Attractiveness to optimists and stocks as lotteries in the cross-section of expected stock returns

Abstract

Theoretical studies find that optimistic investors, who overweight the probabilities of better outcomes, can survive and influence asset prices even in a competitive market. To study the impact of optimistic investors on the cross-section of expected stock returns, I define the measure of attractiveness to optimists of a stock based on rank-dependent probability weighting. In both portfolio-level and firm-level analyses, I find an economically and statistically significant negative relation between the measure of attractiveness to optimists and the expected stock return even after controlling for a set of control variables in the cross-section of U.S. stock returns. Furthermore, this framework both conceptually and empirically subsumes the MAX effect, one of the most common characteristics for lottery-type stocks.

Keywords: Optimistic investor, stocks as lotteries, stock returns, rank-dependent probability weighting

JEL classification: G11 G12

1 Introduction

One of the long lasting questions in finance is that whether irrational investors with wrong beliefs about future prospects could survive or at least influence asset prices. According to the literature, optimistic investors as a special case of irrational investors can influence asset prices substantially. DeLong et al. (1991) find that optimistic investors can survive in a competitive market by holding a riskier portfolio with higher growth rate. Although DeLong et al. (1991) use a partial equilibrium model, Kogan et al. (2006) use a general equilibrium model and find similar results. Specifically, moderately optimistic investors survive even in the long run. The intuition is that optimistic investors overweight the probabilities of better outcomes at the expense of the probabilities of the worse outcomes yielding a higher demand for riskier assets. These riskier assets generate high returns yielding high enough wealth to survive. However, this only works for moderately optimistic investors and not for too extremely optimistic investors taking too much risk. Furthermore, recent theoretical studies also find similar results (Dindo 2019, Borovička 2020). These theoretical results suggest that optimistic investors might have a strong influence on asset prices which could also contribute to explain the cross-section of expected stock returns. To investigate the impact of optimistic investors on the cross-section of expected stock returns, I define the measure of attractiveness to optimists for stocks based on rank-dependent probability weighting capturing optimism (Quiggin 1982, Diecidue and Wakker 2001). Assuming that investors form beliefs based on past returns following, for instance, Bali et al. (2011), Barberis et al. (2016), and Atilgan et al. (2020), I expect that stocks with more attractive return distribution to optimistic investors become overvalued because of the willingness to pay a higher price yielding a lower expected return compared to stocks with less attractive return distribution.

I find that the value-weighted portfolio decile of stocks with the most attractive stocks to optimists earn a 1.23% lower risk-adjusted return (Carhart, 1997) per month than the portfolio decile with the least attractive stocks to optimists. This is a both economically and statistically significant result with a t-statistic of -5.83. I also perform several additional portfolio-level and firm-level tests to mitigate any concern that the predictive power of the measure of attractiveness to optimists can be explained by already known characteristics. First, I perform bivariate sorts to control for several stock characteristics that are known to be predictor of future returns. Second, I also perform Fama-MacBeth regressions (Fama and MacBeth, 1973) to investigate the robustness of the results. I find that the predictive power of the measure of attractiveness to optimists remains substantial and highly significant in each case. Additionally, to mitigate the concern that the measure of attractiveness to optimists predicts future returns only because of its relation to positive skewness, I perform several additional tests in which I control for the skewness of the last month daily returns, the coskewness (Harvey and Siddique, 2000), idiosyncratic skewness (Harvey and Siddique, 2000), and expected idiosyncratic skewness (Boyer et al., 2010). I find that none of these measures could explain the predictive power of the measure of attractiveness to optimists. Finally, these results remain robust even after controlling for augmented Fama-French five factor model (Fama and French, 2015), the model of Stambaugh and Yuan (2017), the model of Daniel et al. (2020), and the model of Hou et al. (2015). These results suggest that the measure of attractiveness to optimists is a robust predictor of future returns consistent with theoretical studies.

This study is related to the studies of Stambaugh et al. (2012) and (2015) but it also differs from these studies both theoretically and empirically. Their studies investigate the empirical implications of the combination of two concepts, specifically, the market wide impact of sentiment (Baker and Wurgler, 2006) and the Miller's argument (Miller, 1977) that short-selling constraints can generate overpricing because of irrational investors. They find that the examined anomalies can be largely explained by this conceptual framework because these anomalies are stronger during high sentiment time periods and they are mainly driven by the short leg. In contrast with their approach, this study builds on the theoretical results of DeLong et al. (1991) and Kogan et al. (2006) and it provides a specific stock level measure for the impact of optimistic investors. Thus, Stambaugh et al. (2012) argue that mispricing is a results of short-selling constraints, while Kogan et al. (2006) argue that irrational, optimistic traders, influence asset prices even without short-selling constraints. This study differs from the studies of Stambaugh et al. (2012) and (2015) not only conceptually but also empirically. First, the predictive power of the measure of attractiveness to optimists can not be explained by mispricing (Stambaugh et al., 2012) and additional analyses show that there is a negative relation between expected returns and the measure of attractiveness to optimists even among the most undervalued stocks according to Stambaugh et al. (2012). Thus, this measure captures something fundamentally different from the mispricing score of Stambaugh et al. (2012) and (2015) since short-selling constraints should not be binding among the most undervalued stocks.

The conceptual framework of the MAX effect, one of the most common lottery like stock characteristic (Bali et al., 2011), is probably the closest to this study. Moreover, the the conceptual framework of this study can be also considered as a generalization of the MAX effect. Bali et al. (2011) also assume that investors form expectations based on past returns distribution, they also motivate their measure based on the model of Brunnermeier et al. (2007) besides other models, and they also assume that probability weighting is an important psychological mechanism in understanding investors pricing behavior. On the other hand, they motivate their measure with prospect theory, while this study motivates its measure with rank-dependent probability weighting to capture the attractiveness of a distribution to optimists. Second, the MAX effect is a special case of the the conceptual framework of this study yielding testable implications on the relation between MAX effect and the measure of attractiveness to optimists.

Consistent with the theoretical studies, I find that the MAX effect is mainly driven by the attractiveness to optimists measure. First of all, the measure of attractiveness to optimists have a stronger predictive power in the cross-section of expected stock returns. Second, the measure of attractiveness to optimist remains a strong predictor of future returns even after controlling for MAX effect, while the predictive power of MAX effect disappears after controlling for the measure of attractiveness to optimists. Furthermore, MAX effect is widely studied and there are several interesting known relations related to it. Thus, I also test these relations from the perspective of the measure of attractiveness to optimists. First, Nguyen and Truong (2018) find that MAX effect disappears around earnings announcement yielding a much stronger effect if there is no earnings announcement in the portfolio formation month. The measure of attractiveness to optimists exhibits the same relation even after controlling for the MAX effect, while this relation for the MAX effect disappears after controlling for the measure of attractiveness to optimists. Second, An et al. (2020) find that the MAX effect is concentrated among stocks in which investors face prior losses. This relation also disappears after controlling for the measure of attractiveness to optimists for the MAX effect, while it remains significant for the measure of attractiveness to optimists even after controlling for the MAX effect.

The approach of this study is also different from the study of Baker and Wurgler (2006). They provide a time-series of sentiment indices arguing that there are time periods when there are more naive, optimistic, retail investors on the market creating a positive and too optimistic environment, while there are also pessimistic time periods when these investors disappear from the market. In this paper, I focus on the cross-section of expected stock returns instead of the time-series of general level of optimism. Similarly this study is also different from the study of Fong and Toh (2014). They find that the MAX effect is stronger during high sentiment time periods. In this paper, I examine the predictive power for future returns of a proxy for the exposure to optimistic investors in the cross-section of expected stock returns, while Fong and Toh (2014) examine the predictive power of the MAX effect in different time periods.

Furthermore, I also investigate the robustness of the measure of attractiveness to optimists for several different specifications. Although similar measures such as the MAX effect is based on the last month daily returns, I use several different time horizons from one month to one year with daily and monthly observation frequency. I find that the predictive power of the measure for each specification is substantial and significant. Second, I create sub-samples based on characteristics that are proxies for limits to arbitrage and sophistication to explore the cross-sectional variation of the predictive power of the measure of attractiveness to optimists. Consistent with the behavioral based explanation, I find that the predictive power of the measure gets weaker for liquid, large stocks with more sophisticated investors suggesting that the source of the predictive power of the measure of attractiveness to optimists is mispricing instead of risk. However, all return spreads remain high and significant for stocks with low arbitrage cost and sophisticated ownership.

The contribution of this study to the literature is at least threefold. First, I add to the literature on optimism in asset pricing. Theoretical studies find that being optimist can help to survive in a market and they can have a substantial impact on asset prices (Kogan et al. 2006, DeLong et al. 1991). In addition, Baker and Wurgler (2006) find that stocks that are subjective to value are overvalued during high sentiment time periods because of the higher number of optimistic investors. I contribute to this literature providing a direct measure of attractiveness to optimists for stocks yielding a cross-sectional measure for the impact of optimism on stocks. I find that this measure has a strong predictive power for future returns.

Second, I contribute to the literature on applying probability weighting in asset pricing. Behavioral finance uses probability weighting to explain many phenomena in asset pricing. For instance, Barberis and Huang (2008) explain the preference for positively skewed securities in a model assuming investors applying probability weighting. Similarly, Barberis et al. (2016) find that the cumulative prospect theory value of a stock can predict the future returns mainly because of the probability weighting feature of cumulative prospect theory (Tversky and Kahneman, 1992). I add to this literature by investigating the potential impact of the rank-dependent probability weighting (Quiggin 1982, Diecidue and Wakker 2001) on the cross-section of expected stock returns.

Third, I add to the literature on stocks as lotteries. Kumar (2009) finds that retail investors have a preference for stocks with lottery-like payoffs creating an abnormal demand for these assets. Consistent with this result, Bali et al. (2011) find that stocks with an extremely high daily return in the last month, exhibiting lottery-like feature, earn a low expected return. I add to this literature by providing novel evidence on the mechanism why lottery-like assets can be overvalued. I find that the MAX effect is not only related to the measure of attractiveness conceptually but the measure of attractiveness to optimists can explain the predictive power of the MAX effect, while MAX effect doesn't explain the predictive power of the measure of attractiveness to optimists. Furthermore, similarly to the MAX effect, the measure of attractiveness to optimists can also provide an explanation for the idiosyncratic volatility puzzle (Ang et al., 2006).

The remainder of the paper is organized as follows. Section 2 describes the conceptual framework of rank-dependent probability weighting, its relation to cumulative prospect theory, construction of measure, and the literature on MAX effect. Section 3 describes the data, the results of the portfolio-level and firm-level tests, and additional tests to explore the robustness of the predictive power of the measure of attractiveness to optimists for future returns. Section 4 concludes.

2 Conceptual Framework

In this section, first, I present an overview of the literature on the MAX effect in the cross-section of expected stock returns. Second, I present the elements of rank-dependent probability weighting (Quiggin 1982, Diecidue and Wakker 2001) and the differences between the probability weightings of rank-dependent utility and cumulative prospect theory (Tversky and Kahneman, 1992). I also discuss the relation between the conceptual framework of rank-dependent utility and the MAX effect to present the similarities and differences. Finally, I present the construction of the measure of attractiveness to optimists.

2.1 MAX Effect

There is a growing number of studies on the preference for lottery-like assets. According to these studies, there is an increased demand for assets with small probability of a large payoff yielding a lower expected return (e.g., Bali et al. 2011, Kumar 2009). The negative relation between the subsequent monthly return and the current month's maximum daily return (MAX effect) as a proxy for lottery-like assets is documented for several stock markets including the U.S. (e.g., Byun et al. 2020; Bali et al. 2011), Europe (Walkshäusl, 2014), Canada (Aboulamer and Kryzanowski, 2016), China (Nartea et al., 2017), Australia (Zhong and Gray, 2016), Africa (Wu et al., 2019), Brazil (Berggrun et al., 2017), and several emerging markets (Seif et al.,

2018) and even in cryptocurrencies (Zhao et al., 2024)[1]. Furthermore, Cheon and Lee (2017) document the MAX effect worldwide in a sample of 42 countries and they find that behavioral explanations such as overconfidence and attention plays an important role in explaining the profitability of the MAX effect across countries. Similarly, Bali et al. (2021) find that assets with lottery-like payoffs are more overvalued for stocks with high retail-ownership and for stocks attracting attention.

Consistent with a behavioral explanation, the MAX effect seems to highly depend on market optimism. Fong and Toh (2014) find that the profitability of a long-short strategy based on the MAX effect is concentrated during high sentiment time periods in the U.S. stock market and Cheema et al. (2018) find similar results in the Chinese stock market. Moreover, the demand for lottery-like stocks can also provide a behavioral explanation for the idiosyncratic puzzle (Bali et al., 2011) and for the beta anomaly (Bali et al., 2017).

The MAX effect is motivated by the concept of probability weighting as a well-documented feature of cumulative prospect theory (Tversky and Kahneman, 1992). Cumulative prospect theory predicts that people overweight a small probability with large payoff. The MAX effect is also motivated (Bali et al., 2011) by the optimal expectations (Brunnermeier and Parker, 2005) and optimal beliefs (Brunnermeier et al., 2007) model. In these models, investors derive utility from expectations too and, as a result, they overestimate the probability of the better outcomes to have better expectations. Although these models are consistent with the MAX effect in many aspects, these models and frameworks are also consistent with the concept that investors exhibit optimism yielding a preference for certain type of stocks. For instance, Brunnermeier and Parker (2005) motivate their optimal expectations model with the literature in psychology on optimism which documents that people often overestimate the probability of the good outcomes (e.g., Weinstein, 1980; Buehler et al., 1994).

2.2 Rank-dependent Probability Weighting

To measure the attractiveness of a stock to optimists, I adapt the probability weighting model of Quiggin (1982) which is also known as anticipation utility or rank-dependent utility. The intuition of the rank-dependent utility is that it can capture optimism and pessimism (Diecidue and Wakker, 2001). The rank-dependent utility is also strongly related to the cumulative prospect theory. Specifically, rank-dependent utility has been applied in cumulative prospect theory (Tversky and Kahneman,

[1]In general, MAX effect became one of the most important characteristic to control for in asset pricing including special asset markets such as cryptocurrencies (e.g. Zhang et al. 2021)

1992) to resolve many critiques to prospect theory. Namely, the original prospect theory (Kahneman and Tversky, 1979) could be applied only to lotteries with two outcomes and it also implies preference for dominated lotteries in certain cases.

In the conceptual framework of rank-dependent utility (Diecidue and Wakker, 2001), optimistic decision-maker overweights the probability of the better outcomes at the expense of the probability of the worse outcomes. Although rank-dependent utility is strongly related to cumulative prospect theory, there are also several important differences. First, probability weighting based on rank-dependent utility ranks all the states of the world based on their payoffs from the worst to the best outcome, while cumulative prospect theory ranks the states of the world for gains and losses in two different rankings. Second, probability weighting based on rank-dependent utility captures optimism by overweighting the probability of the best and better outcomes, while cumulative prospect theory overweights small probabilities and underweights large probabilities for both the best and the worst outcomes. To illustrate some differences, Table 1 provides a detailed comparison of the two conceptual frameworks in an example.

To present the elements of rank-dependent probability weighting, let's assume that there are N states of the world and risky prospects can be defined as a lottery L $(p_1, x_1, \ldots, p_n, x_n)$ that pays x_i in state i with probability of $p_i \geq 0$ for all $i = 1 \ldots N$ and $\sum_i p_i = 1$. Without the loss of generality, it is also assumed that the payoffs are ordered from the smallest to the largest, thus, x_1 is the smallest payoff and x_N is the largest payoff from all possible payoffs. To evaluate a risky prospect, rank-dependent utility use the following formula:

$$\sum_{i}^{N} \pi_i U(x_i) \tag{1}$$

, where π_i is a decision weight and defined in the following way

$$\pi_i = w(p_1 + p_2, \ldots, p_i) - w(p_1 + p_2, \ldots, p_{i-1}) \tag{2}$$

and $\pi_1 = w(p_1)$.

A decision-maker is optimist if $w(\cdot)$ is convex and pessimist if $w(\cdot)$ is concave (Diecidue and Wakker, 2001). To capture this intuition, I define $w(p) = p^{\alpha}$ (following, e.g., Bombardini and Trebbi 2012), where $0 \leq \alpha < 1$ yields pessimism, $\alpha > 1$ yields optimism, and $\alpha = 1$ yields a rational decision-maker using the objective probabilities. In this framework, the level of optimism is an increasing function of α when $\alpha > 1$.

To illustrate the mechanism of rank-dependent probability weighting in Table 1, consider the following example in which there are 20 states of the world with 5% probability each.

The first row in Table 1 presents the objective probabilities 5% for each possible outcome. The second, third, fourth and fifth row presents the subjective probabilities for different level of optimism. In the second row $\alpha = 2$ presents a moderately optimistic investor. In this case, the best outcome's subjective probability almost doubles and the worst outcome's subjective probability becomes only 0.25%, while the rest of the outcomes' subjective probabilities decrease in a linear fashion from the best to the worst. Increasing the level of optimism means that the best outcome's probability gets more and more overweighted, while the probabilities of worse outcomes get more and more negligible. For instance, in the third row, $\alpha = 4$ already means that the best outcome's subjective probability gets more than three and a half times higher, while even the fourth worst outcome's subjective probability is only 0.11%. Thus, there is an exponential decrease in the subjective probabilities from the best to the worst.

The fifth row in Table 1 presents the extremely optimistic beliefs when $\alpha = \infty$ yielding that the decision-maker only considers the best outcome to represent the lottery. Even though it may appear a little bit too extreme case, this case is conceptually is the same as the MAX effect (Bali et al., 2011). According to the MAX effect, investors use past returns to form beliefs about future returns (Bali et al., 2011) and investors only observe the maximum daily return of the last month. Thus, the investors represent a stock's expected return by its best possible outcome. As a consequence, the MAX effect can be considered as a sub-case of this conceptual framework with the specification of infinite optimism.

The sixth, seventh, and eighth row presents the subjective probabilities for pessimistic decision-makers. Similarly to the optimistic case, the more pessimistic the decision-maker is, the more exponentially the probabilities decrease from the worst to the best outcome. The eighth row presents the extremely (infinitely) pessimistic decision-maker's subjective probabilities yielding that the decision-maker represents the lotteries with its worst outcome. Again, assuming that investors use past returns to form beliefs about future returns following Bali et al. (2011) (also Barberis et al. 2016), this specification coincides with the MIN effect (Bali et al., 2011) which is the lowest daily return of the last month. This example also illustrates that rank-dependent probability weighting with optimism does not predict the MIN effect, while cumulative prospect theory does.

Finally, the ninth and tenth row presents the subjective probabilities of cumulative prospect theory (Tversky and Kahneman, 1992) to make them more comparable with the subjective probabilities of rank-dependent utility. Although the sign of the outcome is not important for rank-dependent probability weighting, it becomes important for the cumulative prospect theory. For the sake of comparability, I assume that all outcomes are gains in this example. Using the original estimated parameters (Tversky and Kahneman, 1992) which is often also used in asset pricing literature (e.g., Barberis et al. 2016), it presents two specifications. First, $\delta = 0.61$ is used for gains. Second, $\delta = 0.69$ is used for losses. In each specification, both the best and the worst outcomes' subjective probabilities are overweighted. These specifications capture the intuition of cumulative prospect theory yielding an overweight of the probabilities of the best and the worst outcomes with small probabilities. Thus, in this specification, both the worst and the best outcomes are approximately doubled compared to the objective probabilities, while there is an exponential decrease in subjective probabilities from the extreme outcomes to the outcomes in the middle.

2.3 Construction of Measure

In this section, I define the measure of attractiveness to optimists based on two key assumptions. First, following, e.g., Bali et al. (2011) and Barberis et al. (2016), investors use past returns to form beliefs. Second, optimistic investors distort probabilities based on rank-dependent utility. These two assumptions are also consistent with the results of the study of Kress et al. (2018) which finds that people tend to update their expectations in an optimistic direction with selective attention.

To formulate the measure of attractiveness to optimists (AO), I assume that each day of the last month has the same probability to occur and optimists apply the rank-dependent probability weighting with a given α parameter where $w(p) = p^{\alpha}$ to evaluate the attractiveness of a stock.

Formally,

$$AO_{j,t} = \sum_{i} \pi_{i,j,t} r_{i,j,t} \tag{3}$$

,where

$$\pi_i = w(p_1 + p_2, \ldots, p_i) - w(p_1 + p_2, \ldots, p_{i-1}) \tag{4}$$

and $\pi_1 = w(p_1)$ and $w(p) = p^{\alpha}$.

$AO_{j,t}$ represents the attractiveness to optimists of stock j in month t and $i = 1 \ldots N$ are the trading days of month t, where $i < l$ holds if and only if $r_{i,j,t} \leq r_{l,j,t}$ and $r_{i,j,t}$ is the return of stock j in month t on day i.

I choose the last month daily returns to make the results more comparable with the MAX effect which is the most typical measure for lottery-type stocks. Assuming $\alpha = \infty$ yields exactly the MAX effect, while assuming $\alpha = 0$ yields the MIN effect (Bali et al., 2011) in this conceptual framework. Thus, the MAX effect is a special case of the measure of attractiveness to optimists. Although the specification based on the last month daily returns is the closest to MAX effect, I also present several alternative specifications to investigate the robustness of the measure of attractiveness to optimists. Specifically, I use several different time horizons such as the last quarter daily returns, the last year daily returns, and the last year monthly returns. Furthermore, I use several level of optimism based on the last month daily returns. According to theoretical results of Kogan et al. (2006), I hypothesize that assuming a moderate optimism yields a stronger predictive power for future returns than assuming an infinitely large optimism which is the MAX effect.

Finally, to define moderate optimism, I need to make an assumption on α. Although Das et al. (2019) find that people with higher income and higher level of education tend to be more optimistic about the future including the stock market returns suggesting that optimism play an important role for typical retail investors, it is a difficult task since this study does not argue that all people are optimist or that most of the investors would be optimist. Thus, a population wide or any experimental estimate for optimism would not be relevant in this case. Moreover, theoretical results of DeLong et al. (1991) and Kogan et al. (2006) argue that moderately optimistic investors would be successful instead of optimism in general which is even harder to define empirically. In this study, I use $\alpha = 2$ as a specification of a moderately optimistic investor. Even though I use a given $\alpha = 2$ specification for moderately optimistic investors, in this case, it is enough that the theoretical studies argue that any reasonable value for moderately optimistic specification should be better than the infinitely optimistic specification ($\alpha = \infty$) which is the MAX effect.

3 Empirical Results

In this section, I present an overview of the main empirical results of testing the predictive power of the measure of attractiveness to optimists for the cross-section of expected stock returns. First, I present the data and the variables that I use in the empirical analyses. Second, I perform univariate portfolio-level analyses to show the profitability of long-short strategies based on the measure of attractiveness to optimists with several different specifications. I find that the specification of moderate optimism provides a stronger predictive power than the specification of extreme optimism consistent with the theoretical results of Kogan et al. (2006).

Third, I provide summary statistics of the measure of attractiveness to optimists and an overview of its relation to other stock characteristics that are known to predict future returns. Fourth, I investigate the relation among the predictive power of the MAX effect, the idiosyncratic volatility, and the measure of attractiveness to optimists. I find that the predictive power of both MAX and idiosyncratic volatility is driven by the measure of attractiveness to optimists. Fifth, I also perform several bivariate portfolio-level analyses and firm-level regressions to show the robustness of the results. Sixth, I provide additional firm-level regressions to explore the predictive power of the measure of attractiveness to optimists based on different time horizons. Seventh, I investigate the effect of market sentiment (Baker and Wurgler, 2006) on the predictive power of attractiveness to optimists in the time-series. I find that higher number of optimistic investor on the market yields a stronger predictive power for the measure of attractiveness to optimists. Eight, I present additional tests to investigate the role of limits to arbitrage and sophistication. I find that the predictive power of the measure of attractiveness to optimists is stronger among stocks with higher limits to arbitrage and less sophisticated ownership. However, I also find that the measure of attractiveness to optimists still remains a significant and substantial predictor of future returns for stocks with lower limits to arbitrage and more sophisticated ownership. Finally, I examine the role of earnings announcements and prior gains and losses in the predictive power of attractiveness to optimists since they are known to be important for the MAX effect. I find that all relations disappear for the MAX effect after controlling for the measure of attractiveness to optimists, while they remain significant for the measure of attractiveness to optimists even after controlling for the MAX effect suggesting that these relations are mainly driven by the measure of attractiveness to optimists instead of the MAX effect.

3.1 Data

I obtain daily and monthly stock prices, share volume, holding period returns, number of shares outstanding, and value-weighted market return from CRSP and book value for total assets from COMPUSTAT. The data cover the period from December 1925 to December 2018 for all common shares from CRSP listed on New York Stock Exchange(NYSE), Nasdaq, and American Stock Exchange (AMEX). Extending the book equity data for early dates and values not covered in COMPUSTAT, I use data from Kenneth French's website[2]. I present the results from July 1962 to make it more comparable with the results in the literature. However, all conclusions remain the same for longer time period. I define size as the logarithm of the number of

[2] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

shares outstanding in millions in month t times the price in month t, BTM as the logarithm of the firm's book value divided by its market value where these values were calculated following Fama and French (1992), MOM as the stock's cumulative return from month $t-11$ to the end of month $t-1$ following Jegadeesh and Titman (1993), REV as the stocks' return in month t, ILLIQ as the Amihud (2002) measure using daily return and volume data in month t, Beta as the market beta based on the last month daily returns, IVOL as the volatility of the stocks' daily idiosyncratic volatility in month t (Ang et al., 2006), MAX as the stock's maximum daily return in month t (Bali et al., 2011), MIN as the stock's minimum daily return in month t (Bali et al., 2011), and SKEW as the skewness of the stock's daily return in month t[3]. I also create the prospect theory value based on its probability weighting feature for each stock for each given month t based on the last month daily returns to make it more comparable with the measure of attractiveness to optimists. I use the prospect theory value with a reference point of zero (PT_0) and with a reference point of the market return (PT_m). Finally, I exclude stock-month observations if any of these variables is missing and all penny stocks (<\$5). I winsorize size, BTM, MOM, REV, ILLIQ, Beta, and SKEW at the 1% level in each month.

3.2 Univariate Portfolio-level Analyses

In this section, I perform standard univariate sorts to investigate the profitability of long-short strategies based on the measure of attractiveness to optimists. In this conceptual framework, the MAX effect can be considered as a sub-case when investors are infinitely optimistic. However, theoretical results suggest that assuming a more moderately optimistic investor could be more realistic (Kogan et al., 2006) yielding an even stronger measure to predict future returns. To test this theoretical implication, I provide both equal-weighted and value-weighted portfolio results for four different level of optimism. Table 2 presents the results of the univariate sorts, the return spreads and their t-statistics and the intercept from the Carhart (1997) model.

The MAX effect is at present in this sample as well. In the case of $\alpha = \infty$, the measure of attractiveness to optimists is identical to the MAX effect. Both equal-weighted and value-weighted portfolios exhibit the same patterns and the return spreads and Carhart model's intercepts are also similar to the results of Bali et al. (2011) for the MAX effect. However, these return spreads and corresponding t-statistics are the lowest among all examined specifications. Furthermore, decreasing

[3]Although it is not an established characteristic in the literature, Aretz and Arisoy (2023) find that skewness is more likely to be priced in the short-run.

the level of optimism (α) monotonically increases the return spreads and their corresponding t-statistics. These results are consistent with the theoretical prediction (Kogan et al., 2006) that moderately optimistic investors are more likely to survive in the markets than extremely optimistic investors. The intercept of the Carhart model for equal-weighted (value-weighted) portfolios is -1.59 (-1.23) with a t-statistic of -10.42 (-5.83) for a moderately optimistic case ($\alpha = 2$), while this intercept is -0.92 (-0.67) for equal-weighted (value-weighted) portfolios for the MAX effect (extremely optimistic, $\alpha = \infty$). Thus, the return spreads increase with more than 50% for both equal-weighted and value-weighted portfolios using the specification of moderately optimistic investors instead of the extremely optimistic investors (MAX effect).

I perform several additional analyses to test the robustness of the predictive power of the measure of attractiveness to optimists after controlling for several known factor models. Specifically, I control for the Fama-French five factor model (Fama and French, 2015) augmented with momentum and the liquidity factor (Pástor and Stambaugh, 2003), the model of Stambaugh and Yuan (2017), the model of Daniel et al. (2020), and the Q model of Hou et al. (2015). The results are summarized in Table 3. I find that none of these models can explain the predictive power of the measure of attractiveness to optimists. The return spread between the deciles with the highest and lowest values is at least -1.20% for each case with a t-statistic of -6.45 for equal weighted portfolios. These return spread decrease for value-weighted portfolios but they all still remain both economically and statistically significant for each case.

Furthermore, the subsequent monthly measure of attractiveness to optimists is highly predictable based on the current value of the attractiveness to optimists. Thus, the assumption that investors form belief based on the past return distribution seems to be rational. To investigate this relationship, I run Fama-MacBeth type regressions of subsequent month's measure of attractiveness to optimists on the current measure of attractiveness to optimists and a set of control variables including market beta, size, book-to-market ratio, momentum, short-term reversal, illiquidity, MAX effect, idiosyncratic volatility, and skewness. I find that the time-series average coefficient on the current measure of attractiveness to optimists is 0.66 with the t-statistics of 65.62 even after controlling for these additional characteristics.

All these results suggest that using $\alpha = 2$ specification provides a stronger predictor of future returns than the MAX effect, while other specifications are only a noisy proxy for the attractiveness to optimists. To provide a more direct test to compare the measure of attractiveness to optimists when $\alpha = 2$ with the MAX effect, I perform several additional portfolio-level analyses in a following section.

Although the measure of attractiveness to optimists provide strong and robust results, it could be also interesting to investigate the potential effect of pessimism. According to the theoretical results, pessimists do not survive in a competitive market suggesting that a measure of attractiveness to pessimists should not have a strong and robust predictive power for future returns. Similarly to Table 2, the results of the measure of attractiveness to pessimists are summarized in Table 4.

First of all, these measures seem not to predict future returns. Although the specification of extreme pessimism ($\alpha = 0$), also known as the MIN effect (Bali et al., 2011), seem to have a significant predictive power for the future returns, this predictive power does not seem to be robust. The return spread for value-weighted portfolios is 0.52% and significant, however, this return spread becomes insignificant for equal-weighted portfolios. Furthermore, there is no monotone increase in the expected returns from portfolio 1 with the most attractive stock to pessimists to portfolio 10. These return spreads become even smaller assuming a specification with a more moderate pessimism. These results suggest that measures based on the attractiveness to pessimists do not provide substantial and robust predictive power for future returns, while the measures based on the attractiveness to optimists provide both economically and statistically significant predictive power for future returns consistent with the theoretical results.

3.3 Summary Statistics

In this section, I present the summary statistics to explore the relation between the measure of attractiveness to optimists and several variables that could be related to the measure or strong predictors of future returns. Specifically, I sort stocks into portfolio deciles based on the measure of attractiveness to optimists in each month and I provide the time-series averages of each characteristic for each decile.

Table 5 presents the summary statistics with several striking patterns. First of all, there is a strong positive correlation between the measure of attractiveness to optimists and the MAX effect as expected by construction. To address this similarity between the two measures, I show, in a following section, that the predictive power of MAX effect disappears after controlling for the measure of attractiveness to optimists, while the predictive power for future returns of the measure of attractiveness to optimists remains substantial and significant even after controlling for the MAX effect.

Second, idiosyncratic volatility also has a positive relation with the measure of attractiveness to optimists. This relation is also intuitive based on the construction of the measure of attractiveness to optimists. Optimistic investors overweight the high returns and underweight the low returns, as a consequence, if positive and negative returns are high in terms of absolute values, then the overvaluation of the extremely positive returns and the undervaluation of the extremely negative returns yields a better expected return for an optimistic investor. Consistent with this intuition, the positive relation between the MIN effect and the measure of attractiveness to optimists probably comes from the fact that higher MIN value usually means higher idiosyncratic volatility. To investigate this relation between idiosyncratic volatility and the measure of attractiveness to optimists similarly to the MAX effect, I also provide additional analyses in a following section.

Third, according to Baker and Wurgler (2006), stocks that are highly subjective and difficult to arbitrage are more exposed to optimists in the time series. Consistent with this concept, Table 5 shows that small firms, growth stocks, illiquid stocks, and high volatility stocks tend to have high values of the measure of attractiveness to optimists. To mitigate any concern that these variables might drive any of the results, I control for these variables in both portfolio-level and firm-level tests. I find that none of these variables can explain the predictive power of the measure of attractiveness to optimists.

Fourth, there is a clear positive relation between the short-term reversal and the measure of attractiveness to optimists. The reason behind this relation probably is technical since higher last month return is associated with higher average daily returns of the last month yielding a higher expected return, especially, if the higher returns are even overweighted by optimistic investors. Furthermore, there is a weaker but still positive relation between the momentum effect and the measure of attractiveness to optimists even though this relation is less intuitive. I also include these variables in my analyses to control for them and to separate the effect of the measure of attractiveness to optimists from these well-known variables.

Fifth, there is a positive relation among the measure of attractiveness to optimists, beta and skewness. Both relations probably comes from the construction of the measure since some extreme high daily returns yield higher values for the measure of attractiveness to optimists but similarly higher beta and skewness of the last month daily returns. Although both skewness of the last month daily returns and market beta do not seem to predict future returns, I also include these variables in the analyses to control for them.

Finally, there is a striking positive relation between the measure of attractiveness to optimists and the cumulative prospect theory values using the probability weighting and reference-dependence features defined as Barberis et al. (2016). Although Barberis et al. (2016) find that the last month observation drives substantially their results, they define their prospect theory value on monthly returns instead of the last month daily returns. However, I use the last month daily returns to define this prospect theory values to make it more comparable with the measure of attractiveness to optimists and the MAX effect. To provide evidence that the measure of attractiveness to optimists is different from the cumulative prospect theory approach, I also perform several additional tests in a following section.

3.4 MAX Effect, Idiosyncratic Volatility, and Attractiveness to Optimists

In this section, I explore the relation between the measure of attractiveness to optimists and several other variables including the MAX effect, the MAX effect based on the five highest daily returns, the idiosyncratic volatility, and two measures based on cumulative prospect theory. To test that the measure of attractiveness to optimists can explain the predictive power of these five measures, I regress the measure of attractiveness to optimists on a given control variable, squared control variable and a constant and I take the residuals in each month. I find that these residuals have both economically and statistically significant predictive power for the future returns in each case. In contrast, regressing these variables on the measure of attractiveness to optimists, the squared measure of attractiveness to optimists, and a constant and taking the residuals make these variables' predictive power disappear. Table 6 presents the results of these tests.

As Table 6 reports in panel A, the return spreads between stocks with high and low values of the measure of attractiveness to optimists after controlling for the MAX effect are substantial and significant for both equal-weighted and value-weighted portfolios. Equal-weighted portfolio return spread is -1.03% per month with a t-statistic of -8.42, while the value-weighted portfolio return spread is -0.58% per month with a t-statistic of -3.36. These results are getting even stronger after obtaining the intercept for the Carhart model with four factors. However, as reported in Table 6 in Panel B, MAX effect loses its predictive power entirely for future returns after controlling for the measure of attractiveness to optimists for value-weighted portfolios. Furthermore, the equal-weighted portfolio return spread is even highly positive and significant instead of the expected negative relation. These results suggest that the measure of attractiveness to optimists drives the predictive power of the MAX effect. Consistent with the conceptual framework, it seems that MAX effect is a special extreme case of the measure of attractiveness to optimists and assuming a more moderate optimism generates a measure that is stronger in predicting the future returns.

Although MAX effect seems to lose its predictive power after controlling for the measure of attractiveness to optimists, an alternative specification of MAX effect might keep its predictive power. Using the average of the five highest daily returns of the last month (MAX(5)) defined as an alternative specification of the MAX effect has been already mentioned in Bali et al. (2011) and it has been used in other studies as well (e.g., Nartea et al., 2017) to measure lottery-like feature of a stock. As Table 6 reports, this alternative specification of MAX effect yields the same conclusions. The predictive power of the measure of attractiveness to optimists remains substantial and significant after controlling for MAX(5), while MAX(5) doesn't predict negatively the future returns anymore after controlling for the measure of attractiveness to optimists.

The MAX effect can also provide an explanation for the idiosyncratic volatility puzzle (Ang et al., 2006)[4]. Since the measure of attractiveness to optimists seem to drive the results of MAX effect, the measure of attractiveness to optimists might also provide an explanation for the idiosyncratic volatility puzzle. Data supports this hypothesis as Table 6 reports. Similarly to previous results, the idiosyncratic volatility puzzle disappears for value-weighted portfolios after controlling for the measure of attractiveness to optimists and the relation between idiosyncratic volatility and future returns becomes even positive and significant for equal-weighted portfolios. Furthermore, the measure of attractiveness to optimists keep its statistically strong and substantial predictive power for future returns even after controlling for the idiosyncratic volatility.

Finally, I also create the prospect theory values based on the last month daily returns using the probability weighting function of cumulative prospect theory following Barberis et al. (2016) to show that the measure of attractiveness to optimists is not only conceptually different from the probability weighting of cumulative prospect theory but it is also empirically different. Table 6 shows that, similarly to MAX effect and idiosyncratic volatility, these measures do not make the predictive power of the measure of attractiveness to optimists disappear, while they do not have significant predictive power for future returns after controlling for the measure of attractiveness to optimists.

To present additional evidence on the relation between the measure of attractiveness and these variables including the MAX, MAX(5), idiosyncratic volatility, and cumulative prospect theory values, I provide standard bivariate sorts similarly to the following section. Table 7 reports the results of the bivariate sort. Panel A in Table 7 reports the returns of the portfolio deciles of the measure of attractiveness to op-

[4]According to (Baars and Mohrschladt, 2024), idiosyncratic volatility drives the MAX effect in experiments confirming the need to control for idiosyncratic volatility in my tests. Furthermore, idiosyncratic volatility seem to have large impact on returns using this time horizon (Bergbrant and Kassa, 2021).

timists after controlling for MAX, MAX(5), idiosyncratic volatility, and cumulative prospect theory values. Consistent with previous results, the return spreads between the portfolio deciles with the most and the least attractive stocks to optimists are at least 0.63% for both equal-weighted and value-weighted portfolios and these return spreads are statistically significant in each case. These results confirms that these variables can not explain the predictive power of the measure of attractiveness to optimists even though these measure are quite similar to the measure of attractiveness to optimists.

Panel B in Table 7 reports the returns of the portfolio deciles of MAX, MAX(5), idiosyncratic volatility, and cumulative prospect theory values after controlling for the measure of attractiveness to optimists. Similarly to previous results, these results show that none of these measures have significant predictive power for the future returns for both equal-weighted and value-weighted portfolios after controlling for the measure of attractiveness to optimists. Furthermore, the return spreads based on equal-weighted portfolios are even positive and significant for MAX, MAX(5), and idiosyncratic volatility instead of the expected negative sign. These results confirm that the measure of attractiveness to optimists can explain the predictive power of the MAX effect and idiosyncratic volatility, while these measure do not explain the predictive power of the measure of attractiveness to optimists.

3.5 Bivariate Portfolio-level Analyses

In this section, I provide the results of bivariate sorts to show that the profitability of long-short trading strategies based on the measure of attractiveness to optimists remains large and significant even after controlling for a set of variables including market beta, market capitalization, book-to-market ratio, momentum, short-term reversal, illiquidity, and skewness of the last month daily returns. Specifically, I sort stocks into portfolio deciles based on the control variable in each month, then, I sort stocks based on the measure of attractiveness to optimists again into portfolio deciles in each portfolio of the control variables creating ten times ten portfolios. Finally, I form portfolio deciles based on their measure of attractiveness to optimists across the control variable deciles. This method provides new portfolio deciles which has still large variation in the measure of attractiveness to optimists, while it has little variation in the control variable.

Table 8 presents the results of the equal-weighted and the value-weighted bivariate portfolio returns. Panel A in Table 8 reports the equal-weighted portfolio returns and the return differences between the portfolios with high and low values of the measure of attractiveness to optimists. These return differences remain large and significant in each case and they are at least 0.68% with a t-statistic of -3.00. Thus, these variables seem to have limited impact on the predictive power of the measure of attractiveness to optimists. Panel B in Table 8 presents the value-weighted portfolio returns and the return differences. Similarly to the equal-weighted portfolio bivariate sorts results, return differences remain at least as large as 0.67% and significant in each case. Furthermore, the intercepts obtained from the Carhart (1997) model are substantial and highly significant in each case.

Thus, the measure of attractiveness to optimists not only explains the predictive power of MAX effect and idiosyncratic volatility but it also keeps its predictive power for future returns after controlling for additional standard known characteristics in bivariate sorts.

3.6 Firm-level Regressions

Portfolio-level analyses suggest that the measure of attractiveness to optimists can predict future returns and this predictive power can't be explained by other variables that are similar to it or already known to be predictors of future returns. Although portfolio-level analyses provide strong tests to investigate the predictive power of a measure, it also has some weaknesses. In this section, to provide additional information on the robustness of the measure of attractiveness to optimists, I perform several firm-level regressions.

In each month, I normalize each variable to make them more comparable to each other and, in each month, I regress the subsequent monthly excess return of each stock on the measure of attractiveness to optimists and a set of control variables including market beta, logarithm of market capitalization in millions, logarithm of book-to-market ratio, momentum, short-term reversal, illiquidity, MAX effect, idiosyncratic volatility, and a constant.

Table 9 reports the time-series averages of the coefficients of the Fama-MacBeth regressions (Fama and MacBeth, 1973). First column of Table 9 presents the time-series average coefficient of the measure of attractiveness to optimists when it stands alone in the regression. Consistent with the results of univariate sorts, the predictive power of the measure of attractiveness to optimists is both economically and statistically significant. One standard deviation increase in the measure of attractiveness to optimists predicts 0.41% lower expected return with a t-statistic of -6.30.

The second and the third columns of Table 9 present the time-series averages of the firm-level regressions' coefficients when several control variables are also included such as the market beta, market capitalization, book-to-market ratio, momentum, short-term reversal, and illiquidity. Including market beta, size, book-to-market ratio, and momentum even increased the predictive power of the measure of attractiveness to optimists, while including the short-term reversal and illiquidity decreased the predictive power a little. All in all, the time-series averages of the coefficients of the measure of attractiveness to optimists remain large and highly significant. One standard deviation change in the measure of attractiveness to optimists yield a -0.38% lower expected return with a t-statistic of -5.90 at least in each specification.

The fourth, fifth, and sixth column of Table 9 reports the time-series averages of the coefficients when the previous control variables are included plus the MAX effect and the idiosyncratic volatility. Consistent with portfolio-level analyses, both MAX effect and the idiosyncratic volatility becomes insignificant or even significantly positive, while the time-series averages of the coefficient of the measure of attractiveness to optimists remain substantial and highly significant. Including the MAX effect even increases the predictive power of the measure of attractiveness. Additional firm-level regressions' results reported in the seventh, eights, and ninth column of Table 9 confirm again the results of the bivariate sorts. Specifically, the negative relation between MAX and future returns disappears after controlling for the measure of attractiveness to optimists. The relation between MAX effect and future returns become positive and significant when only the measure of attractiveness to optimists and MAX effect are included in the regression, while the puzzling negative relation between idiosyncratic volatility and future returns also disappears when the measure of attractiveness to optimists is also included in the regressions. Similarly to the inclusion of the MAX effect, including the idiosyncratic volatility also increases the predictive power of the measure of attractiveness to optimists.

3.7 Skewness Measures

Although the predictive power of the measure of attractiveness to optimists based on portfolio and firm-level analyses seem to be strong and robust, these results can maybe be explained by the preference for positive skewness. Positively skewed returns are not only related to lottery-like assets but it is also related to the measure of attractiveness to optimists. As the summary statistics shows, there is a positive correlation between the skewness of the daily returns and the measure of attractiveness to optimists. In this section, in additional firm-level regressions (Fama and MacBeth, 1973), I control for several additional variables that are related to skewness including the skewness of the last month daily returns, the coskewness (Harvey and Siddique, 2000), idiosyncratic skewness (Harvey and Siddique, 2000), and the expected idiosyncratic skewness (Boyer et al., 2010) to show that the predictive power for future returns of the measure of attractiveness to optimists is not strongly affected by these skewness measures.

Table 10 reports the time-series averages of the coefficients when the measure of attractiveness to optimists, eight control variables and the set of four different types of skewness measures are included. Including any of the additional skewness variable in the regressions or including all of them do not change the relation between the measure of attractiveness to optimists and future returns. In each case, the predictive power of the measure of attractiveness to optimists remains large and highly significant with at least an average coefficient of -0.38 and a t-statistic of -3.77. All of these results suggest that the predictive power of the measure of attractiveness to optimists are not driven by these variables that are known to be related to the preference for positive skewness.

3.8 Time-series and Alternative Specifications

Although the measure of attractiveness to optimists based on the last month daily returns is the most comparable to the MAX effect and the idiosyncratic volatility puzzle, there are at least two additional interesting empirical questions related to the measure of attractiveness to optimists based on the inuition of the conceptual framework. First, does this concept provide a significant predictor of future returns based on alternative specifications of the time horizon? Second, is the predictive power for future returns of the measure of attractiveness to optimists stronger during time periods with more optimists and more optimistic sentiment? In these tests, data starts from July 1965 because of data availability of the sentiment index based on Baker and Wurgler (2006).

To address the first question, I create four different type of measures of attractiveness to optimists based on daily and monthly frequency observations and three different time horizons. Specifically, I create the measure of attractiveness to optimists based on the last month daily returns, the last quarter daily returns, the last year daily returns, and the last year monthly returns.

Panel A in Table 11 reports the time-series averages of the coefficient of the Fama-MacBeth (1973) regressions of the measure of attractiveness to optimists with different specifications after controlling for several variables including market beta, size, book-to-market ratio, momentum, short-term reversal, and illiquidity. In each specification, the measure of attractiveness to optimists has both economically and statistically significant predictive power for future returns. One standard deviation of increase in the measure of attractiveness to optimists based on the last month daily returns yield a 0.36% lower expected return with a t-statistic of -5.41. There are weaker but still substantial and highly significant results of the measure of attractiveness to optimists based on the daily returns of the last quarter or based on the daily returns of the last year. One standard deviation increase in the measure of attractiveness yields at least a 0.26% lower expected return with a t-statistic of -3.08 at least. Finally, using the monthly returns of the last year instead of the daily returns of the last year to construct the measure of attractiveness to optimists even increases the predictive power of the measure. One standard deviation increase in the measure of attractiveness to optimists based on monthly returns of the last year yields a 0.31% lower expected return with a t-statistic of -3.94. These results suggest that the measure of attractiveness to optimists can predict the future returns with several different specifications of the frequency and the time horizon. It seems that the measure of attractiveness to optimists remains significant predictor of future returns even with alternative specifications.

To address the second question, I split the sample based on the level of sentiment (Baker and Wurgler, 2006) into optimistic time periods when the sentiment index is above its historical median and into a pessimistic (lack of optimism) time periods when the sentiment index is below the median. Consistent with expectations, the predictive power of the measure of attractiveness to optimists becomes stronger and statistically even more significant for each specification of the measure during optimistic time periods as reported in panel B in Table 11, while the predictive power of the measure for each specification decreases dramatically or even disappears during pessimistic time periods as reported in panel C in Table 11. For instance, the time-series average of the coefficient of the measure of attractiveness to optimists based on the last month daily returns is -0.55 for optimistic time periods and it is only -0.18 for non-optimistic time periods. Similarly, the time-series average of the coefficients of the measure of attractiveness to optimists based on the monthly returns of the last year is -0.49 with a t-statistic of -4.52 during optimistic time periods and it is only -0.13 with an insignificant t-statistic of -1.27 during non-optimistic time periods. The time-series averages of the coefficients of the measure of attractiveness to optimists based on the daily returns of the last year generates the biggest difference between the optimistic and pessimistic time periods. The time-series average coefficient is -0.46 for optimistic time periods, while it is only -0.06 for non-optimistic time periods.

First of all, these results suggest that the predictive power of the measure of attractiveness to optimists is concentrated in optimistic time periods which is consistent with the hypothesis that this measure is related to optimism. Second, these results also show that several different specifications of the measure do not only have robust predictive power but the predictive power of all of these specifications is concentrated in optimistic time periods suggesting that all of these specifications are strongly related to optimism.

3.9 Limits to Arbitrage

In this section, I investigate the role of limits to arbitrage in the predictive power of the measure of attractiveness to optimists. A negative relation between the limits to arbitrage and the predictive power of the measure of attractiveness to optimists would suggest a behavioral explanation for the results instead of a risk based explanation consistent with the conceptual framework.

To test this hypothesis, I test whether the predictive power of the measure of attractiveness to optimists is stronger among small or illiquid stocks. Furthermore, I also investigate the impact of sophistication of the investors on the predictive power of the measure of attractiveness to optimists using the ratio between the institutional ownership and the total number of common shares outstanding as a proxy for sophistication.

Each month, I sort stocks into two groups based on the median of the market capitalization, illiquidity, and idiosyncratic volatiltiy to explore the effect of limits to arbitrage on the predictive power of the measure of attractiveness to optimists. Within these sub-samples, I sort stocks into portfolio deciles based on the measure of attractiveness to optimists and I form equal-weighted and value-weighted portfolio returns and the return differences between the portfolios with the most attractive stocks and the least attractive stocks to optimists. I use market capitalization, illiquidity, and idiosyncratic volatility as a proxy for the cost of arbitrage following Brav et al. (2009). However, the measure of idiosyncratic volatility is not a perfect measure for the cost of arbitrage in this case because it is highly correlated with and related to the measure of attractiveness to optimists. It could be considered as an even stronger test since stocks in the low idiosyncratic volatility sub-sample have not only lower arbitrage cost but, in this sample, the variation of the measure of attractiveness to optimists is also smaller. Finally, I also create two sub-samples, using the one-quarter lagged institutional ownership as a proxy for sophistication of the owners of the stock. In this case, I use the 67th percentile to split the sample in each month because of the high number of zero values especially in the beginning of the sample. The sample starts in 1980 for institutional ownership data. Higher institutional ownership suggests more sophisticated investors. The results are summarized in Table 12.

As Table 12 reports, there is a striking difference for the predictive power of the measure of attractiveness to optimists for future returns between low arbitrage and high arbitrage cost sub-samples. Although the measure of attractiveness to optimists is a significant predictor of future returns in both sub-samples, the return differences between the two extreme portfolio deciles doubles almost in each specification for higher arbitrage costs. For instance, the value-weighted (equal-weighted) return difference is -1.57% (-1.81%) per month for illiquid stocks, while this return difference is only -0.59% (-0.81%) with a t-statistic of -2.17 (-3.21) per month for liquid stocks. Similarly, institutional ownership also has an impact on the results suggesting that the measure of attractiveness to optimists has a weaker predictive power for future returns among stocks with higher institutional ownership consistent with expectations. However, the return differences remain substantial and statistically significant in each case, specifically, they are at least -0.83% with a t-statistic of -2.51.

These results suggest that arbitrage cost and sophistication are important to explain the cross-sectional variation of the predictive power of the measure of attractiveness to optimists. However, these results also suggest that the measure of attractiveness to optimists remains an important and substantial predictor of future returns even among large, liquid stocks with low idiosyncratic volatility and high institutional ownership[5].

To investigate the impact of mispricing on the predictive power on the measure of attractiveness to optimists, I also perform bivariate sorts using the mispricing

[5] The significant predictive power among stock with high institutional ownership does not mean that professional investors also exhibit the same behavior since even these stock are not fully owned by institutional investor.

score of Stambaugh et al. (2015). I find that the impact of optimistic investors are much stronger among overvalued stocks than among undervalued stocks as Table 13 reports. It supports the hypothesis that the predictive power of the measure of attractiveness is strongly related to mispricing and it is less likely that it would be driven by risk.

3.10 Robustness

In this section, I perform several additional firm-level regressions on different subsamples to explore the robustness of the results. Table 14 reports the results.

First, I exclude any stock with a market capitalization lower than the 50th percentile in the NYSE in a month. This is a stricter requirement compared to previous tests since the median firm size is much smaller than the 50th percentile in the NYSE. The predictive power of the attractiveness to optimists measure gets smaller in this sample but it is still both economically and statistically significant. One standard deviation change in the measure yields a 0.19% lower expected return per month.

Second, I exclude the 10% most illiquid stocks in each month to control for the impact of illiquid stocks. I find that the predictive power of the measure in this subsample is similar to previous results. One standard deviation change in the measure leads to a 0.36% lower expected return per month.

Third, I exclude stocks in financials ($6000 \leq$ SIC <7000) and utilities ($4900 \leq$ SIC <5000). I find that excluding these stocks even improves the predictive power of the measure suggesting that they don't drive the results.

Fourth, I exclude all illiquid stocks, smaller firms than the 50th percentile in NYSE, and financials and utilities to provide a strong robustness test. The predictive power of the attractiveness to optimists measure still remains substantial and statistically significant. One standard deviation change increase in the measure yields a 0.24% lower expected return per month.

Finally, to present historical trends, Table 14 also presents the time-series average coefficients for subperiods including the period of 1962-1979, 1980-1999, and 2000-2018. In each subperiod, the time-series average coefficient of the measure is substantial and significant. Furthermore, there is no decreasing trend in the coefficients suggesting that this impact of optimistic investors do not disappear in time.

All these results show that the predictive power of the measure of attractiveness to optimists is robust across time periods and for large and liquid stocks.

3.10.1 MAX Effect and Attractiveness to Optimists

The measure of attractiveness to optimists seems to explain the predictive power of MAX effect, however, the MAX effect seems to be related to other phenomena as well. First, Nguyen and Truong (2018) find that the maximum daily return does not seem to capture lottery-type characteristic in the month of earnings announcement. Second, An et al. (2020) find that the predictive power of MAX effect is concentrated among stocks with prior losses. In this section, I provide additional analyses to explore the relations among the measure of attractiveness to optimists, MAX effect, earnings announcements, and reference-dependent preferences.

Nguyen and Truong (2018) argue that maximum daily return is not a good proxy for lottery demand in a month with fundamentally relevant information such as the month of earnings announcements. Similarly, I argue that the measure of attractiveness to optimists is based on the assumption that investors use past return distribution to form belief about the future returns distribution. Thus, it is intuitive to assume, similarly to Nguyen and Truong (2018), that investors do not use the past return distribution when it is driven by news. To test this hypothesis, I run Fama-macBeth regressions including the interaction term between the measure of attractiveness to optimists and the dummy variable of earnings announcements (which is equal to one in the month of earnings announcement). The results are summarized in Table 15. The first column of Table 15 reports the time-series average coefficients when only the measure of attractiveness to optimists, its interaction with earnings announcement dummy variable, and the dummy variable of earnings announcements are included. The time-series average coefficient of the measure of attractiveness to optimists is -0.54 with the t-statistic of -7.36. It shows that predictive power of the measure becomes even stronger if there was no earnings announcement in a given month. Consistent with the prediction, the interaction term between the measure of attractiveness and the dummy variable is positive and highly significant with the coefficient of 0.33 and the t-statistic of 6.66. It means that one standard deviation change in the measure of attractiveness to optimists yields a 0.33% smaller change in the expected returns if there was an earnings announcement in a given month. These conclusions remain the same even after controlling for several variables in the regressions as Table 15 reports.

To explore the relation between the MAX effect and the measure of attractiveness to optimists regarding earnings announcements, I perform several additional regressions reported in Table 16. First, I replicate the results of Nguyen and Truong (2018) in the first three columns of Table 16 and I find that there is a strong impact of earnings announcements on the predictive power of MAX effect which is consistent with their results. Second, I include both the interaction term between the MAX effect and the earnings announcement dummy and the interaction term between the measure of attractiveness to optimists and the earnings announcement dummy. In these specifications, I can explore the strength of the relation between the MAX effect and the earnings announcement dummy after controlling for the measure of attractiveness to optimists. I find that this relation becomes weak and statistically insignificant in each case, while the interaction between the measure of attractiveness to optimists and the earnings announcement dummy remains substantial and statistically significant. Finally, I also considered an alternative case. Instead of using the MAX effect, I use the the residual of MAX effect (ORT-MAX) after controlling for the measure of attractiveness to optimists as I did in previous tests. The results of these regressions are reported in the last three columns of Table 16. Again, I find that the relation between the MAX effect and the earnings announcement dummy is no longer significant. All these results suggest that the measure of attractiveness to optimists can capture this relation between the MAX effect and earnings announcements.

An et al. (2020) argue that the impact of the lottery characteristic of a stock is stronger among stocks with prior losses because investors facing prior losses tend to invest in lottery-type assets to gain their losses back. Specifically, they use the capital gain overhang measure of Grinblatt and Han (2005) as a proxy whether investors face prior losses and gains and they find that the predictive power of MAX effect is concentrated among stocks with prior losses, while it disappears or even becoming positive for stocks with prior gains. To explore the relations among the measure of attractiveness to optimists, MAX effect and the capital gain overhang measure, I perform additional tests in the same vein as An et al. (2020).

First, I sort stocks into portfolio quintiles based on the capital gain overhang measure in each month, then I sort stock into portfolio deciles based on the attractiveness top optimists in each portfolio quintile in each month. I find that the return spread between the portfolio deciles with the highest and lowest values of attractiveness to optimists is more than 3% per month for both equal-weighted and value-weighted portfolios among stocks with prior losses. However, this return spread becomes insignificant for stocks with prior gains. Table 17 reports the results in details. These conclusions are similar to the results of An et al. (2020). Table 18 reports the same test for the MAX effect to make it comparable with previous results. Thus, I find that both MAX and the measure of attractiveness to optimists exhibit similar patterns based on capital gain overhang measure.

Second, instead of using the MAX, I use the residual of MAX after controlling for the measure of attractiveness to optimists to explore the robustness of the relation between the capital gain overhang measure and the MAX effect. As Table 19 reports, I find that the relation disappears for both equal-weighted and value-weighted portfolios. However, using the residual of the measure of attractiveness to optimists after controlling for MAX effect instead of the original measure, I find that the relation remains the same even if it gets a little bit weaker as Table 20 presents.

4 Conclusion

Optimistic investors can survive and influence asset prices even in a competitive general equilibrium framework. In this framework, optimistic investors overweight the probabilities of better outcomes and underweight the probabilities of worse outcomes. Although, beyond theoretical studies, there is empirical evidence on the role of optimism in the cross-section of stock returns, these empirical studies use indirect measures to approximate which stocks could be more exposed to the impact of optimistic investors.

In this study, I provide a measure for the attractiveness of a stock to optimists based on rank-dependent utility. Rank-dependent utility, also known as anticipation utility, ranks all the possible states of the world from the worst to the best and it distorts the probability of a state of the world based on its outcome's rank. Conceptually, this framework can capture the intuition of optimism and pessimism. However, the measure of attractiveness to optimists based on rank-dependent utility is quite similar to the MAX effect, the known characteristic of stocks as lotteries. Specifically, the MAX effect is a special case of the measure of attractiveness to optimists in this conceptual framework. Thus, I also present additional tests to differentiate the measure of attractiveness to optimists and the MAX effect.

I find supporting evidence on the impact of optimistic investors on asset prices. First, I find that the measure of attractiveness to optimists negatively predicts the future returns in both portfolio-level and firm-level tests. Second, consistent with the theoretical results, the specification of moderately optimistic investors provides a measure with a stronger predictive power for future returns than the MAX effect. Third, the predictive power of the measure of attractiveness to optimists remains large and statistically significant for large, liquid firms with sophisticated investors. Finally, the predictive power of the measure of attractiveness to optimists is concentrated in optimistic time periods confirming that this measure is strongly related to optimism and optimistic investors.

Modelling optimism with rank-dependent utility might have interesting implications for several other fields in finance and asset pricing. It can contribute to approaches based on probability weighting and understanding several puzzles related to such topics as the cross-section of expected stock returns, option pricing, or merge and acquisition.

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Table 1 Example to Illustrate the Impact of Probability Weighting

Assuming N=20 possible states of the world with equal chances, ranked from the worst outcome to the best, this Table presents the subjective probabilities for several different specifications of optimism ($\alpha > 1$), pessimism ($\alpha < 1$), and the cumulative prospect theory (CPT) (Tversky and Kahneman, 1992).

	Worst	2	3	4	...	18	19	Best
p_i	5%	5%	5%	5%	...	5%	5%	5%
π_i ($\alpha = 2$)	0.25%	0.75%	1.25%	1.75%	...	8.75%	9.25%	9.75%
π_i ($\alpha = 4$)	0.00%	0.01%	0.04%	0.11%	...	13.41%	15.84%	18.55%
π_i ($\alpha = 16$)	0.00%	0.00%	0.00%	0.00%	...	11.11%	25.48%	55.99%
π_i ($\alpha = \infty$)	0.00%	0.00%	0.00%	0.00%	...	0.00%	0.00%	100%
π_i ($\alpha = 0.5$)	22.36%	9.26%	7.11%	5.99%	...	2.67%	2.60%	2.53%
π_i ($\alpha = 0.25$)	47.29%	8.95%	6.00%	4.64%	...	1.38%	1.33%	1.27%
π_i ($\alpha = 0$)	100%	0.00%	0.00%	0.00%	...	0.00%	0.00%	0.00%
CPT (δ=0.61)	10.04%	5.33%	4.41%	3.95%	...	5.69%	7.23%	14.93%
CPT (δ=0.69)	9.15%	5.59%	4.76%	4.32%	...	5.60%	6.81%	11.91%

Table 2 Returns and Alphas on Portfolio Deciles of Stocks Sorted on the Measure of Attractiveness to Optimists

Decile portfolios are formed every month from July 1962 to November 2018 by sorting stocks based on the measure of attractiveness to optimists (AO). Portfolio 1 is the portfolio with the least attractive stocks to optimists (AO) over the current month. This Table reports, for each decile, the equal-weighted (EW) and the value-weighted (VW) subsequent monthly returns of the portfolios and the intercepts obtained from the four factor model (Carhart, 1997) (market, size, book-to-market, momentum) for several different levels of optimism ($\alpha = 2; 4; 16; \infty$). Newey and West (1987) corrected t-statistics are reported in parentheses.

	EW Portfolios				VW Portfolios			
Decile	$\alpha = 2$	$\alpha = 4$	$\alpha = 16$	$\alpha = \infty$	$\alpha = 2$	$\alpha = 4$	$\alpha = 16$	$\alpha = \infty$
Lowest	1.14	0.94	0.87	0.87	0.96	0.78	0.67	0.67
2	1.06	1.00	0.94	0.92	0.72	0.70	0.61	0.60
3	1.04	1.01	0.96	0.95	0.67	0.61	0.65	0.63
4	0.98	0.98	0.95	0.94	0.61	0.58	0.57	0.57
5	0.85	0.91	0.94	0.91	0.49	0.62	0.60	0.63
6	0.82	0.83	0.88	0.93	0.49	0.49	0.69	0.69
7	0.78	0.83	0.83	0.76	0.58	0.65	0.56	0.53
8	0.60	0.69	0.73	0.71	0.47	0.49	0.53	0.53
9	0.34	0.40	0.43	0.43	0.26	0.26	0.35	0.45
Highest	-0.24	-0.21	-0.15	-0.05	-0.03	-0.08	-0.05	0.01
Difference	-1.38	-1.15	-1.02	-0.92	-0.99	-0.86	-0.72	-0.67
t-stat	(-6.12)	(-4.82)	(-4.32)	(-4.12)	(-3.59)	(-2.92)	(-2.58)	(-2.50)
4F α	-1.59	-1.40	-1.25	-1.12	-1.23	-1.10	-0.92	-0.85
t-stat	(-10.42)	(-9.82)	(-9.32)	(-9.07)	(-5.83)	(-6.07)	(-4.87)	(-4.78)

Table 3 Factor Models

Decile portfolios are formed every month from July 1962 to November 2018 by sorting based on the measure of attractiveness to optimists. This table reports the next month equal-weighted and value-weighted alphas for several models. The sample period depends on the availability of the factors. The 7F is the Fama-French five factor model (Fama and French, 2015) augmented with the momentum factor and the liquidity factor (Pástor and Stambaugh, 2003), SY is the model of Stambaugh and Yuan (2017), DHS is the model of Daniel et al. (2020), and Q is the model of Hou et al. (2015). Newey and West (1987) corrected t-statistics are reported in parentheses.

	EW				VW			
Decile	7F	SY	DHS	Q	7F	SY	DHS	Q
Lowest	0.48	0.53	0.54	0.50	0.40	0.43	0.49	0.38
2	0.35	0.38	0.37	0.36	0.12	0.12	0.13	0.08
3	0.31	0.34	0.33	0.30	0.10	0.09	0.13	0.06
4	0.23	0.27	0.22	0.23	-0.01	-0.00	0.01	-0.07
5	0.07	0.13	0.10	0.07	-0.11	-0.10	-0.10	-0.12
6	0.04	0.10	0.07	0.05	-0.16	-0.07	-0.07	-0.11
7	0.02	0.09	0.05	0.06	0.00	0.07	-0.00	-0.02
8	-0.15	-0.07	-0.13	-0.07	-0.12	-0.03	-0.16	-0.07
9	-0.38	-0.29	-0.35	-0.31	-0.23	-0.07	-0.26	-0.11
Highest	-0.85	-0.84	-0.86	-0.71	-0.47	-0.38	-0.48	-0.29
Difference	-1.33	-1.37	-1.40	-1.20	-0.87	-0.81	-0.97	-0.67
t-stat	(-8.13)	(-8.58)	(-7.99)	(-6.45)	(-4.21)	(-3.70)	(-4.13)	(-2.87)

Table 4 Returns and Alphas on Portfolio Deciles of Stocks Sorted on the Measure of Attractiveness to Pessimists

Decile portfolios are formed every month from July 1962 to November 2018 by sorting stocks based on the measures of attractiveness to pessimists ($\alpha = 0; 0.25; 0.5$). Portfolio 10 is the portfolio with the least attractive stocks to pessimists over the current month. The Table reports, for each decile, the equal-weighted (EW) and the value-weighted (VW) subsequent monthly returns of the portfolios and the intercepts obtained from the four factor model (Carhart, 1997) (market, size, book-to-market, momentum) for several different levels of pessimism ($\alpha = 0.5; 0.25; 0$). Newey and West (1987) corrected t-statistics are reported in parentheses.

	EW Portfolios			VW Portfolios		
Decile	$\alpha = 0.5$	$\alpha = .25$	$\alpha = 0$	$\alpha = 0.5$	$\alpha = .25$	$\alpha = 0$
Lowest	0.59	0.35	0.29	0.06	-0.07	-0.07
2	0.84	0.72	0.64	0.62	0.55	0.52
3	0.91	0.85	0.83	0.75	0.59	0.60
4	0.93	0.95	0.92	0.73	0.82	0.80
5	0.94	0.91	0.89	0.76	0.72	0.61
6	0.83	0.92	0.91	0.76	0.65	0.70
7	0.77	0.81	0.87	0.63	0.67	0.64
8	0.67	0.75	0.77	0.58	0.65	0.58
9	0.56	0.64	0.70	0.41	0.46	0.55
Highest	0.35	0.47	0.56	0.31	0.37	0.45
Difference	-0.24	0.12	0.28	0.25	0.44	0.52
t-stat	(-1.24)	(0.55)	(1.39)	(0.98)	(1.70)	(2.15)
4F α	-0.10	0.31	0.46	0.38	0.61	0.67
t-stat	(-0.58)	(2.01)	(3.19)	(1.98)	(3.36)	(3.87)

Table 5 Summary Statistics for the Measure of Attractiveness to Optimists

Decile portfolios are formed every month from July 1962 to November 2018 by sorting on the measure of attractiveness to optimists (AO). Portfolio 1 contains the least attractive stocks to optimists over the current month. This Table reports, for each decile, the time-series averages of the average monthly values of various characteristics for the deciles: measure of attractiveness to optimists (AO), market beta (Beta), logarithm of book-to-market ratio (BTM), logarithm of market capitalization in millions (Size), momentum (MOM) following Jegadeesh and Titman (1993), short-term reversal (REV) following Jegadeesh (1990), maximum daily return (MAX), minimum daily return (MIN) (Bali et al., 2011), idiosyncratic volatility (IVOL) (Ang et al., 2006), a measure of illiquidity (Amihud, 2002) (Illiq), skewness of the last month's returns (Skew), PT_0 is the cumulative prospect theory value based on the last month daily returns applying the cumulative prospect theory's probability weighting with the reference point of zero return, while PT_m is with the reference point of the market return similarly to Barberis et al. (2016).

	AO	Beta	BTM	Size	MOM	REV	MAX	MIN	IVOL	Illiq	Skew	PT_0	PT_m
1	0.31	0.50	-0.43	5.71	15.89	-7.16	2.11	3.31	1.24	5.05	-0.18	-0.38	-0.45
2	0.58	0.63	-0.47	5.89	14.92	-3.90	2.75	3.31	1.31	5.00	-0.24	-0.18	-0.25
3	0.75	0.72	-0.51	5.85	15.39	-2.51	3.28	3.55	1.53	5.40	0.05	-0.10	-0.17
4	0.91	0.82	-0.54	5.77	15.89	-1.32	3.78	3.80	1.81	5.86	0.11	-0.04	-0.11
5	1.07	0.90	-0.57	5.65	16.46	-0.21	4.32	4.08	2.15	6.52	0.16	0.02	-0.04
6	1.25	0.99	-0.61	5.51	17.34	0.93	4.95	4.40	2.61	7.16	0.22	0.09	0.02
7	1.46	1.09	-0.64	5.34	18.57	2.29	5.72	4.79	3.28	8.25	0.28	0.17	0.10
8	1.73	1.19	-0.68	5.14	19.88	4.17	6.72	5.26	4.18	9.39	0.36	0.27	0.20
9	2.14	1.33	-0.74	4.91	21.88	7.25	8.28	5.90	5.78	11.30	0.46	0.44	0.37
10	3.34	1.49	-0.81	4.52	23.72	16.52	13.50	7.33	13.52	16.33	0.74	0.96	0.89

Table 6 Returns and Alphas on Portfolio Deciles of Stocks Sorted on Residuals

Decile portfolios are formed every month from July 1962 to November 2018 by sorting stocks based on residuals. Specifically, in Panel A, I regress the measure of attractiveness to optimists on a constant, control variable and its square and I take the residuals in each month, where the control variable could be the MAX, MAX(5), IVOL, PT_0, and PT_m. In Panel B, I regress the control variable on a constant, measure of attractiveness to optimists, and its square and I take the residuals in each month. "Difference" is the average subsequent monthly return difference between portfolio 10 and 1. In the last rows, the intercept of the four factor model (Carhart, 1997) and the corresponding Newey and West (1987) corrected t-statistics are also reported.

Panel A: Residuals of the measure of attractiveness to optimists

	MAX		MAX(5)		IVOL		PT_0		PT_m	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Lowest	1.01	0.72	1.02	0.67	1.09	0.91	0.71	0.66	0.74	0.67
2	1.09	0.90	1.02	0.84	1.11	0.81	0.85	0.65	0.86	0.66
3	1.01	0.83	1.00	0.89	1.02	0.74	0.89	0.65	0.89	0.64
4	0.89	0.72	0.95	0.81	0.96	0.68	0.90	0.64	0.90	0.62
5	0.86	0.60	0.83	0.69	0.88	0.62	0.88	0.51	0.84	0.48
6	0.78	0.58	0.72	0.58	0.76	0.50	0.90	0.58	0.93	0.61
7	0.67	0.51	0.66	0.48	0.72	0.50	0.90	0.59	0.87	0.63
8	0.61	0.38	0.59	0.50	0.53	0.42	0.79	0.52	0.80	0.47
9	0.46	0.34	0.44	0.35	0.37	0.38	0.60	0.41	0.60	0.42
Highest	-0.02	0.13	0.15	0.15	-0.06	0.17	-0.06	0.26	-0.07	-0.25
Difference	-1.03	-0.58	-0.86	-0.53	-1.15	-0.74	-0.77	-0.92	-0.81	-0.92
t-stat	(-8.42)	(-3.36)	(-6.01)	(-2.69)	(-6.34)	(-3.28)	(-3.50)	(-3.09)	(-3.64)	(-3.11)
4F α	-1.13	-0.73	-0.85	-0.50	-1.31	-0.97	-1.01	-1.09	-1.04	-1.08
t-stat	(-9.34)	(-4.08)	(-5.46)	(-2.48)	(-9.23)	(-4.85)	(-7.40)	(-6.24)	(-7.86)	(-6.25)

Panel B: Residuals of the control variables

	MAX		MAX(5)		IVOL		PT_0		PT_m	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Lowest	0.16	0.29	0.28	0.23	0.11	0.19	0.67	0.19	0.70	0.26
2	0.55	0.37	0.47	0.42	0.57	0.47	0.91	0.63	0.90	0.54
3	0.65	0.49	0.65	0.51	0.70	0.48	0.94	0.68	0.90	0.69
4	0.78	0.59	0.71	0.54	0.77	0.54	0.93	0.80	0.91	0.79
5	0.85	0.63	0.80	0.67	0.86	0.67	0.86	0.69	0.83	0.68
6	0.88	0.66	0.86	0.78	0.92	0.76	0.80	0.70	0.78	0.65
7	0.98	0.76	0.96	0.79	0.92	0.80	0.70	0.56	0.74	0.60
8	0.99	0.84	0.99	0.83	1.05	0.83	0.57	0.40	0.66	0.47
9	0.92	0.75	0.92	0.80	0.90	0.49	0.58	0.44	0.51	0.37
Highest	0.62	0.44	0.73	0.37	0.57	0.22	0.41	0.44	0.45	0.49
Difference	0.46	0.15	0.46	0.14	0.46	0.03	-0.26	0.25	-0.25	0.23
t-stat	(4.97)	(0.89)	(2.88)	(0.58)	(4.26)	(0.18)	(-1.85)	(1.33)	(-1.74)	(1.19)
4F α	0.49	0.17	0.39	0.03	0.45	-0.00	-0.18	0.34	-0.18	0.31
t-stat	(4.90)	(0.94)	(2.60)	(0.13)	(4.05)	(-0.00)	(-1.19)	(2.04)	(-1.21)	(1.86)

Table 7 Returns and Alphas on Bivariate Portfolio Deciles

Double sorted portfolio deciles are formed every month from July 1962 to November 2018 by sorting stocks based on a control variable, then, sorting again based on the main variable into portfolio deciles in each portfolio decile of the control variable. In Panel A, I create portfolio deciles of the measure of attractiveness to optimist (AO) after controlling for MAX, MAX(5), IVOL, PT_0, and PT_m. In Panel B, I create portfolio deciles based on the variables of MAX, MAX(5), IVOL, PT_0, and PT_m after controlling for the measure of attractiveness to optimists (AO). "Difference" is the average subsequent monthly return difference between portfolio 10 and 1. In the last rows, the intercept of the four factor model (Carhart, 1997) and the corresponding Newey and West (1987) corrected t-statistics are also reported.

Panel A: Attractiveness to Optimists

	MAX		MAX(5)		IVOL		PT_0		PT_m	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Lowest	1.29	0.92	1.31	0.85	1.24	0.96	0.76	0.66	0.79	0.66
2	1.09	0.81	1.06	0.80	1.11	0.78	0.86	0.67	0.85	0.70
3	0.93	0.77	0.91	0.83	1.00	0.72	0.85	0.63	0.85	0.61
4	0.86	0.67	0.84	0.65	0.93	0.68	0.88	0.60	0.87	0.56
5	0.77	0.58	0.79	0.66	0.81	0.60	0.86	0.51	0.87	0.60
6	0.69	0.49	0.67	0.57	0.75	0.56	0.84	0.53	0.84	0.52
7	0.63	0.58	0.58	0.53	0.63	0.47	0.82	0.57	0.84	0.55
8	0.53	0.43	0.56	0.51	0.49	0.36	0.74	0.60	0.72	0.55
9	0.37	0.38	0.41	0.38	0.32	0.39	0.64	0.51	0.64	0.50
Highest	0.20	0.29	0.23	0.24	0.07	0.22	0.12	0.04	0.08	-0.04
Difference	-1.09	-0.63	-1.08	-0.61	-1.18	-0.75	-0.64	-0.63	-0.71	-0.70
t-stat	(-9.72)	(-4.56)	(-8.05)	(-3.72)	(-7.42)	(-4.23)	(-3.14)	(-2.34)	(-3.45)	(-2.57)
4F α	-1.19	-0.77	-1.05	-0.66	-1.33	-0.91	-0.89	-0.88	-0.94	-0.94
t-stat	(-10.21)	(-4.86)	(-7.72)	(-4.07)	(-10.46)	(-5.22)	(-7.14)	(-4.79)	(-7.67)	(-4.98)

Panel B: Controlling for the Measure of Attractiveness to Optimists

	MAX		MAX(5)		IVOL		PT_0		PT_m	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Lowest	0.53	0.37	0.41	0.30	0.60	0.46	0.98	0.35	1.00	0.40
2	0.59	0.48	0.62	0.46	0.61	0.53	0.99	0.67	0.92	0.62
3	0.68	0.54	0.62	0.52	0.71	0.53	0.89	0.72	0.93	0.73
4	0.68	0.59	0.71	0.62	0.62	0.59	0.87	0.72	0.82	0.70
5	0.81	0.58	0.68	0.63	0.71	0.60	0.79	0.71	0.77	0.68
6	0.75	0.61	0.80	0.64	0.76	0.69	0.66	0.68	0.70	0.63
7	0.85	0.69	0.85	0.70	0.81	0.68	0.67	0.49	0.68	0.53
8	0.80	0.84	0.89	0.81	0.86	0.72	0.59	0.46	0.59	0.48
9	0.87	0.73	0.88	0.75	0.83	0.63	0.48	0.41	0.49	0.46
Highest	0.84	0.62	0.91	0.62	0.88	0.43	0.45	0.48	0.46	0.48
Difference	0.31	0.24	0.51	0.32	0.29	-0.02	-0.53	0.14	-0.54	0.07
t-stat	(2.68)	(1.43)	(2.99)	(1.53)	(2.52)	(-0.12)	(-3.47)	(0.73)	(-3.64)	(-0.38)
4F α	0.26	0.25	0.37	0.22	0.23	-0.08	-0.39	0.27	-0.43	0.18
t-stat	(2.66)	(1.47)	(2.70)	(1.19)	(2.62)	(-0.45)	(-2.53)	(1.41)	(-2.94)	(1.02)

Table 8 Bivariate Sorts

Double sorted, equal-weighted and value-weighted decile portfolios are formed every month from July 1962 to November 2018 by sorting stocks based on the measure of attractiveness to optimists after controlling for REV, skewness (Skew), Illiquidity (Illiq), Size, BTM, MOM, and market beta. In each case, first, I sort stocks into deciles using the control variable, then within each decile I sort stocks into decile portfolios based on the measure of attractiveness to optimists over the current month. I form portfolio deciles of stocks based on their measure of attractiveness to optimists across the control variable deciles in each month. So decile 1 contains the least attractive stocks to optimists across the portfolio deciles of the control variable. "Difference" is the average subsequent monthly return difference between portfolio 10 and 1. Corrected (Newey and West, 1987) t-statistics are reported in parentheses.

Panel A: EW Portfolios

Decile	Beta	Size	BTM	MOM	REV	Illiq	Skew
Lowest	1.20	1.17	1.18	1.28	0.66	1.16	1.14
2	1.09	1.16	1.05	1.13	0.83	1.10	1.04
3	1.02	1.10	1.03	1.05	0.86	1.09	1.00
4	0.94	0.96	0.93	0.92	0.93	0.98	0.98
5	0.84	0.94	0.88	0.86	0.90	0.90	0.89
6	0.79	0.76	0.80	0.71	0.86	0.78	0.81
7	0.67	0.69	0.79	0.65	0.90	0.73	0.72
8	0.57	0.51	0.59	0.54	0.78	0.49	0.59
9	0.34	0.22	0.35	0.28	0.65	0.26	0.41
Highest	-0.12	-0.17	-0.24	-0.06	-0.02	-0.15	-0.22
Difference	-1.32	-1.34	-1.42	-1.34	-0.68	-1.31	-1.35
t-stat	(-6.73)	(-6.33)	(-7.56)	(-7.56)	(-3.00)	(-6.00)	(-6.33)
4F α	-1.49	-1.50	-1.60	-1.61	-0.94	-1.49	-1.57
t-stat	(-10.24)	(10.24)	(-11.64)	(-12.14)	(-7.73)	(-9.69)	(-11.03)

Panel B: VW Portfolios

Decile	Beta	Size	BTM	MOM	REV	Illiq	Skew
Lowest	0.97	0.92	0.91	1.02	0.55	0.91	0.94
2	0.77	0.75	0.70	0.77	0.58	0.76	0.72
3	0.69	0.75	0.66	0.74	0.65	0.73	0.71
4	0.61	0.63	0.51	0.56	0.65	0.70	0.62
5	0.50	0.66	0.58	0.56	0.69	0.60	0.49
6	0.49	0.46	0.41	0.43	0.58	0.43	0.44
7	0.42	0.44	0.47	0.44	0.67	0.48	0.49
8	0.46	0.47	0.43	0.42	0.58	0.43	0.44
9	0.39	0.30	0.18	0.22	0.55	0.40	0.27
Highest	0.06	0.21	0.01	0.15	-0.13	-0.21	0.05
Difference	-0.92	-0.71	-0.90	-0.87	-0.67	-0.70	-0.89
t-stat	(-4.01)	(-2.91)	(-3.89)	(-4.16)	(-2.27)	(-2.79)	(-3.25)
4F α	-1.11	-0.88	-1.11	-1.17	-0.97	-0.91	-1.11
t-stat	(-6.11)	(-4.82)	(-6.29)	(-6.90)	(-5.35)	(-4.86)	(-5.66)

Table 9 Fama-MacBeth Regression Analyses

Each month from July 1962 to November 2018 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the measure of attractiveness to optimists (AO) in the current month and several control variables including market beta, Size, BTM, MOM, REV, Illiquidity (Illiq), MAX, idiosyncratic volatility (IVOL), and a constant. I normalize each variable at monthly level to make the coefficients comparable. In each row, the Table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey and West (1987) corrected t-statistics (in parentheses).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AO	-0.41	-0.51	-0.38	-0.44	-0.36	-0.42	-0.54	-0.44	-0.55
	(-6.30)	(-10.48)	(-5.90)	(-5.07)	(-4.74)	(-4.66)	(-7.10)	(-6.19)	(-7.21)
Beta		0.03	-0.03	0.00	0.00	0.01			
		(0.77)	(-0.12)	(0.11)	(0.13)	(0.25)			
Size		-0.18	-0.19	-0.19	-0.19	-0.19			
		(-3.17)	(-3.33)	(-3.43)	(-3.39)	(-3.43)			
BTM		0.18	0.18	0.18	0.18	0.18			
		(3.30)	(3.38)	(3.38)	(3.37)	(3.38)			
MOM		0.39	0.41	0.41	0.41	0.41			
		(6.90)	(7.16)	(7.24)	(7.14)	(7.23)			
REV			-0.16	-0.15	-0.17	-0.16			
			(-2.71)	(-2.28)	(-2.65)	(-2.39)			
Illiq			-0.07	-0.06	-0.06	-0.06			
			(-2.04)	(-1.90)	(-1.95)	(-1.80)			
MAX				0.06		0.08	0.15		0.15
				(1.47)		(2.08)	(3.16)		(3.65)
IVOL					-0.02	-0.04		0.04	-0.00
					(-0.85)	(-1.72)		(1.44)	(-0.15)

Table 10 Fama-MacBeth Regression Analyses and Skewness

Each month from July 1962 to November 2018 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the measure of attractiveness to optimists (AO) in the current month and eight control variables including market beta, Size, BTM, MOM, REV, MAX, idiosyncratic volatility (IVOL), and Illiquidity (Illiq). Additionally, several different types of skewness measures are also included such as the skewness of the last month daily returns (Skew), coskewness (CoSkew) (Harvey and Siddique, 2000), idiosyncratic skewness (ISkew) (Harvey and Siddique, 2000), and expected idiosyncratic skewness (ESkew) (Boyer et al., 2010). I normalize each variable at monthly level to make the coefficients comparable. In each row, this Table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey and West (1987) corrected t-statistics (in parentheses).

	(1)	(2)	(3)	(4)	(5)	(6)
AO	-0.42	-0.42	-0.41	-0.43	-0.38	-0.38
	(-4.66)	(-4.67)	(-4.54)	(-4.74)	(-3.92)	(-3.77)
Beta	0.01	0.01	0.01	0.01	0.03	0.03
	(0.25)	(0.25)	(0.31)	(-0.25)	(0.94)	(1.13)
Size	-0.19	-0.19	-0.19	-0.20	-0.20	-0.21
	(-3.43)	(-3.43)	(-3.50)	(-3.62)	(-3.41)	(-3.59)
BTM	0.18	0.18	0.17	0.18	0.21	0.19
	(3.38)	(3.36)	(3.31)	(3.41)	(3.55)	(3.39)
MOM	0.41	0.41	0.41	0.43	0.45	0.47
	(7.23)	(7.23)	(7.20)	(7.39)	(7.33)	(7.55)
REV	-0.16	-0.16	-0.17	-0.16	-0.18	-0.17
	(-2.39)	(-2.38)	(-2.48)	(-2.29)	(-2.61)	(-2.40)
Illiq	-0.06	-0.06	-0.06	-0.06	-0.06	-0.07
	(-1.80)	(-1.80)	(-1.98)	(-1.93)	(-1.73)	(-1.64)
MAX	0.08	0.08	0.07	0.10	0.00	0.03
	(2.08)	(2.11)	(2.02)	(2.83)	(0.03)	(0.71)
IVOL	-0.04	-0.04	-0.05	-0.05	-0.01	0.01
	(-1.72)	(-1.73)	(-1.80)	(-1.80)	(-0.22)	(0.18)
Skew		-0.01				-0.03
		(-0.87)				(-1.29)
CoSkew			-0.01			-0.03
			(-0.48)			(-1.68)
ISkew				-0.08		-0.10
				(-4.86)		(-5.00)
ESkew					0.00	0.01
					(0.27)	(0.59)

Table 11 Fama-MacBeth Regression Analyses for Optimitic and Pessimistic Time Periods with Several Specifications of the Measure of Attractiveness to Optimists

Each month from July 1965 to November 2018 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including measure of attractiveness to optimists (AO) with four different specifications based on the last month daily returns, the last quarter daily returns, the last year daily returns, and the last year monthly returns in the current month and several control variables including market beta, Size, BTM, MOM, REV, and Illiquidity (Illiq). Because of data availability of sentiment index (Baker and Wurgler, 2006) the time period of this sample differs from previous samples. I normalize each variable at monthly level to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey and West (1987) corrected t-statistics (in parentheses).

	Panel A: All months				Panel B: Optimistic time periods				Panel C: Pessimistic time periods			
Horizon	month	quarter	year	year	month	quarter	year	year	month	quarter	year	year
Frequency	daily	daily	daily	month	daily	daily	daily	month	daily	daily	daily	month
AO	-0.36	-0.28	-0.26	-0.31	-0.55	-0.45	-0.46	-0.49	-0.18	-0.10	-0.06	-0.13
	(-5.41)	(-4.42)	(-3.08)	(-3.94)	(-5.98)	(-5.83)	(-4.09)	(-4.52)	(-2.13)	(-1.27)	(-0.53)	(-1.27)
Beta	-0.01	-0.03	-0.03	-0.06	-0.05	-0.09	-0.09	-0.13	0.04	0.03	0.03	0.02
	(-0.17)	(-0.96)	(-1.08)	(-1.73)	(-1.42)	(-2.53)	(-2.67)	(-3.65)	(0.90)	(0.64)	(0.67)	(0.36)
Size	-0.19	-0.20	-0.22	-0.18	-0.10	-0.12	-0.16	-0.08	-0.28	-0.27	-0.28	-0.27
	(-3.29)	(-3.44)	(-4.21)	(-3.10)	(-1.46)	(-1.78)	(-2.44)	(-1.23)	(-2.97)	(-2.92)	(-3.34)	(-2.93)
BTM	0.18	0.18	0.16	0.18	0.25	0.26	0.22	0.28	0.09	0.10	0.10	0.09
	(3.10)	(3.24)	(3.14)	(3.25)	(3.23)	(3.25)	(3.09)	(3.45)	(1.19)	(1.33)	(1.39)	(1.19)
MOM	0.41	0.46	0.48	0.63	0.47	0.56	0.61	0.82	0.35	0.37	0.35	0.44
	(6.82)	(7.74)	(7.94)	(8.02)	(7.52)	(9.25)	(9.61)	(9.52)	(3.57)	(3.80)	(3.64)	(3.63)
REV	-0.17	-0.34	-0.40	-0.37	-0.02	-0.25	-0.35	-0.28	-0.32	-0.42	-0.46	-0.45
	(-2.74)	(-6.77)	(-8.10)	(-7.01)	(-0.26)	(-3.98)	(-5.30)	(-4.31)	(-3.40)	(-5.65)	(-6.21)	(-5.73)
Illiq	-0.07	-0.09	-0.10	-0.12	-0.03	-0.06	-0.07	-0.11	-0.11	-0.12	-0.12	-0.13
	(-2.12)	(-2.66)	(-2.99)	(-4.13)	(-0.74)	(-1.40)	(-1.79)	(-3.10)	(-2.14)	(-2.29)	(-2.44)	(-2.81)

Table 12 Analyses of Limits to Arbitrage

Double sorted, equal-weighted and value-weighted decile portfolios are formed every month from July 1962 to November 2018. In each case, I first sort the stocks into two sub-samples based on their median size (small and large), their median illiquidity, their median idiosyncratic volatility (IVOL), and their 67th percentile institutional ownership then, within each sub-sample, I sort stocks into decile portfolios based on the measure of attractiveness to optimists over the current month. Data starts in 1980 in the case of institutional ownership because of data availability. "Difference" is the average subsequent monthly return difference between portfolio 10 and 1. Corrected t-statistics are reported in parentheses (Newey and West, 1987).

	Small		Large		Illiquid		Liquid	
Decile	EW	VW	EW	VW	EW	VW	EW	VW
Lowest	1.29	1.22	1.07	0.92	1.26	1.09	1.05	0.89
2	1.38	1.29	0.88	0.70	1.31	1.08	0.91	0.70
3	1.32	1.21	0.88	0.71	1.29	1.12	0.87	0.72
4	1.07	1.00	0.81	0.61	1.06	0.84	0.83	0.60
5	1.03	0.92	0.78	0.56	1.02	0.76	0.74	0.52
6	1.00	0.87	0.65	0.39	0.96	0.65	0.69	0.44
7	0.77	0.70	0.59	0.50	0.74	0.56	0.63	0.50
8	0.49	0.44	0.50	0.46	0.50	0.23	0.64	0.51
9	0.16	0.14	0.40	0.34	015	0.04	0.39	0.30
Highest	-0.48	-033	0.15	0.20	-0.55	-0.48	0.24	0.30
Difference	-1.77	-1.55	-0.93	-0.72	-1.81	-1.57	-0.81	-0.59
t-stat	(-8.02)	(-6.47)	(-3.87)	(-2.73)	(-8.41)	(-6.30)	(-3.21)	(-2.17)
4F	-1.97	-1.73	-1.08	-0.91	-2.01	-1.75	-1.01	-0.83
t-stat	(-11.60)	(-9.61)	(-6.20)	(-4.59)	(-12.49)	(-9.51)	(-5.41)	(-4.08)

	High IVOL		Low IVOL		Low IO		High IO	
Decile	EW	VW	EW	VW	EW	VW	EW	VW
Lowest	1.38	0.89	1.07	1.00	1.08	1.01	1.33	1.21
2	1.20	0.80	1.03	0.82	1.11	0.85	1.18	0.96
3	1.04	0.72	1.00	0.67	1.11	0.85	1.04	0.81
4	0.90	0.61	0.98	0.72	1.06	0.70	0.98	1.02
5	0.88	0.67	0.92	0.65	0.91	0.59	0.86	0.69
6	0.69	0.43	0.87	0.54	0.85	0.51	0.86	0.75
7	0.52	0.32	0.75	0.48	0.85	0.61	0.77	0.63
8	0.28	0.35	0.68	0.42	0.54	0.41	0.67	0.67
9	0.07	0.22	0.63	0.41	0.27	0.17	0.53	0.35
Highest	-0.53	-0.31	0.41	0.39	-0.30	-0.18	0.16	0.38
Difference	-1.90	-1.20	-0.67	-0.61	-1.38	-1.18	-1.17	-0.83
t-stat	(-8.40)	(-4.13)	(-4.47)	(-2.89)	(-4.74)	(-3.02)	(-3.88)	(-2.51)
4F	-2.04	-1.32	-0.89	-0.81	-1.60	-1.40	-1.25	-0.92
t-stat	(-11.04)	(-5.15)	(-8.06)	(-4.49)	(-7.75)	(-4.40)	(-5.02)	(-3.63)

Table 13 Impact of Mispricing

Double sorted, equal-weighted and value-weighted portfolios are formed every month from July 1962 to November 2016 by sorting stocks based on the mispricing score (Stambaugh et al., 2015) into quintiles, then, in each quintile, portfolio deciles are formed in each month. This table reports the time-series average of the portfolio returns within the portfolio quintiles. The column "All" presents the results of standard bivariate sorts. "Difference" is the average subsequent monthly return difference between portfolio 10 and 1. Corrected t-statistics are reported in parentheses (Newey and West, 1987).

	EW				VW			
	1	3	5	All	1	3	5	All
1	1.45	1.23	0.71	1.14	1.19	0.98	0.53	0.90
2	1.27	1.00	0.65	1.01	0.81	0.68	0.37	0.67
3	1.30	1.10	0.44	1.00	0.87	0.69	0.32	0.70
4	1.25	1.05	0.37	0.91	0.69	0.60	0.15	0.56
5	1.18	0.92	0.27	0.85	0.67	0.43	-0.10	0.49
6	1.10	0.84	0.17	0.77	0.65	0.63	-0.04	0.43
7	1.10	0.96	-0.12	0.73	0.71	0.60	-0.25	0.52
8	1.06	0.89	-0.27	0.61	0.78	0.53	-0.35	0.52
9	1.10	0.47	-0.45	0.41	0.91	0.28	-0.48	0.35
10	0.77	0.24	-1.30	0.00	0.65	0.35	-1.11	0.18
Difference	-0.68	-1.00	-2.01	-1.13	-0.54	-0.62	-1.64	-0.72
t-stat	(-3.10)	(-4.04)	(-6.94)	(-5.25)	(-2.05)	(-2.11)	(-4.30)	(-2.62)
4F	-1.00	-1.33	-2.17	-1.41	-0.82	-0.86	-1.88	-1.02
t-stat	(-5.57)	(-7.51)	(-10.61)	(-9.39)	(-3.38)	(-3.55)	(-6.11)	(-4.61)

Table 14 Robustness Tests

Each month from July 1962 to November 2018, on several sub-samples, I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the measure of attractiveness to optimists (AO) in the current month and several control variables including market beta, Size, BTM, MOM, REV, Illiquidity (Illiq), and a constant. I normalize each variable at monthly level to make the coefficients comparable. In each row, the Table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey and West (1987) corrected t-statistics (in parentheses). There are three subperiods of the sample: 1962-1979, 1980-1999, 2000-2018. Large firm size corresponds to a sample of stocks with higher market capitalization than the 50th percentile of NYSE in a month. Excluding illiquid stocks corresponds to a sample without the 10% most illiquid stocks in a month. Finally, Fin&Uti represents the stocks in the financials (6000≤SIC<7000) and utilities (4900≤SIC<5000).

Subperiod:	All	All	All	All	62-79	80-99	00-18
Firm size:	Large	All	All	Large	All	All	All
Illiquid	Included	Excluded	Included	Excluded	Included	Included	Included
Fin&Uti	Included	Included	Excluded	Excluded	Included	Included	Included
AO	-0.19	-0.36	-0.40	-0.24	-0.31	-0.44	-0.37
	(-2.13)	(-5.20)	(-5.97)	(-2.72)	(-2.94)	(-5.12)	(-2.87)
Beta	0.01	-0.00	-0.02	0.01	0.08	-0.00	-0.08
	(0.44)	(-0.09)	(-0.62)	(0.42)	(2.08)	(-0.10)	(-1.44)
Size	-0.07	-0.19	-0.18	-0.08	-0.33	-0.12	-0.12
	(-2.09)	(-3.50)	(-3.06)	(-2.00)	(-2.50)	(-1.46)	(-1.79)
BTM	0.12	0.17	0.20	0.13	0.21	0.19	0.15
	(2.36)	(3.15)	(3.41)	(2.34)	(2.27)	(2.06)	(1.57)
MOM	0.30	0.40	.44	0.34	0.46	0.59	0.17
	(4.56)	6.79	(7.29)	(4.77)	(5.53)	(9.74)	(1.51)
REV	-0.17	(-0.11)	-0.15	-0.14	-0.42	-0.07	-0.02
	(2.05)	(-1.84)	(-2.32)	(-1.88)	(-3.52)	(-0.88)	(-0.22)
Illiq	-0.02	-0.07	-0.07	-0.03	-0.07	-0.03	-0.11
	(-1.12)	(-2.26)	(-2.17)	(-1.33)	(-1.07)	(-0.54)	(-2.07)

Table 15 Fama-MacBeth Regression Analyses: Earnings Announcements

Each month from July 1962 to November 2018 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the measure of attractiveness to optimists (AO) in the current month and several control variables including market beta, Size, BTM, MOM, REV, Illiquidity (Illiq), MAX, idiosyncratic volatility (IVOL), and a constant. I normalize each variable at monthly level to make the coefficients comparable. In each row, the Table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey and West (1987) corrected t-statistics (in parentheses).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AO	-0.54	-0.60	-0.49	-0.60	-0.49	-0.58	-0.67	-0.57	-0.67
	(-7.36)	(-10.47)	(-7.04)	(-6.27)	(-5.96)	(-5.90)	(-7.42)	(-6.90)	(-7.39)
AO×E	0.33	0.32	0.34	0.33	0.33	0.32	0.34	0.34	0.34
	(6.66)	(6.93)	(7.20)	(6.99)	(7.07)	(6.81)	(6.97)	(6.82)	(6.69)
E	0.06	0.07	0.08	0.07	0.08	0.08	0.05	0.06	0.05
	(1.48)	(1.88)	(2.13)	(2.03)	(2.19)	(2.05)	(1.27)	(1.43)	(1.25)
Beta		0.02	-0.01	-0.00	-0.01	-0.00			
		(0.43)	(-0.35)	(-0.14)	(-0.22)	(-0.11)			
Size		-0.16	-0.18	-0.18	-0.18	-0.18			
		(-3.24)	(-3.48)	(-3.56)	(-3.53)	(-3.55)			
BTM		0.19	0.20	0.20	0.20	0.20			
		(3.07)	(3.18)	(3.19)	(3.19)	(3.20)			
MOM		0.38	0.41	0.41	0.40	0.41			
		(5.95)	(6.15)	(6.22)	(6.11)	(6.21)			
REV			-0.15	-0.12	-0.15	-0.13			
			(-2.24)	(-1.64)	(-2.07)	(-1.69)			
Illiq			-0.08	-0.08	-0.08	-0.08			
			(-2.49)	(-2.32)	(-2.50)	(-2.31)			
MAX				0.11		0.12	0.15		0.16
				(2.47)		(3.03)	(3.34)		(3.79)
IVOL					0.00	-0.00		0.04	-0.00
					(-0.12)	(-0.78)		(1.46)	(-0.07)

Table 16 Fama-MacBeth Regression Analyses: Earnings Announcements with MAX and AO

Each month from July 1962 to November 2018 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the measure of attractiveness to optimists (AO) in the current month and several control variables including market beta, Size, BTM, MOM, REV, Illiquidity (Illiq), MAX, idiosyncratic volatility (IVOL), and a constant. I normalize each variable at monthly level to make the coefficients comparable. In each row, the Table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey and West (1987) corrected t-statistics (in parentheses).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MAX	-0.43	-0.34	-0.28	0.09	0.06	0.07			
	(-6.64)	(-8.04)	(-5.70)	(1.65)	(1.15)	(1.58)			
MAX×E	0.33	0.33	0.33	0.12	0.09	0.08			
	(5.74)	(7.08)	(6.84)	(1.53)	(1.22)	(1.08)			
AO				-0.62	-0.56	-0.55			
				(-6.72)	(-6.22)	(-5.58)			
AO×E				0.23	0.24	0.25			
				(2.90)	(3.14)	(3.24)			
ORT-MAX							0.07	-0.02	0.02
							(2.20)	(-0.77)	(0.68)
ORT-MAX×E							0.07	0.07	0.06
							(1.67)	(1.72)	(1.57)
E	0.04	0.05	0.06	0.05	0.08	0.08	-0.01	0.05	0.06
	(0.96)	(1.57)	(1.57)	(1.25)	(2.08)	(2.05)	(-0.13)	(1.34)	(1.59)
Beta		-0.04	-0.04		0.01	-0.00		-0.08	-0.06
		(-1.06)	(-1.11)		(0.17)	(-0.07)		(-1.92)	(-1.42)
Size		-0.09	-0.15		-0.14	-0.18		-0.04	-0.12
		(-1.90)	(-2.71)		(-3.07)	(-3.54)		(-0.74)	(-2.13)
BTM		0.22	0.23		0.19	0.20		0.25	0.25
		(3.25)	(3.42)		(3.08)	(3.20)		(3.44)	(3.52)
MOM		0.39	0.39		0.40	0.41		0.39	0.40
		(5.94)	(5.89)		(6.19)	(6.20)		(5.96)	(5.92)
REV		-0.30	-0.31		-0.12	-0.13		-0.37	-0.34
		(-5.92)	(-6.05)		(-1.66)	(-1.68)		(-6.73)	(-6.31)
Illiq			-0.11			-0.08			-0.11
			(-3.47)			(-2.29)			(-3.52)
IVOL			-0.07			-0.03			-0.16
			(-2.70)			(-0.98)			(-7.69)

Table 17 Double sorted, equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2018. In each case, I first sort stocks into quintiles using the capital gain overhang variable (CGO) then within each quintile I sort stocks into decile portfolios based on the attractiveness to optimists measure over the current month so decile 1 contains the stocks with the lowest attractiveness to optimists. "Return difference" is the average subsequent monthly excess return difference between portfolio 10 and 1 and the corresponding Carhart (1997) alphas are also reported. The Newey-West corrected t-statistics are reported in parentheses.

	EW				VW			
	CGO1	CGO3	CGO5	Diff	CGO1	CGO3	CGO5	Diff
Lowest	1.45	1.14	1.26		1.32	1.08	1.12	
2	1.40	1.11	1.08		1.07	0.86	0.76	
3	1.03	0.93	1.10		0.81	0.73	0.86	
4	0.88	0.96	0.99		0.61	0.78	0.69	
5	0.79	0.79	0.98		0.37	0.54	0.66	
6	0.56	0.80	0.92		0.36	0.43	0.58	
7	0.15	0.71	0.93		0.02	0.53	0.51	
8	-0.19	0.58	0.93		-0.52	0.22	0.64	
9	-0.70	0.38	1.01		-0.77	0.31	0.57	
Highest	-1.79	0.26	0.98		-1.72	0.09	0.75	
Difference	-3.23	-0.88	-0.27	2.96	-3.04	-0.99	-0.37	2.67
t-stat	(-12.02)	(-3.49)	(-1.24)	(10.90)	(-9.75)	(-2.82)	(-1.51)	(9.18)
4F α	-3.36	-1.13	-0.69	2.67	-3.27	-1.14	-0.74	2.68
t-stat	(-13.59)	(-6.13)	(-3.82)	(9.21)	(-12.42)	(-3.90)	(-3.31)	(8.78)

Table 18 Double sorted, equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2018. In each case, I first sort stocks into quintiles using the capital gain overhang variable (CGO) then within each quintile I sort stocks into decile portfolios based on the MAX measure over the current month so decile 1 contains the stocks with the lowest MAX. "Return difference" is the average subsequent monthly excess return difference between portfolio 10 and 1 and the corresponding Carhart (1997) alphas are also reported. The Newey-West corrected t-statistics are reported in parentheses.

	EW				VW			
	CGO1	CGO3	CGO5	Diff	CGO1	CGO3	CGO5	Diff
Lowest	1.16	0.90	0.90		1.08	0.88	0.73	
2	1.16	0.92	0.95		0.77	0.74	0.49	
3	0.98	0.90	0.97		0.49	0.67	0.71	
4	0.91	0.89	0.97		0.66	0.66	0.71	
5	0.58	0.82	1.01		0.50	0.56	0.64	
6	0.44	0.88	0.97		0.12	0.56	0.72	
7	0.20	0.75	1.09		-0.05	0.57	0.96	
8	-0.10	0.69	1.05		-0.11	0.40	0.76	
9	-0.38	0.55	1.11		-0.52	0.40	0.71	
Highest	-1.40	0.36	1.17		-1.43	0.16	1.01	
Difference	-2.56	-0.53	0.27	2.83	-2.51	-0.73	0.28	2.78
t-stat	(-9.92)	(-2.17)	(1.28)	(10.74)	(-7.00)	(-2.44)	(1.14)	(8.39)
4F α	-2.70	-0.84	-0.10	2.59	-2.73	-0.95	0.00	2.73
t-stat	(-12.56)	(-5.27)	(-0.60)	(9.64)	(-9.40)	(-4.35)	(0.00)	(8.38)

Table 19 Double sorted, equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2018. In each case, I first sort stocks into quintiles using the capital gain overhang variable (CGO) then within each quintile I sort stocks into decile portfolios based on the orthogonal MAX measure over the current month so decile 1 contains the stocks with the lowest orthogonal MAX. "Return difference" is the average subsequent monthly excess return difference between portfolio 10 and 1 and the corresponding Carhart (1997) alphas are also reported. The Newey-West corrected t-statistics are reported in parentheses.

	EW				VW			
	CGO1	CGO3	CGO5	Diff	CGO1	CGO3	CGO5	Diff
Lowest	-0.89	0.31	0.66		-0.15	0.65	0.69	
2	0.07	0.58	0.78		0.38	0.66	0.94	
3	0.47	0.64	0.81		0.75	0.97	0.81	
4	0.60	0.77	0.87		0.91	1.02	1.01	
5	0.70	0.90	0.98		1.04	1.12	1.07	
6	0.77	0.91	0.93		0.96	1.02	1.04	
7	0.67	0.93	1.13		0.97	1.12	1.27	
8	0.72	0.90	1.29		1.18	1.16	1.28	
9	0.51	0.97	1.33		0.74	1.13	1.52	
Highest	-0.03	0.77	1.39		0.26	0.88	1.52	
Difference	0.86	0.46	0.73	-0.13	0.42	0.22	0.83	0.41
t-stat	(5.47)	(3.89)	(6.41)	(-0.74)	(1.63)	(1.17)	(5.44)	(1.42)
4F α	0.84	0.45	0.84	-0.01	0.36	0.29	0.96	0.59
t-stat	(4.91)	(3.39)	(7.18)	(-0.04)	(1.36)	(1.44)	(5.90)	(1.97)

Table 20 Double sorted, equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2018. In each case, I first sort stocks into quintiles using the capital gain overhang variable (CGO) then within each quintile I sort stocks into decile portfolios based on the orthogonal AO measure over the current month so decile 1 contains the stocks with the lowest orthogonal MAX. "Return difference" is the average subsequent monthly excess return difference between portfolio 10 and 1 and the corresponding Carhart (1997) alphas are also reported. The Newey-West corrected t-statistics are reported in parentheses.

	EW				VW			
	CGO1	CGO3	CGO5	Diff	CGO1	CGO3	CGO5	Diff
Lowest	0.77	1.05	1.60		0.61	0.76	1.19	
2	0.94	1.08	1.30		0.82	0.93	1.17	
3	0.82	0.93	1.15		0.83	0.85	1.00	
4	0.87	0.90	1.02		0.75	0.81	0.72	
5	0.64	0.85	1.01		0.68	0.66	0.83	
6	0.60	0.79	0.88		0.52	0.60	0.59	
7	0.39	0.73	0.83		0.21	0.54	0.63	
8	0.20	0.60	0.84		0.20	0.36	0.47	
9	-0.28	0.44	0.79		-0.30	0.16	0.40	
Highest	-1.37	0.29	0.76		-1.19	0.22	0.40	
Difference	-2.14	-0.77	-0.84	1.31	-1.80	-0.54	-0.79	1.01
t-stat	(-9.91)	(-5.36)	(-5.49)	(5.43)	(-7.05)	(-2.28)	(-3.82)	(3.27)
4F α	-2.17	-0.84	-1.04	1.12	-1.90	-0.67	-1.05	0.85
t-stat	(-9.39)	(-5.73)	(-7.75)	(4.17)	(-7.06)	(-2.72)	(-5.22)	(2.50)