(6.75)	(5.10)	
	2	0.041	0.024	-0.628	0.017	0.651	0.634	
		(0.27)	(0.20)	(-4.70)	(0.16)	(5.94)	(3.93)	
	CGO	0.184	0.222	-0.247	-0.038	0.469	0.507	
		(1.36)	(2.03)	(-2.23)	(-0.33)	(5.07)	(3.35)	
	4	0.498	0.369	-0.040	0.129	0.409	0.280	
		(3.61)	(3.29)	(-0.32)	(1.15)	(4.03)	(1.80)	
	High	1.206	0.677	0.428	0.529	0.249	-0.281	
		(8.16)	(6.07)	(3.31)	(5.19)	(2.60)	(-1.75)	
	High-Low				0.435***	-0.734***	-1.170***	2.550***
					(3.47)	(-4.43)	(-5.81)	(12.62)

		(1) Low	(3) Mid	(5) High	(6) Low-(3)	(7) (3)-High	(7) - (6)	XRP
		EXTV						
FF 3	Low	-0.340	-0.469	-1.397	-0.011	1.008	1.019	
		(-2.56)	(-5.09)	(-10.92)	(-0.06)	(5.29)	(3.60)	
	2	-0.024	-0.088	-0.688	0.165	0.374	0.209	
		(-0.22)	(-1.27)	(-8.04)	(1.12)	(2.25)	(0.89)	
	CGO	0.124	0.124	-0.300	-0.022	0.258	0.280	
		(1.23)	(1.95)	(-4.25)	(-0.16)	(1.86)	(1.35)	
	4	0.46	0.299	-0.070	0.221	0.358	0.137	
		(4.60)	(4.10)	(-0.80)	(1.59)	(3.50)	(0.72)	
	High	1.219	0.645	0.446	0.317	0.222	-0.096	
		(11.59)	(8.33)	(4.40)	(2.45)	(1.30)	(-0.38)	
	High-Low				0.328*	-0.786***	-1.114***	1.941***
					(1.71)	(-3.16)	(-3.19)	(7.38)
FF 5	Low	-0.209	-0.454	-1.335	0.084	1.056	0.972	
		(-1.22)	(-3.50)	(-8.66)	(0.46)	(4.83)	(3.32)	
	2	0.011	-0.181	-0.717	0.343	0.362	0.019	
		(0.09)	(-2.23)	(-6.95)	(2.49)	(2.24)	(0.09)	
	CGO	0.178	-0.003	-0.336	0.199	0.176	-0.023	
		(1.60)	(-0.04)	(-4.48)	(1.43)	(1.17)	(-0.11)	
	4	0.444	0.168	-0.102	0.296	0.316	0.020	
		(4.78)	(2.45)	(-1.03)	(2.05)	(3.17)	(0.10)	
	High	1.261	0.555	0.450	0.371	0.132	-0.239	
		(9.31)	(7.03)	(3.32)	(2.84)	(0.72)	(-0.96)	
	High-Low				0.287	-0.924***	-1.211***	2.017***
					(1.53)	(-3.38)	(-3.40)	(7.05)

Panel B: Independent Sorting on CGO and EXTV (value-weighted)																
		(1) Low	(3) Mid	(5) High	(6) Low-(3)	(7) (3)-High	(7) - (6)	XRP		(1) Low	(3) Mid	(5) High	(6) Low-(3)	(7) (3)-High	(7) - (6)	XRP
		EXTV								*EXTV*						
Excess ret	Low	0.844	0.611	-0.346	0.144	0.967	0.823		FF 3	-0.340	-0.469	-1.397	0.129	0.928	0.799	
		(2.90)	(2.35)	(-1.23)	(0.82)	(4.84)	(2.76)			(-2.56)	(-5.09)	(-10.92)	(1.03)	(6.80)	(5.17)	
	2	1.098	0.918	0.324	0.281	0.368	0.087			-0.024	-0.088	-0.688	0.064	0.600	0.536	
		(4.26)	(4.50)	(1.31)	(1.88)	(2.33)	(0.35)			(-0.22)	(-1.27)	(-8.04)	(0.65)	(5.78)	(4.02)	
	CGO	1.205	1.080	0.687	0.047	0.270	0.223			0.124	0.124	-0.300	0.000	0.424	0.424	
		(4.99)	(5.61)	(3.06)	(0.33)	(1.86)	(0.94)			(1.23)	(1.95)	(-4.25)	(0.00)	(4.89)	(3.28)	
	4	1.498	1.217	0.900	0.331	0.328	-0.003			0.46	0.299	-0.070	0.161	0.369	0.208	
		(6.12)	(6.14)	(3.84)	(2.35)	(3.24)	(-0.02)			(4.60)	(4.10)	(-0.80)	(1.44)	(3.40)	(1.34)	
	High	2.186	1.550	1.350	0.370	0.227	-0.143			1.219	0.645	0.446	0.574	0.199	-0.375	
		(8.75)	(7.37)	(5.70)	(2.87)	(1.45)	(-0.58)			(11.59)	(8.33)	(4.40)	(6.00)	(1.81)	(-2.24)	
	High-Low				0.225	-0.740***	-0.966***	1.792***					0.445***	-0.729***	-1.174***	2.616***
					(1.23)	(-3.12)	(-2.80)	(6.22)					(3.37)	(-4.22)	(-5.33)	(12.22)
CAPM	Low	-0.266	-0.360	-1.343	-0.020	1.035	1.056		FF 5	-0.209	-0.454	-1.335	0.245	0.881	0.636	
		(-1.57)	(-2.55)	(-7.49)	(-0.11)	(5.32)	(3.69)			(-1.22)	(-3.50)	(-8.66)	(2.01)	(6.38)	(4.22)	
	2	0.041	0.024	-0.628	0.140	0.415	0.275			0.011	-0.181	-0.717	0.192	0.535	0.344	
		(0.27)	(0.20)	(-4.70)	(0.89)	(2.58)	(1.09)			(0.09)	(-2.23)	(-6.95)	(1.87)	(5.11)	(2.64)	
	CGO	0.184	0.222	-0.247	-0.081	0.313	0.394			0.178	-0.003	-0.336	0.181	0.333	0.153	
		(1.36)	(2.03)	(-2.23)	(-0.53)	(2.07)	(1.60)			(1.60)	(-0.04)	(-4.48)	(1.67)	(3.72)	(1.14)	
	4	0.498	0.369	-0.040	0.225	0.372	0.147			0.444	0.168	-0.102	0.275	0.270	-0.006	
		(3.61)	(3.29)	(-0.32)	(1.59)	(3.73)	(0.76)			(4.78)	(2.45)	(-1.03)	(2.45)	(2.30)	(-0.03)	
	High	1.206	0.677	0.428	0.309	0.252	-0.056			1.261	0.555	0.450	0.706	0.105	-0.600	
		(8.16)	(6.07)	(3.31)	(2.34)	(1.59)	(-0.23)			(9.31)	(7.03)	(3.32)	(6.08)	(0.83)	(-2.90)	
	High-Low				0.329*	-0.783***	-1.112***	1.923***					0.461***	-0.776***	-1.237***	2.596***
					(1.76)	(-3.30)	(-3.26)	(6.89)					(3.09)	(-4.19)	(-4.77)	(9.39)

Table A5. Performance Persistence

This table presents the performance of the *XRP* strategy during different holding periods. Following (Jegadeesh & Titman, 1993), at the end of each month *t*-1, the strategies hold a series of portfolios that are selected based on current month as well as the preceding *K*-1 months, where *K* represents the holding periods. In each month *t*, the strategy holds *K XRP* value-weighted long-short portfolios. Then we revise the weights on 1/*K* of these portfolios to get the average strategy returns. The excess returns, CAPM alphas, Fama-French three-factor model alphas, and Fama-French five-factor model alphas of the long-short strategy are shown in this table. *T*-statistics based on Newey-West standard errors with 13 lags are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	XRP Strategy, K = Holding Period								
K	2	3	4	5	6	7	8	9	10
Excess ret	1.263***	0.881***	0.648***	0.605***	0.495***	0.486***	0.464***	0.389**	0.379**
	(6.20)	(4.71)	(3.56)	(3.38)	(2.98)	(2.95)	(2.80)	(2.31)	(2.31)
CAPM	1.417***	0.996***	0.753***	0.709***	0.594***	0.584***	0.562***	0.493***	0.480***
	(7.04)	(5.34)	(4.05)	(3.92)	(3.55)	(3.50)	(3.34)	(2.86)	(2.85)
FF 3	1.604***	1.196***	0.955***	0.917***	0.804***	0.794***	0.781***	0.719***	0.698***
	(8.97)	(7.47)	(6.02)	(6.10)	(5.90)	(5.85)	(5.94)	(5.45)	(5.54)
FF 5	1.457***	1.046***	0.834***	0.793***	0.667***	0.645***	0.641***	0.575***	0.556***
	(7.13)	(5.89)	(4.75)	(4.62)	(4.36)	(4.30)	(4.44)	(4.15)	(4.32)

Table A6. Robustness Check on Fama-Macbeth Regressions using Different Thresholds

This table presents the robustness check on Fama-Macbeth return predictive regressions using different thresholds. The dependent variable is the monthly return in month *t*. *Motivated pessimism* is an indicator variable, which equals one if the stock belongs to the highest CGO group and lowest EXTV group. *Motivated optimism* equals one if the stock belongs to the lowest CGO group and highest EXTV group. Panel A reports the results using 30% as the threshold. Panel B presents the results using the 10% threshold. The control variables are the same as those in Table 4. *T*-statistics based on Newey-West standard errors with 13 lags are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: 30% threshold						
	(1)	(2)	(3)	(4)	(5)	(6)
Motivated pessimism	0.753***	0.847***	0.648***	0.146**	0.118*	0.122**
	(9.19)	(12.27)	(10.97)	(2.20)	(1.96)	(2.17)
Motivated optimism	-0.861***	-0.966***	-0.703***	-0.214***	-0.181***	-0.128**
	(-8.30)	(-10.14)	(-8.52)	(-3.03)	(-3.20)	(-2.28)
Rank CGO				0.792***	0.986***	0.289**
				(4.67)	(5.95)	(2.00)
Rank EXTV				-0.994***	-1.214***	-1.197***
				(-7.08)	(-8.68)	(-8.75)
Size		0.000	-0.048		0.003	-0.033
		(0.01)	(-1.50)		(0.07)	(-1.02)
logBM		0.598***	0.645***		0.618***	0.597***
		(6.39)	(8.51)		(6.86)	(8.03)
Gross Profitability		1.169***	1.171***		1.153***	1.151***
		(7.12)	(7.51)		(7.20)	(7.50)
Asset growth		0.624***	0.576***		0.585***	0.596***
		(5.88)	(6.33)		(5.73)	(6.57)
MOM (12, 2)			0.671***			0.738***
			(4.67)			(4.93)
IVOL			-0.233***			-0.231***
			(-5.49)			(-5.61)
Skew			-0.047**			-0.012
			(-2.14)			(-0.62)
Kurt			-0.018*			-0.021**
			(-1.85)			(-2.29)
Adj-Rsquare	0.007	0.042	0.062	0.024	0.055	0.07
Observations	1701469	1545554	1544045	1701469	1545554	1544045
Long-Short	1.615***	1.813***	1.350***	0.359***	0.299***	0.250***
	(10.92)	(13.20)	(12.14)	(4.38)	(3.95)	(3.42)

Panel B: 10% threshold						
	(1)	(2)	(3)	(4)	(5)	(6)
Motivated pessimism	1.457***	1.565***	1.201***	0.638***	0.658***	0.572***
	(8.40)	(10.04)	(8.49)	(4.16)	(4.71)	(4.54)
Motivated optimism	-1.914***	-2.023***	-1.422***	-1.074***	-1.053***	-0.799***
	(-9.06)	(-10.25)	(-8.42)	(-6.31)	(-7.14)	(-5.71)
Rank CGO				0.816***	0.991***	0.314**
				(4.70)	(6.06)	(2.18)
Rank EXTV				-1.019***	-1.221***	-1.210***
				(-7.52)	(-9.19)	(-9.29)
Size		0.006	-0.046		0	-0.033
		(0.17)	(-1.43)		(0.01)	(-1.03)
logBM		0.552***	0.627***		0.616***	0.598***
		(5.78)	(8.22)		(6.78)	(7.97)
Gross Profitability		1.160***	1.163***		1.147***	1.145***
		(6.94)	(7.42)		(7.12)	(7.42)
Asset growth		0.667***	0.595***		0.582***	0.592***
		(6.20)	(6.50)		(5.68)	(6.50)
MOM (12, 2)			0.794***			0.723***
			(5.55)			(4.88)
IVOL			-0.249***			-0.224***
			(-5.79)			(-5.47)
Skew			-0.056**			-0.011
			(-2.46)			(-0.53)
Kurt			-0.014			-0.021**
			(-1.43)			(-2.30)
Adj-Rsquare	0.004	0.040	0.061	0.024	0.056	0.071
Observations	1701469	1545554	1544045	1701469	1545554	1544045
Long-Short	3.372***	3.588***	2.623***	1.711***	1.711***	1.371***
	(11.45)	(12.48)	(10.78)	(8.07)	(8.52)	(7.31)

Table A7. Detailed Specification of Return Decomposition

This table describe the methodology of return decomposition, following Huang et al., (2022). At the end of each month *t*-1, we sort the stocks into 5×5 portfolios according to their *EXTV* and *CGO*. The portfolios within the 2-4 of CGO ranking range are consolidated into a single group. Specifically, we conduct the following regressions model:

$$
\begin{aligned}
Ret_{i,t} = {} & b_0 + b_1 D_{rank\ CGO=1} + b_2 D_{rank\ CGO=5} + b_3 D_{rank\ EXTV=1} + b_4 D_{rank\ EXTV=2} + b_5 D_{rank\ EXTV=4} \\
& + b_6 D_{rank\ EXTV=5} + b_7 D_{rank\ CGO\ in\ (2,3,4)\ and\ rank\ EXTV=1} \\
& + b_8 D_{rank\ CGO\ in\ (2,3,4)\ and\ rank\ EXTV=2} + b_9 D_{rank\ CGOin(2,3,4)\ and\ rank\ EXTV=4} \\
& + b_{10} D_{rank\ CGOin(2,3,4)\ and\ rank\ EXTV=5} + b_{11} D_{rank\ CGO=1\ and\ rank\ EXTV=4} \\
& + b_{12} D_{rank\ CGO=5\ and\ rank\ EXTV=2} + b_{13} D_{rank\ CGO=1\ and\ rank\ EXTV=5} \\
& + b_{14} D_{rank\ CGO=5\ and\ rank\ EXTV=1} + \varepsilon_{i,t},
\end{aligned}
$$

where μ is the benchmark return, representing the average returns of stocks with neither extreme *CGO* nor extreme *EXTV*. The variables A_h and A_l capture the returns associated with high and low CGO, respectively. Similarly, the variables E_{gg}, E_g, E_b, and E_{bb} capture returns for different levels of *EXTV*, where *gg* represents *EXTV* 5, *g* represents *EXTV* 4, *b* represents *EXTV* 2, and *bb* represents *EXTV* 1. The interaction effect between *EXTV* and *CGO* is represented by $I_{..}$. Specifically, $I_{gg,l}$ captures the returns of stocks with high *EXTV* and low *CGO*, while $I_{bb,h}$ captures the returns of stocks with low *EXTV* and high *CGO*.

Panel A: Return Decomposition including the Interaction Effect					
	EXTV 1（Low）	EXTV 2	EXTV 3	EXTV 4	EXTV 5 (High)
CGO 1 (Low)	$\mu + A_l + E_{bb}$	$\mu + A_l + E_b$	$\mu + A_l$	$\mu + A_l + E_g + I_{g,l}$	$\mu + A_l + E_{gg} + I_{gg,l}$
CGO 2-4	$\mu + E_{bb} + I_{bb,m}$	$\mu + E_b + I_{b,m}$	μ	$\mu + E_g + I_{g,m}$	$\mu + E_{gg} + I_{gg,m}$
CGO 5 (High)	$\mu + A_h + E_{bb} + I_{bb,h}$	$\mu + A_h + E_b + I_{b,h}$	$\mu + A_h$	$\mu + A_h + E_g$	$\mu + A_h + E_{gg}$
CGO 1 (Low)	$b_0 + b_1 + b_3$	$b_0 + b_1 + b_4$	$b_0 + b_1$	$b_0 + b_1 + b_5 + b_{11}$	$b_0 + b_1 + b_6 + b_{13}$
CGO 2-4	$b_0 + b_3 + b_7$	$b_0 + b_4 + b_8$	b_0	$b_0 + b_5 + b_9$	$b_0 + b_6 + b_{10}$
CGO 5 (High)	$b_0 + b_2 + b_3 + b_{14}$	$b_0 + b_2 + b_4 + b_{12}$	$b_0 + b_2$	$b_0 + b_2 + b_5$	$b_0 + b_2 + b_6$
Pure extrapolation			$E_{gg} - E_{bb} = b_6 - b_3$		
Pure CGO			$A_h - A_l = b_2 - b_1$		
Interaction Effect			$I_{bb,h} - I_{gg,l} = b_{14} - b_{13}$		

Panel B: Return Decomposition excluding the Interaction Effect					
	EXTV 1（Low）	EXTV 2	EXTV 3	EXTV 4	EXTV 5 (High)
CGO 1 (Low)	$\mu + A_l + E_{bb}$	$\mu + A_l + E_b$	$\mu + A_l$	$\mu + A_l + E_g$	$\mu + A_l + E_{gg}$
CGO 2-4	$\mu + E_{bb}$	$\mu + E_b$	μ	$\mu + E_g$	$\mu + E_{gg}$
CGO 5 (High)	$\mu + A_h + E_{bb}$	$\mu + A_h + E_b$	$\mu + A_h$	$\mu + A_h + E_g$	$\mu + A_h + E_{gg}$

Table A8. Robustness Check on Return Decomposition using Different Threshold

This table presents the results of return decomposition using different threshold. Stocks are sorted into portfolios based on the *CGO* and *EXTV* values, using a scheme of (30% low-40% median-30% high) for both dimensions. The returns are then decomposed into several components: the benchmark return, the pure *CGO* effect ($A_h - A_l$), the pure *EXTV* effect ($E_{gg} - E_{bb}$) and the interaction effect ($I_{bb,l} - I_{gg,h}$). Panel A presents the return decomposition including the interaction effect. Panel B reports the results excluding the interaction effect. The excess returns, CAPM alphas, Fama-French three-factor model alphas, and Fama-French five-factor model alphas of the pure *CGO* effect, the pure *EXTV* effect, and the interaction effect are shown in this table. T-statistics based on Newey-West standard errors with 13 lags are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Interaction Effect Included					
model	Pure CGO	Pure EXTV	Interaction	$I_{bb,l}$	$I_{gg,h}$
Excess ret	0.432***	-0.532***	0.645***	0.227**	-0.418***
	(3.62)	(-4.91)	(4.39)	(2.52)	(-3.72)
CAPM	0.532***	-0.455***	0.659***		
	(4.79)	(-4.14)	(4.55)		
FF 3	0.663***	-0.423***	0.670***		
	(6.43)	(-3.72)	(4.40)		
FF 5	0.549***	-0.437***	0.705***		
	(3.84)	(-3.48)	(4.19)		
Panel B: Interaction Effect Excluded					
Excess ret	0.634***	-0.774***			
	(5.15)	(-8.51)			
CAPM	0.738***	-0.698***			
	(6.53)	(-7.23)			
FF 3	0.872***	-0.673***			
	(8.02)	(-6.91)			
FF 5	0.767***	-0.715***			
	(4.71)	(-7.21)			

Table A9. Return Decomposition with Controls

This table presents the results of return decomposition controlling for other characteristics. Stocks are sorted into portfolios based on the CGO and *EXTV* values, using a scheme of (30% low-40% median-30% high) for both dimensions. The returns are then decomposed into several components: the benchmark return, the pure CGO effect ($A_h - A_l$), the pure *EXTV* effect ($E_{gg} - E_{bb}$) and the interaction effect ($I_{bb,l} - I_{gg,h}$). Panel A presents the return decomposition including the interaction effect. Panel B reports the results excluding the interaction effect. The excess returns, CAPM alphas, Fama-French three-factor model alphas, and Fama-French five-factor model alphas of the pure *CGO* effect, the pure *EXTV* effect, and the interaction effect are shown in this table. We also control for other characteristics which are the same as the baseline table. *T*-statistics based on Newey-West standard errors with 13 lags are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Interaction Effect Included (with Controls)					
model	Pure CGO	Pure EXTV	Interaction	$I_{bb,l}$	$I_{gg,h}$
Excess ret	0.140	-0.908***	0.707***	0.169*	-0.538***
	(1.29)	(-7.54)	(4.52)	(1.65)	(-4.33)
CAPM	0.279***	-0.806***	0.726***		
	(2.73)	(-6.49)	(4.70)		
FF 3	0.319***	-0.803***	0.704***		
	(3.22)	(-6.28)	(4.50)		
FF 5	0.181*	-0.852***	0.746***		
	(1.69)	(-6.43)	(4.56)		
Panel B: Interaction Effect Excluded (with Controls)					
Excess ret	0.288***	-1.110***			
	(3.09)	(-10.39			
CAPM	0.427***	-1.015***			
	(5.08)	(-8.74)			
FF 3	0.463***	-0.997***			
	(5.79)	(-8.45)			
FF 5	0.336***	-1.059***			
	(3.71)	(-8.56)			

Table A10. Robustness Check on Motived Beliefs and Survey Expectations with Different Thresholds

This table presents the results associated with regressions of survey expectations of future stock market returns on motivated extrapolative beliefs as follows:

$$Expectation_t = a + b \times Motivated\ Optimism_t + c \times Motivated\ Pessimism_t + d \times Controls_t + u_t,$$

where $Expectation_t$ represents the monthly AAI survey expectations in month *t*, which is calculated as the average of weekly bullish-bear spreads. The aggregate levels *CGO* and *EXTV* are calculated as the median value or the value weighted average of stock-level CGO and EXTV. *Motivated optimism* is an indicator variable, which equals one if $CGO_t < CGO\ Low$ percentile and $EXTV_t > EXTV\ High$ percentile . *Motivated pessimism* equals one if $CGO_t > CGO\ Low$ percentile and $EXTV_t < EXTV$ High percentile. Here we use Low (High)=30 (70) or 50 (70) for robustness check. The control variables include the market excess return in month *t* (*MKT*), the dividend-to-price ratio (*DP*), the earnings-to-price ratio (*EP*), the risk-free rate (*Rf*), the lagged 12-month market return (*R12*), and the unemployment rate (*Unrate*). The sample period spans from September 1987 to December 2021. *T*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep. Var=	Expectation			
Threshold:	(30, 70)		(50, 50)	
Aggregation Method	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)
Motived optimism	0.060**	0.045*	0.031**	0.055***
	(2.47)	(1.83)	(2.11)	(3.38)
Motivated pessimism	-0.018	-0.010	-0.023	-0.010
	(-0.67)	(-0.36)	(-1.12)	(-0.70)
EXTV	7.411***	9.897***	7.503***	8.215***
	(3.31)	(3.62)	(3.25)	(3.46)
CGO	0.529***	0.355	0.532***	0.407*
	(2.92)	(1.59)	(3.14)	(1.93)
MKTt	0.009***	0.009***	0.009***	0.009***
	(4.90)	(4.68)	(4.76)	(4.76)
Dp	-0.006***	-0.006***	-0.006***	-0.005***
	(-3.74)	(-3.23)	(-3.41)	(-3.26)
Ep	0.000	0.000	0.000	0.000
	(0.67)	(0.35)	(0.45)	(0.16)
Rf	-39.405***	-31.855***	-38.898***	-32.413***
	(-4.64)	(-4.71)	(-4.54)	(-4.86)
R12	0.179**	0.266***	0.172*	0.270***
	(1.99)	(3.73)	(1.78)	(3.78)
Unrate	-0.039***	-0.039***	-0.039***	-0.039***
	(-5.60)	(-5.18)	(-5.50)	(-5.38)
t-stat: (Motivated optimism- Motivated pessimism = 0)	3.46***	2.89***	2.90***	2.18**
Adj-Rsquare	0.384	0.383	0.395	0.411
Observations	412	412	412	412

Table A11. Who are Trading on/against Motivated Extrapolative Beliefs

This table presents the results of the quarterly holding changes of different investor types on motivated extrapolative beliefs:

$$\%Holding\ Change_{i,t} = a + b \times Motivated\ optimism_{i,t} + c \times Motivated\ pessimism_{i,t} + d \times Controls + u_{i,t},$$

where the institutional holding change ($\%Holding\ Change_{i,t}$) measures the difference in holding ratios for stock *i* between the end of quarter t and the end of quarter t-1. Investor types include households, banks, insurance companies, mutual funds, investor advisors, and pension funds, as defined in Kojien and Yogo (2019). The quarterly value of *CGO* and *EXTV* are the average of monthly data. The motivated optimistic belief (*Motivated optimism*) is an indicator variable, which equals one if $CGO_{i,t} < CGO\ 20^{th}$percentile $and\ EXTV_{i,t} > EXTV\ 80^{th}$ percentile. *Motivated pessimism* equals one if $CGO_{i,t} > CGO\ 80^{th}$percentile $and\ EXTV_{i,t} < EXTV\ 20^{th}$ percentile .The control variables include *Size* (logarithmic market capitalization), *logBM* (logarithmic book-to-market ratio), *Gross Profitability*, *Asset growth* (growth rate of total assets), *Lagged return* (the last-month return in quarter *t*), *MOM (12, 2)* (cumulative returns from *t*-12 month to *t*-2 month), *IVOL* (idiosyncratic volatility), *Skew* (skewness), and *Kurt* (kurtosis). We control for the quarter- and stock-fixed effects. Standard errors double-clustered at firm and quarter level are shown in the parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Investor Type:	Household				Bank				Insurance			
Motivated optimism	0.947***	0.932***	0.607***	0.649***	-0.146***	-0.069*	-0.091***	-0.045	-0.081***	-0.067***	-0.027	-0.025
	(12.06)	(6.67)	(7.74)	(7.73)	(-5.66)	(-1.80)	(-3.61)	(-1.51)	(-4.96)	(-2.75)	(-1.62)	(-1.25)
Motivated pessimism	-0.409***	-0.409***	-0.088	-0.148*	0.044	-0.006	-0.004	-0.032	0.036***	0.028	-0.001	-0.000
	(-5.64)	(-3.79)	(-1.18)	(-1.85)	(1.57)	(-0.18)	(-0.13)	(-1.03)	(2.69)	(1.41)	(-0.11)	(-0.02)
EXTV		-42.023***		-29.495***		0.486		-0.291		2.492***		2.204**
		(-6.91)		(-6.06)		(0.44)		(-0.25)		(2.62)		(2.46)
CGO		-1.239***		-0.983***		0.234***		0.174***		0.114**		0.102***
		(-4.06)		(-4.84)		(3.28)		(3.25)		(2.57)		(4.62)
Size			0.163***	0.215***			0.011	0.003			-0.005	-0.009
			(3.57)	(4.53)			(0.96)	(0.24)			(-0.66)	(-1.31)
logBM			0.306***	0.188***			-0.063***	-0.046***			-0.029***	-0.018**
			(5.98)	(3.93)			(-5.34)	(-4.15)			(-3.28)	(-1.99)
Gross Profitability			-0.013	0.065			0.016	0.004			-0.010	-0.016
			(-0.12)	(0.60)			(0.70)	(0.16)			(-0.55)	(-0.86)
Asset Growth			-0.060*	-0.059*			0.008**	0.007**			0.006	0.006
			(-1.89)	(-1.86)			(2.21)	(2.07)			(0.75)	(0.75)
Lagged return			-2.044***	-1.538***			0.064	0.053			-0.002	-0.041
			(-10.23)	(-8.77)			(1.35)	(1.12)			(-0.05)	(-1.07)
MOM (12, 2)			-0.855***	-0.698***			0.121***	0.101***			0.078***	0.063***
			(-8.45)	(-7.35)			(5.45)	(4.43)			(6.26)	(5.55)
IVOL			0.198***	0.178***			-0.031***	-0.025***			-0.025***	-0.022***
			(9.22)	(7.80)			(-5.55)	(-4.29)			(-6.18)	(-5.29)
Skew			-0.060***	-0.042***			-0.004	-0.005			0.005	0.003
			(-4.02)	(-3.01)			(-0.92)	(-1.05)			(1.34)	(0.94)
Kurt			0.022***	0.024***			-0.002	-0.002			-0.002	-0.002
			(4.54)	(4.77)			(-0.87)	(-1.23)			(-1.26)	(-1.51)
Observations	410,516	410,516	381,831	381,831	394,148	394,148	367,724	367,724	337,542	337,542	320,755	320,755
R-squared	0.073	0.078	0.088	0.090	0.050	0.051	0.055	0.055	0.032	0.033	0.036	0.036
YearQ FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Stock	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

(Continued)

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Investor Type:	Mutual Fund				Investment Advisor				Pension Fund			
Motivated optimism	-0.152***	-0.209***	-0.158***	-0.142***	-0.575***	-0.631***	-0.336***	-0.469***	-0.031**	-0.004	-0.022	-0.006
	(-3.83)	(-4.83)	(-4.40)	(-3.60)	(-10.77)	(-6.64)	(-6.19)	(-8.15)	(-2.198)	(-0.273)	(-1.554)	(-0.460)
Motivated pessimism	0.037	0.076*	0.024	0.020	0.294***	0.337***	0.068	0.181***	-0.003	-0.021**	-0.004	-0.016*
	(1.02)	(1.89)	(0.68)	(0.51)	(5.43)	(4.56)	(1.42)	(3.52)	(-0.276)	(-2.069)	(-0.354)	(-1.677)
EXTV		13.593***		4.466**		31.653***		27.445***		-3.636***		-2.592***
		(6.60)		(2.18)		(7.44)		(8.74)		(-5.652)		(-5.215)
CGO		0.225***		0.238***		0.749***		0.536***		-0.023		-0.039**
		(3.79)		(2.99)		(3.61)		(4.14)		(-1.543)		(-2.069)
Size			-0.097***	-0.109***			-0.097***	-0.128***			0.012*	0.014*
			(-7.04)	(-7.68)			(-2.99)	(-3.73)			(1.726)	(1.968)
logBM			-0.036*	-0.010			-0.171***	-0.099***			-0.010	-0.016**
			(-1.87)	(-0.46)			(-4.70)	(-2.80)			(-1.437)	(-2.148)
Gross Profitability			-0.002	-0.019			-0.031	-0.073			0.053***	0.055***
			(-0.03)	(-0.32)			(-0.41)	(-0.97)			(3.564)	(3.641)
Asset Growth			0.014	0.014			0.018	0.019			0.007*	0.006*
			(1.09)	(1.05)			(1.05)	(1.10)			(1.922)	(1.857)
Lagged return			0.828***	0.745***			1.379***	0.942***			-0.178***	-0.141***
			(10.02)	(9.88)			(8.94)	(6.76)			(-6.539)	(-5.547)
MOM (12, 2)			0.119***	0.085***			0.568***	0.466***			-0.018**	-0.009
			(3.69)	(2.72)			(9.63)	(8.78)			(-2.586)	(-1.486)
IVOL			-0.006	0.000			-0.149***	-0.141***			-0.001	-0.002
			(-0.53)	(0.03)			(-9.93)	(-9.35)			(-0.261)	(-0.553)
SKEW			0.044***	0.041***			0.032**	0.017			-0.011***	-0.009***
			(5.71)	(5.27)			(2.57)	(1.46)			(-5.112)	(-4.529)
KURT			0.009***	0.009***			-0.031***	-0.031***			0.001	0.001
			(2.94)	(2.74)			(-7.42)	(-7.31)			(0.931)	(0.956)
Observations	389,336	389,336	364,232	364,232	399,073	399,073	373,287	373,287	320,743	320,743	303,674	303,674
R-squared	0.044	0.045	0.048	0.048	0.085	0.090	0.100	0.102	0.125	0.125	0.134	0.134
YearQ FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Stock	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A12. Factor Spanning Test on Different Momentum Portfolios Using CGO and EXTV

This table presents the factor spanning tests on different momentum portfolios using single *CGO* factor, single *EXTV* factor and *CGO* factor and *EXTV* factor added to CAPM model. The portfolios include 41 testing portfolios, which are from *q-data library* and two factors, *UMD* from Kenneth French's website and industry-adjusted *UMD** from Novy-Marx's website. The *CGO* factor is the long-short spread of the stocks within highest *CGO* decile lowest *CGO* decile. The *EXTV* factor is the long-short spread of the stocks within highest *EXTV* decile lowest *EXTV* decile. The *t*-statistics based on standard errors adjusted Newey-West HAC with 13 lags are shown in the parentheses. The unexplained strategies are highlighted in red. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Model	Param	abr_1	abr_6	abr_12	cim_1	cim_6	cim_12	cm_1	cm_12	def_1	def_6	def_12
CAPM+CGO	*Alpha*	**0.555*****	**0.218*****	**0.122***	**0.732*****	**0.192****	**0.179****	**0.714*****	0.035	**0.687*****	**0.260***	0.081
		(4.19)	(2.81)	(1.90)	(3.36)	(1.98)	(2.37)	(3.40)	(0.69)	(3.70)	(1.88)	(0.79)
	β_{mkt}	0.026	0.056*	0.077***	-0.014	0.001	0.028	-0.031	0.051*	0.042	0.110**	0.061
		(0.72)	(1.83)	(2.79)	(-0.22)	(0.04)	(1.24)	(-0.34)	(1.95)	(0.81)	(2.48)	(1.46)
	β_{CGO}	0.211***	0.138***	0.109***	0.170***	0.201***	0.169***	0.079	0.089***	0.301***	0.291***	0.223***
		(6.78)	(5.99)	(5.96)	(3.96)	(7.37)	(7.73)	(1.37)	(5.59)	(8.89)	(9.37)	(7.81)
CAPM+EXTV	*Alpha*	**0.884*****	**0.415*****	**0.274*****	**1.159*****	**0.508*****	**0.453*****	**0.867*****	**0.170*****	**1.104*****	**0.685*****	**0.416*****
		(7.10)	(4.64)	(3.33)	(5.32)	(4.26)	(4.77)	(4.27)	(3.02)	(5.52)	(4.16)	(3.23)
	β_{mkt}	-0.041	0.005	0.037	-0.027	-0.069**	-0.029	-0.041	0.022	-0.069	0.012	-0.012
		(-1.19)	(0.19)	(1.22)	(-0.41)	(-1.98)	(-1.06)	(-0.54)	(0.77)	(-1.07)	(0.22)	(-0.23)
	β_{EXTV}	0.170***	0.082***	0.062***	0.357***	0.158***	0.145***	0.127	0.066***	0.138**	0.172***	0.148***
		(3.67)	(3.28)	(3.36)	(5.16)	(4.43)	(4.93)	(1.57)	(3.64)	(2.17)	(3.88)	(4.25)
CAPM +CGO + EXTV	*Alpha*	**0.639*****	**0.248*****	**0.142****	**1.008*****	**0.279*****	**0.263*****	**0.786*****	0.06	**0.714*****	**0.318****	0.138
		(4.86)	(3.07)	(2.02)	(4.77)	(2.81)	(3.24)	(3.39)	(1.19)	(3.72)	(2.24)	(1.31)
	β_{mkt}	0.04	0.061*	0.081***	0.028	0.014	0.040**	-0.016	0.057**	0.047	0.121***	0.071*
		(1.07)	(1.95)	(2.89)	(0.45)	(0.62)	(2.02)	(-0.19)	(2.23)	(0.94)	(2.85)	(1.83)
	β_{EXTV}	0.102**	0.035	0.025	0.319***	0.101***	0.097***	0.106	0.037**	0.036	0.075*	0.075**
		(2.28)	(1.45)	(1.38)	(4.91)	(3.77)	(4.03)	(1.25)	(2.53)	(0.58)	(1.76)	(2.20)
	β_{CGO}	0.194***	0.132***	0.104***	0.124***	0.186***	0.155***	0.06	0.082***	0.294***	0.278***	0.210***
		(6.02)	(5.81)	(5.96)	(3.26)	(7.62)	(8.18)	(1.01)	(5.44)	(8.98)	(8.59)	(7.26)

Model	Param	ile_1	ilr_1	ilr_6	ilr_12	im_1	im_6	im_12	nei_1	p52w_6	p52w_12	r6_1
CAPM +CGO	*Alpha*	**0.406*****	**0.568*****	**0.221****	**0.211*****	**0.362***	**0.273***	**0.304****	0.146	**0.366***	**0.287***	0.172
		(2.93)	(3.30)	(2.50)	(3.24)	(1.88)	(1.77)	(2.36)	(1.58)	(1.93)	(1.77)	(0.82)
	β_{mkt}	0.001	-0.095*	-0.014	0.024	0.009	0.092*	0.111**	0.036	-0.457***	-0.402***	0.017
		(0.02)	(-1.82)	(-0.53)	(1.13)	(0.15)	(1.68)	(2.07)	(0.94)	(-7.09)	(-7.73)	(0.29)
	β_{CGO}	0.158***	0.196***	0.219***	0.186***	0.513***	0.442***	0.348***	0.170***	0.606***	0.487***	0.670***
		(3.76)	(5.02)	(13.53)	(12.37)	(11.07)	(9.78)	(7.76)	(5.95)	(13.01)	(10.12)	(11.76)
CAPM + EXTV	*Alpha*	**0.605*****	**0.976*****	**0.534*****	**0.474*****	**1.067*****	**0.836*****	**0.753*****	**0.389*****	**1.222*****	**0.968*****	**1.104*****
		(3.82)	(5.22)	(5.63)	(6.12)	(4.89)	(4.45)	(4.22)	(3.63)	(5.61)	(4.92)	(4.75)
	β_{mkt}	-0.068	-0.134**	-0.099**	-0.049	-0.198**	-0.098	-0.037	-0.034	-0.694***	-0.594***	-0.249***
		(-1.26)	(-1.99)	(-2.42)	(-1.48)	(-2.24)	(-1.27)	(-0.51)	(-0.86)	(-7.60)	(-7.67)	(-2.60)
	β_{EXTV}	0.056	0.294***	0.130***	0.105***	0.264***	0.165**	0.137**	0.092***	0.343***	0.266***	0.359***
		(1.25)	(4.78)	(4.13)	(3.86)	(3.02)	(2.27)	(2.48)	(3.20)	(4.49)	(4.13)	(3.98)
CAPM +CGO + EXTV	*Alpha*	**0.413*****	**0.779*****	**0.277*****	**0.255*****	**0.458****	**0.299***	**0.331****	**0.182***	**0.508*****	**0.392****	0.311
		(2.96)	(4.53)	(3.15)	(3.83)	(2.39)	(1.90)	(2.43)	(1.94)	(2.91)	(2.52)	(1.57)
	β_{mkt}	0.002	-0.063	-0.006	0.031	0.023	0.096*	0.115**	0.041	-0.435***	-0.386***	0.038
		(0.04)	(-1.15)	(-0.21)	(1.45)	(0.42)	(1.78)	(2.17)	(1.13)	(-7.08)	(-7.63)	(0.68)
	β_{EXTV}	0.008	0.245***	0.065***	0.050***	0.111*	0.031	0.031	0.042	0.165***	0.122**	0.160**
		(0.18)	(3.80)	(3.29)	(2.66)	(1.78)	(0.59)	(0.72)	(1.42)	(2.95)	(2.37)	(2.27)
	β_{CGO}	0.157***	0.160***	0.210***	0.179***	0.497***	0.437***	0.344***	0.164***	0.582***	0.469***	0.646***
		(3.54)	(3.62)	(13.26)	(11.94)	(10.36)	(9.02)	(7.52)	(5.60)	(12.11)	(9.51)	(10.67)

Model	Param	r6_6	r6_12	r11_1	r11_6	r11_12	re_1	re_6	resid6_6	resid6_12	resid11_1	resid11_6
CAPM +CGO	*Alpha*	**0.360****	0.135	**0.512****	0.247	-0.003	**0.575*****	0.215	**0.257****	**0.173****	**0.355****	**0.253****
		(2.07)	(1.00)	(2.55)	(1.31)	(-0.02)	(3.03)	(1.36)	(2.37)	(2.14)	(2.36)	(2.17)
	β_{mkt}	0.061	0.101*	0.044	0.086	0.102	-0.143**	-0.098*	0.021	0.033	0.082	0.067
		(0.82)	(1.67)	(0.55)	(1.03)	(1.40)	(-2.01)	(-1.66)	(0.48)	(0.99)	(1.49)	(1.38)
	β_{CGO}	0.523***	0.410***	0.733***	0.588***	0.456***	0.380***	0.343***	0.144***	0.152***	0.200***	0.197***
		(11.93)	(10.12)	(13.91)	(12.99)	(8.97)	(6.04)	(7.85)	(6.19)	(7.63)	(6.76)	(7.49)
CAPM + EXTV	*Alpha*	**1.100*****	**0.711*****	**1.577*****	**1.099*****	**0.655*****	**1.157*****	**0.736*****	**0.454*****	**0.378*****	**0.600*****	**0.519*****
		(5.26)	(3.75)	(6.32)	(4.69)	(2.77)	(6.11)	(4.32)	(3.80)	(4.04)	(3.79)	(3.92)
	β_{mkt}	-0.143	-0.061	-0.234**	-0.138	-0.072	-0.263***	-0.209***	-0.037	-0.029	-0.007	-0.014
		(-1.56)	(-0.74)	(-2.04)	(-1.27)	(-0.74)	(-3.69)	(-3.22)	(-0.85)	(-0.74)	(-0.12)	(-0.25)
	β_{EXTV}	0.299***	0.228***	0.456***	0.363***	0.278***	0.264***	0.231***	0.073**	0.072***	0.06	0.095**
		(4.87)	(4.13)	(5.03)	(4.85)	(4.02)	(4.18)	(5.10)	(2.43)	(2.65)	(1.51)	(2.58)
CAPM +CGO + EXTV	*Alpha*	**0.485*****	**0.227**	**0.721*****	**0.412****	0.121	**0.682*****	**0.305***	**0.283****	**0.197****	**0.354****	**0.283****
		(2.90)	(1.56)	(3.90)	(2.21)	(0.65)	(3.69)	(1.93)	(2.46)	(2.25)	(2.31)	(2.20)
	β_{mkt}	0.08	0.115**	0.076	0.111	0.121*	-0.123*	-0.082	0.025	0.037	0.082	0.072
		(1.11)	(1.98)	(1.01)	(1.40)	(1.77)	(-1.85)	(-1.50)	(0.58)	(1.10)	(1.48)	(1.48)
	β_{EXTV}	0.144***	0.106**	0.241***	0.190***	0.144**	0.139**	0.118**	0.03	0.027	-0.002	0.036
		(2.83)	(2.16)	(3.49)	(2.98)	(2.27)	(2.36)	(2.50)	(1.02)	(1.07)	(-0.04)	(0.96)
	β_{CGO}	0.502***	0.395***	0.698***	0.560***	0.435***	0.356***	0.323***	0.140***	0.148***	0.200***	0.192***
		(10.83)	(9.50)	(12.86)	(11.82)	(8.45)	(5.63)	(7.13)	(6.24)	(7.71)	(6.84)	(7.20)

		resid11_12	rs_1	sim_1	sim_12	sm_1	sm_12	sue_1	sue_6	UMD	UMD*	(#) Sig,
CAPM +CGO	*Alpha*	0.112	**0.274****	**0.633*****	0.013	0.382	0.024	**0.309*****	0.017	**0.286****	**0.396*****	30
		(1.06)	(2.04)	(2.69)	(0.18)	(1.52)	(0.36)	(2.98)	(0.21)	(2.29)	(4.27)	
	β_{mkt}	0.059	0.016	0.033	0.069**	-0.018	0.047**	-0.016	0.039	0.064	0.037	
		(1.45)	(0.27)	(0.58)	(2.27)	(-0.32)	(2.46)	(-0.37)	(0.99)	(1.13)	(0.97)	
	β_{CGO}	0.176***	0.158***	0.187***	0.137***	0.113**	0.123***	0.226***	0.212***	0.438***	0.293***	
		(6.19)	(5.37)	(3.60)	(6.60)	(2.33)	(8.91)	(6.48)	(5.92)	(13.25)	(14.00)	
CAPM + EXTV	*Alpha*	**0.361*****	**0.482*****	**1.060*****	**0.214*****	**0.652*****	**0.212*****	**0.648*****	**0.326*****	**0.875*****	**0.798*****	43
		(3.10)	(3.36)	(4.99)	(2.64)	(2.77)	(2.97)	(5.23)	(3.13)	(5.79)	(7.68)	
	β_{mkt}	-0.01	-0.051	0.006	0.017	-0.016	0.007	-0.099**	-0.041	-0.106	-0.083	
		(-0.23)	(-0.92)	(0.13)	(0.53)	(-0.28)	(0.26)	(-2.20)	(-1.00)	(-1.33)	(-1.40)	
	β_{EXTV}	0.101***	0.068**	0.331***	0.088***	0.244***	0.079***	0.155***	0.133***	0.227***	0.140***	
		(3.23)	(2.14)	(3.93)	(4.07)	(3.71)	(3.31)	(4.99)	(4.09)	(4.15)	(3.57)	
CAPM +CGO + EXTV	*Alpha*	0.154	**0.291****	**0.881*****	0.054	**0.550****	0.054	**0.387*****	0.079	**0.370*****	**0.448*****	34
		(1.33)	(2.04)	(4.04)	(0.67)	(2.32)	(0.80)	(3.47)	(0.92)	(3.06)	(5.08)	
	β_{mkt}	0.066	0.018	0.071	0.075**	0.013	0.052***	-0.004	0.048	0.077	0.042	
		(1.63)	(0.32)	(1.30)	(2.53)	(0.23)	(2.78)	(-0.10)	(1.27)	(1.37)	(1.10)	
	β_{EXTV}	0.049	0.02	0.286***	0.048**	0.217***	0.038**	0.090***	0.072**	0.099***	0.048*	
		(1.63)	(0.60)	(3.47)	(2.17)	(3.32)	(2.06)	(3.10)	(2.47)	(2.95)	(1.81)	
	β_{CGO}	0.169***	0.155***	0.145***	0.130***	0.075	0.117***	0.213***	0.201***	0.423***	0.286***	
		(5.98)	(5.01)	(2.88)	(6.01)	(1.56)	(9.18)	(6.02)	(5.56)	(12.79)	(13.09)	

Table A13. The Momentum Strategies

This table tabulates the definitions of momentum-related test strategies, which could also be found in Lu Zhang's personal website. The strategies that could not be explained by *XRP* are highlighted in red.

1. Abr1 ("abr_1"), cumulative abnormal returns around earnings announcement dates, 1-month holding period;
2. Abr6 ("abr_6"), cumulative abnormal returns around earnings announcement dates, 6-month holding period;
3. Abr12 ("abr_12"), cumulative abnormal returns around earnings announcement dates, 12-month holding period;
4. Cim1 ("cim_1"), customer industries momentum, 1-month holding period;
5. Cim6 ("cim_6"), customer industries momentum, 6-month holding period;
6. Cim12 ("cim_12"), customer industries momentum, 12-month holding period;
7. Cm1 ("cm_1"), customer momentum, 1-month holding period;
8. Cm12 ("cm_12"), customer momentum, 12-month holding period;
9. dEf1 ("def_1"), changes in analyst earnings forecasts, 1-month holding period;
10. dEf6 ("def_6"), changes in analyst earnings forecasts, 6-month holding period;
11. dEf12 ("def_12"), changes in analyst earnings forecasts, 12-month holding period;
12. Ile1 ("ile_1"), industry lead-lag effect in earnings surprises, 1-month holding period;
13. Ilr1 ("ilr_1"), industry lead-lag effect in prior returns, 1-month holding period;
14. Ilr6 ("ilr_6"), industry lead-lag effect in prior returns, 6-month holding period;
15. Ilr12 ("ilr_12"), industry lead-lag effect in prior returns, 12-month holding period;
16. Im1 ("im_1"), industry momentum, 1-month holding period;
17. Im6 ("im_6"), industry momentum, 6-month holding period;
18. Im12 ("im_12"), industry momentum, 12-month holding period;
19. Nei1 ("nei_1"), the number of quarters with consecutive earnings increase, 1-month holding period;
20. 52w6 ("p52w_6"), 52-week high, 6-month holding period;
21. 52w12 ("p52w_12"), 52-week high, 12-month holding period;
22. R6_1 ("r6_1"), prior 6-month returns, 1-month holding period;
23. R6_6 ("r6_6"), prior 6-month returns, 6-month holding period;
24. R6_12 ("r6_12"), prior 6-month returns, 12-month holding period;
25. R11_1 ("r11_1"), prior 11-month returns, 1-month holding period;
26. R11_6 ("r11_6"), prior 11-month returns, 6-month holding period;
27. R11_12 ("r11_12"), prior 11-month returns, 12-month holding period;
28. Re1 ("re_1"), revisions in analyst earnings forecasts, 1-month holding period;
29. Re6 ("re_6"), revisions in analyst earnings forecasts, 6-month holding period;
30. Resid6_6 ("resid6_6"), 6-month residual momentum, 6-month holding period;
31. Resid6_12 ("resid6_12"), 6-month residual momentum, 12-month holding period;
32. Resid11_1 ("resid11_1"), 11-month residual momentum, 1-month holding period;
33. Resid11_6 ("resid11_6"), 11-month residual momentum, 6-month holding period;
34. Resid11_12 ("resid11_12"), 11-month residual momentum, 12-month holding period;
35. Rs1 ("rs_1"), revenue surprises, 1-month holding period;
36. Sim1 ("sim_1"), supplier industries momentum, 1-month holding period;
37. Sim12 ("sim_12"), supplier industries momentum, 12-month holding period;
38. Sm1 ("sm_1"), segment momentum, 1-month holding period;
39. Sm12 ("sm_12"), segment momentum, 12-month holding period;
40. Sue1 ("sue_1"), standard unexpected earnings, 1-month holding period;
41. Sue6 ("sue_6"), standard unexpected earnings, 6-month holding period

Table A14. Motivated Extrapolative Beliefs and LDB Trading Records

This table presents the results of panel regressions of selling and buying on motivated extrapolative beliefs. The dependent variables are indicators for investors' selling or buying decisions (multiplied by 100). The independent variables, $Motivated\ optimism$, is an indicator variable, which equals one if $CGO_{i,t} < CGO_t\ 20^{th}$ percentile $and\ EXTV_{i,t} > EXTV_t\ 80^{th}$ percentile. *Motivated pessimism* equals one if $CGO_{i,t} > CGO_t\ 80^{th}$percentile $and\ EXTV_{i,t} < EXTV_t\ 20^{th}$ percentile. The control variables include I (ret = 0), which is an indicator if return is zero, I (ret >0), which is an indicator if return is positive, the rank of *CGO* and *EXTV*, the square of holding days from the last transaction (Sqrt (Time owned)), logarithm of purchase price. Volatility$^+$ measures the stock return volatility when return is positive in the past 250 days and Volatility$^-$ is equal to stock volatility when return is negative. In columns (2) and (4), we decompose the *Rank CGO$_{LDB}$* into two components depending on whether the value of *CGO$_{LDB}$* is positive or negative. We also control for investor- and day-fixed effects. The *t*-statistics clustered at the investor level are shown in the parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var =	I (Sell stock) × 100		I (Buy stock) × 100	
Motivated pessimism	0.361***	0.326***	-0.077*	-0.125***
	(7.72)	(6.98)	(-1.71)	(-2.79)
Motivated optimism	0.018	0.008	0.178***	0.088**
	(0.48)	(0.23)	(4.69)	(2.36)
Rank CGO$_{LDB}$	0.073***		1.080***	
	(2.76)		(31.00)	
Rank CGO$_{LDB}$ $\times I(CGO_{LDB} > 0)$		0.034		0.894***
		(1.45)		(30.12)
Rank CGO$_{LDB}$ $\times I(CGO_{LDB} < 0)$		-0.359***		-0.016
		(-9.08)		(-0.39)
Rank EXTV	-0.385***	-0.414***	0.350***	0.336***
	(-11.33)	(-12.18)	(9.28)	(8.91)
I(Ret = 0)	-0.331***	-0.334***	-0.186***	-0.183***
	(-23.59)	(-23.80)	(-12.37)	(-12.16)
I(Ret > 0)	-0.234***	-0.246***	0.114***	0.100***
	(-14.83)	(-15.52)	(5.41)	(4.72)
Sqrt (Time Owned)	-0.272***	-0.274***	-0.019**	-0.026***
	(-28.96)	(-29.17)	(-2.47)	(-3.45)
Log(Buy Price)	-0.047***	-0.043***	0.180***	0.176***
	(-4.48)	(-4.18)	(15.72)	(15.51)
Volatility$^+$	6.391***	5.956***	6.168***	4.736***
	(8.96)	(8.36)	(8.41)	(6.50)
Volatility$^-$	2.741***	2.719***	3.612***	3.465***
	(6.53)	(6.50)	(7.31)	(7.08)
Investor FE	YES	YES	YES	YES
Trading Day FE	YES	YES	YES	YES
Adj-Rsq	0.016	0.016	0.021	0.021
Observations	4,990,013	4,990,013	4,990,013	4,990,013