Investor Gambling Preference and the Asset Growth Anomaly

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November 25, 2017

Abstract

The negative relation between asset growth (AG) and stock returns is particularly featured by the overvaluation of high AG stocks. We propose that such overvaluation is related to investors' gambling behavior toward stocks with high maximum daily returns (MAX). As a result, the AG premium should be stronger among high MAX stocks. Our empirical evidence confirms this prediction. We further show that the impact of gambling preference on the AG anomaly is robust to several alternative explanations, including overinvestment, limits-to-arbitrage, and the q-theory. Our study provides a new insight into the understanding of the AG anomaly.

JEL Classification: G11; G12; G14.
Keywords: Asset growth; Gambling preferences; Lottery-like payoffs; Extreme returns; Skewness.

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1 Introduction

Titman, Wei, and Xie (2004), Anderson and Garcia-Feijóo (2006), Cooper, Gulen, and Schill (2008) and Fama and French (2008), among others, indicate that corporate asset investment is negatively correlated with future stock returns. This negative investment-return relation is often referred to as the investment or asset growth (AG) anomaly. One particular feature of the anomaly is that its profitability is attributed to the subsequent underperformance of stocks that have been initially overvalued by extremely high AG. Despite the ample evidence in support of mispricing and rational explanations, our study aims to provide a new insight into the understanding of the overvaluation of high AG stocks.[1]

According to Cooper, Gulen, and Schill (2008), there is strong persistence in firms' AG rates and returns prior to the portfolio formation year. In particular, firms in the highest AG decile on average generate monthly returns of 3.86% and 3.49% in years -2 and -3 before they adopt extremely high growth rates. As a comparison, firms in the lowest AG decile generate only -0.64% and 0.04% returns in corresponding years. Such features of high past return performance and willingness to invest are attractive to investors who seek for possible gambling targets in financial markets. These observations thus lead us to believe that investors' gambling preference in trading high AG stocks plays an important role for the AG anomaly.

We adopt Bali, Cakici, and Whitelaw's (2011) maximum daily return over past month (MAX) to capture investors' gambling preference. Because extreme past return represents a form of lottery-like payoff, investors are willing to pay a higher price for stocks with such feature, which in turn leads to overvaluation. We exam-

[1]The mispricing-based explanations include the overinvestment argument (Titman, Wei, and Xie, 2004) and the limits-to-arbitrage hypothesis (Li and Zhang, 2010; Lam and Wei, 2011) while the rational explanation is associated with the q-theory (Li and Zhang, 2010; Lam and Wei, 2011; Lipson, Mortal, and Schill, 2011; Titman, Wei, and Xie, 2013; Watanabe, Xu, Yao, and Yu, 2013).

ine whether the overvaluation of high AG stocks is related to investors' gambling preference in trading these stocks. Using a double-sorting procedure based on AG and MAX, we show that high AG stocks within the highest MAX quintile on average generate an equally-weighted (value-weighted) return of 0.029% (-0.187%) per month; the corresponding return of high AG stocks within the lowest MAX quintile is 1.698% (0.938%) based on equal (value) weights. As a result, the equally-weighted return difference between high and low AG stocks is -1.071% for the highest MAX quintile and is 0.082% for the lowest MAX quintile. The corresponding returns for portfolios constructed based on value weights are -1.227% and -0.140%, respectively. Apparently, these observations reconcile the important role of investors' gambling preferences toward stocks with lottery-like payoffs in explaining the AG anomaly.

We next employ the Fama and MacBeth (1973) cross-sectional regressions of returns on a set of anomalies within each MAX quintile. This approach enables us to demonstrate the robustness of our evidence controlling for several cross-sectional determinants of stock returns. The results indicate that the AG slope is significantly greater in the highest MAX quintile (-0.764 with a t-statistic of -6.59) than in the lowest MAX quintile (-0.187 with a t-statistic of -1.46), resulting a significant difference of -0.577 which is more than 3.43 standard errors from zero. We also obtain similar results for size and book-to-market (BM) anomalies; the two effects are more pronounced in the highest MAX quintile. The growth profitability (GP) anomaly of Novy-Marx (2013), however, displays opposite evidence; the GP premium is significantly higher in lower MAX stocks. This finding is not surprising because Novy-Marx (2013) has demonstrated a negative relation between GP and BM premia.[2]

[2]Based on the dividend discount model, Fama and French (2006) illustrate the intuition that BM and profitability are negatively correlated. Novy-Marx (2013) proposes that gross profits is the cleanest accounting measure of firm profitability and confirm the negative relation between GP and BM premia predicted by Fama and French (2006).

To contrast with existing explanations of the AG anomaly, we set up overinvestment, limits-to-arbitrage, and the q-theory as alternative hypotheses and investigate how gambling preference interacts with these explanations for the AG premium. Titman, Wei, and Xie (2004) attribute the AG anomaly to the overinvestment hypothesis by arguing that the overvaluation in stock prices is induced because investors overvalue potential future cash flows of stocks with high investments. To test the overinvestment hypothesis, we follow Titman, Wei, and Xie (2004) by using cash flow and debt-to-asset ratio to proxy for the tendency of overinvestment. According to Jensen's (1986) prediction, firms with higher cash flows and lower leverage ratios are more likely to overinvest. Hence the overinvestment hypothesis suggests that the negative AG-return relation is stronger for firms with higher cash flows and lower leverage ratios.

The limits-to-arbitrage argument indicates that because arbitrage is risky and costly, the overvaluation of high investment stocks is more difficult to correct if they are subject to higher arbitrage constraints or costs. Because investors may have paid high prices for stocks that have experienced extreme asset expansions, the mispricing arguments generally assert that subsequent low returns thus reflect a correction of the initial overvaluation. To test the limits-to-arbitrage hypothesis, we follow Li and Zhang (2010) and Lam and Wei (2011) by considering idiosyncratic return volatility, cash flow volatility, stock price, and dollar volume to measure the degree of limits-to-arbitrage. Stocks with higher idiosyncratic return volatility and cash flow volatility and lower price and dollar volume are more difficult to arbitrage. Hence the limits-to-arbitrage hypothesis predicts that the AG premium is expected to be more pronounced among stocks with these features.

The rational explanation, however, argues from the q-theory which proposes that the AG anomaly is induced because of managers' ability to align corporate investments when expected returns (i.e., costs of capital) are lower. Tests associated with the q-theory involve measures of investment frictions, including firm age, asset size, payout ratio, and credit rating. The q-theory implies that stocks with lower firm age, asset size, and payout ratio, and are not rated are more financially constrained and hence generate higher AG premium.

We verify existing evidence by showing that when considered alone, the limits-to-arbitrage hypothesis and the q-theory are supported by a fair amount of evidence to explain the AG anomaly. The results for the overinvestment hypothesis, however, are weaker and less robust across overinvestment measures. To sort out the relative importance of the gambling preference hypothesis in understanding the AG anomaly, we estimate the Fama and MacBeth (1973) cross-sectional regressions in the subsamples split jointly by MAX and each measure proxying for the three alternative hypotheses. The results indicate that the explanatory power of MAX remains strong when each of the three hypotheses are tested jointly.

To have a comprehensive analysis and direct comparisons for all hypotheses, we adopt the cross-sectional regressions by including interaction terms between AG and all measures proxying for gambling preference, overinvestment, limits-to-arbitrage, and investment frictions. The estimation results show that the interaction term between AG and MAX is significantly negative and robust to several specifications, while the majority of other variables fail to provide reliable explanatory power for the AG effect. We thus conclude that investors tend to exhibit lottery-chasing behavior in trading stocks that have experienced extreme asset expansions, and more importantly, that the evidence based on MAX reorients current explanations of the AG anomaly. This promising channel plays a determinant role in inducing the AG effect in the cross section of stock returns.

Our study has important implications to the literature. Existing explanations mostly attribute the AG effect to the biased behavior or superior ability of corporate managers (i.e., overinvestment or the q-theory) or firm-level characteristic associated with limits-to-arbitrage. We provide the first study to highlight the importance of investors' behavior, in particular, the preference for lottery-like payoffs, to explain the anomaly. Our results indicate that the overvaluation of high AG firms deserves an in-depth investigation to understand the underlying reason of the AG anomaly.

The remainder of this paper is organized as follows. We develop the gambling preference hypothesis for the AG anomaly and set up overinvestment, limits-to-arbitrage, and the q-theory as alternative hypotheses in Section 2. Section 3 describes the data and variable definitions used in this paper. Main results regarding portfolio-level analyses and cross-sectional regressions that comprehensively examine the impacts of MAX on the AG premium are presented in Section 4. Section 5 provides the investigation concerning the incremental explanatory power of MAX on the AG premium beyond measures of overinvestment, limits-to-arbitrage, and investment frictions. Section 6 concludes this paper.

2 Literature review and hypotheses development

The relation between a firm's investment and stock returns is initiated by the evidence of Baker, Stein, and Wurgler (2003) that current capital expenditures are negatively associated with future stock returns. Titman, Wei, and Xie (2004) propose that the negative relation between corporate investment and stock returns is due to investors' underreactions to overinvestment pursued by empire-building managers. Cooper, Gulen, and Schill (2008) attribute the anomaly to investors' overreactions to firms' future business prospects implied by asset expansions or reductions. These studies point to the mispricing argument for the AG anomaly.

In a market without frictions, if a stock is mispriced, arbitrageurs will be attracted by such profit opportunities and engage in correcting the mispricing. Then the stock price would be corrected to the fundamental value, and the mispricing disappears immediately. Because arbitrage is risky and costly in reality, arbitrageurs' willingness to trade is abated when arbitrage opportunities are limited, or in other words, when limits-to-arbitrage is severer. As a result, limits-to-arbitrage enhances the existence of asset-pricing anomalies. The literature has generally demonstrated supportive evidence for limits-to-arbitrage in explaining the positive relation between BM ratio and stock returns (Ali, Hwang, and Trombley, 2003) and the negative relation between accruals and stock returns (Mashruwala, Rajgopal, and Shevlin, 2006).

Motivated by the argument that lower cost of capital implies higher net present values (NPVs) of new projects, the literature proposes that the q-theory of Cochrane (1991, 1996) predicts a rational negative relation between corporate investments and stock returns because value-maximizing managers adopt investment projects with higher NPVs implied by low expected returns. The literature generally demonstrates supportive evidence for the q-theory of investment in explaining a wide range of asset-pricing anomalies (Zhang, 2005; Li, Vassalou, and Xing, 2006; Xing, 2008; Li, Livdan, and Zhang, 2009; Livdan, Sapriza, and Zhang, 2009; Wu, Zhang, and Zhang, 2010).

Li and Zhang (2010) empirically show that the q-theory with investment frictions fails to explain the AG anomaly, while limits-to-arbitrage seems to plays a dominant role for the anomaly. Lam and Wei (2011), by contrast, show that proxies for the q-theory and proxies for limits-to-arbitrage are often highly correlated, and that both hypotheses are supported in explaining the AG anomaly. Using data from international markets, Titman, Wei, and Xie (2013) and Watanabe, Xu, Yao, and Yu (2013) show that the AG anomaly is more pronounced among more developed and more efficient markets. Their evidence is consistent with the prediction of the q-theory.

An important feature of high AG firms documented in Cooper, Gulen, and Schill (2008) is the strong persistence in firms' AG rates and returns prior to the portfolio formation year. They show that firms with highest AG on average generate 3.86% and 3.49% returns in years -2 and -3 before they adopt the policy of such high growth rates. Corresponding returns of lowest AG firms are -0.64% and 0.04%, respectively. In other words, the high past return performance of high AG stocks attracts lottery-like investors' attention.

Although the literature has detected the relation between investor attention and accounting information like earnings, accruals, cash flow, and profitability (Hales, 2007; Hirshleifer, Lim, and Teoh, 2011; Drake, Roulstone, and Thornock, 2012), whether AG is an attention-grabbing information to investors has yet examined in the literature. A theoretical support for this conjecture is provided by Peng (2005), who proposes a model to show that assets with greater fundamental volatility attract more capacity allocation from investors. As AG represents a form of fundamental volatility, whether its magnitude causes investors' attention becomes an empirical issue.

We thus hypothesize that extremely high AG serves as an attention-grabbing information to investors, but AG alone is insufficient enough to induce overvaluation. Bali, Cakici, and Whitelaw (2011) and Bordalo, Gennaioli, and Shleifer (2012, 2013) propose alternative explanations based on assets' lottery-like payoffs for stocks' overvaluation. Motivated by the vast literature that investors exhibit preferences in chasing lottery-like assets (Thaler and Ziemba, 1988; Garrett and Sobel, 1999;

Walker and Young, 2001; Barber and Odean, 2008; Kumar, 2009), they show that stocks with lottery-like or salient payoffs are subject to severer overvaluation and poor subsequent performance. In these studies, lottery-like or salient features are often identified by market information such as low price, high idiosyncratic volatility, high (idiosyncratic) skewness, and extreme past return.

We thus hypothesize that once extremely high AG is salient to investors, their aggressive trading is triggered when the market information, i.e., lottery-like payoff, is eventually realized. That is, overvaluation is magnified in stocks with the presence of both features. In such case, overvaluation results in severer subsequent underperformance among stocks with both high AG and lottery-like payoffs. If the AG anomaly is driven by the overvaluation of high AG stocks, investors' trading behavior toward stocks with lottery-like payoffs would strengthen the profitability of the AG anomaly. We thus propose the first testable hypothesis:

Hypothesis 1 (H1): The gambling preference hypothesis predicts that the negative relation between AG and future stock returns is more pronounced among firms with lottery-like payoffs (i.e., high MAX firms).

To contrast with existing explanations of the AG anomaly, it is important to compare the relative explanatory ability of variables that are associated with different hypotheses. That is, it is critical to demonstrate the dominant role of the gambling preference under the considerations of alternative explanations based on overinvestment, limits-to-arbitrage, and q-theory with investment frictions. To this end, we test the second hypothesis as follows:

Hypothesis 2 (H2): Controlling for overinvestment, limits-to-arbitrage, and investment frictions, the negative relation between AG and future stock returns is more pronounced among firms with lottery-like payoffs.

3 Variable definitions, data, and summary statistics

3.1 Measures of asset growth and asset-pricing variables

The main variable of interest in this project is a firm's asset growth. In particular, we follow Cooper, Gulen, and Schill (2008) and several follow-up studies by using changes in total asset (AG) to measure the degree of asset expansion. From July of year y to June of year $y+1$, we define $AG_{i,y}$ as the growth rate of stock i's total assets (TA) from year $y-2$ to year $y-1$, expressed as:

$$AG_{i,y} \equiv \frac{TA_{i,y-1} - TA_{i,y-2}}{TA_{i,y-2}}. \tag{1}$$

In addition to asset growth, we also incorporate several determinants that are related to the cross-sectional variations of stock returns as control variables. Following Fama and French (1992), we include firm size (SIZE) and book-to-market ratio (BM). To control for the momentum effect initiated by Jagadeesh and Titman (1993), we incorporate past returns (PR6). We also consider gross profitability (GP) because Novy-Marx (2013) indicates that GP captures the complementary effect of the value strategy. SIZE is the natural logarithm of a stock's market capitalization at the end of June in year y. BM is the natural logarithm of a stock's book value of equity at the end of the fiscal year ending in calendar year $y-1$ divided by its market value of equity at the end of December in year $y-1$. PR6 is the a stock's cumulative return over the previous six months with a 1-month skip calculated at the beginning of every month t.[3] Finally, GP is defined as gross profits (revenues minus cost of goods sold) scaled by total assets at the end of the fiscal year ending in calendar year $y-1$.

[3] We skip one month between the formation and holding periods to avoid the short-term return reversals documented in Jegadeesh (1990) and Lo and MacKinlay (1990).

3.2 The measure of investors' gambling preference

To measure investors' gambling preferences, we follow Bali, Cakici, and Whitelaw (2011) by adopting the maximum daily return within the previous month (MAX) as the main proxy in this project. That is, MAX is defined as $\text{Max}\{r_{i,d}\}$, where $r_{i,d}$ is stock i's return on day d within month t. Comparing across stocks, MAX by construction captures the extreme positive returns in the cross-sectional pricing of stocks. The adoption of MAX has two major advantages. First, taking advantage of the fact that investors exhibit a preference for lottery-like payoffs, the maximum return occurs with a low probability but large magnitude. Hence MAX serves a good proxy for lottery-like payoffs and captures the magnitude of investors' gambling preferences. Second, Bali, Cakici, and Whitelaw (2011) demonstrate that the impact of MAX on stock returns remains robust to controls for measures of skewness. More importantly, MAX subsumes the pricing ability of skewness measures and thus serves as a better proxy for investors' gambling preferences.

3.3 The proxies of overinvestment, limits-to-arbitrage, and investment frictions

To examine the relative explanatory power of the gambling preference measure controlling for alternative effects, we include several variables that are associated with overinvestment, limits-to-arbitrage, and the q-theory with investment frictions. The proxies of overinvestment include cash flow (FCF) and the debt ratio (DEBT). FCF is defined as a firm's operating income before depreciation minus interest expenses, taxes, preferred dividends, and common dividends, divided by total assets. DEBT is defined as a firm's debt-to-assets ratio.

The proxies of limits-to-arbitrage include idiosyncratic volatility (IVOL), volatility of cash flow from operations (CVOL), share price (PRICE), dollar trading volume

(DVOL), and illiquidity (ILLIQ). The calculation of IVOL involves the time-series regressions of stock returns on the market portfolio over a maximum of 250 days ending in June of year y. IVOL is then calculated as the standard deviation of the residuals. At the end of June in year y, CVOL is measured as the standard deviation of cash flow from operations over the previous 5 years (requiring a minimum of 3 years). PRICE is the closing stock price at the end of June of year y. DVOL is defined as the time-series average of monthly share trading volume multiplied by the monthly closing price over the past 12 months ending in June of year y. Finally, ILLIQ is the time-series average of the Amihud (2002) illiquidity measure over the past 12 months ending in June of year y, in which the Amihud measure is calculated as the absolute daily return divided by daily dollar trading volume.

The measures of the q-theory with investment frictions include firm age (AGE), asset size (ASSET), payout ratio (PAYOUT), and bond ratings (RATING). AGE is the number of years a stock has appeared in the CRSP database at the end of year $y - 1$. ASSET is the book value of total assets at the end of year $y - 1$. PAYOUT is defined as total dividends divided by earnings at the end of year $y - 1$. RATING is a dummy variable, which is 0 if a firm has never had a Standard & Poor's long-term credit rating in the Compustat database in the sample period and 1 otherwise.

3.4 Data, sample selection, and summary statistics

We focus our analyses on a sample consisting of all common listed stocks with shares codes of 10 and 11 trading on NYSE, Amex, and Nasdaq for the period from July 1963 to December 2016. We exclude financial firms with 4-digit SIC codes between 6000 and 6999. Daily and monthly return data of individual stocks are obtained from the Center for Research in Security Prices database. Accounting data are retrieved from the COMPUSTAT database. As in Fama and French (1993), a firm is required to be listed on COMPUSTAT for 2 years before it is included in the sample to mitigate backfilling biases. To obtain abnormal returns, we use Carhart's (1997) four-factor model and Fama and French's (2015) five-factor model as risk adjustments. Data on corresponding factors are downloaded from Ken French's website.[4]

We construct AG portfolios by allocating individual stocks into deciles based on their values of AG at the end of June for each year. The portfolios are formed starting from July to next June and are rebalanced every year. We calculate equally- and value-weighted monthly returns for each portfolio and define the AG premium as the difference in returns between highest and lowest deciles. In addition to raw returns, we also calculate risk-adjusted returns by obtaining intercepts from time-series regressions of returns on Carhart's (1997) four-factor model and Fama and French's (2015) five-factor model, respectively.

Panel A of Table 1 shows the average portfolio returns and intercepts, as well as corresponding t-statistics adjusting for autocorrelation and heteroskedasticity based on Newey and West's (1987) standard errors. Consistent with Cooper, Gulen, and Schill (2008), we document significant AG premium, which amounts to -1.506% (-0.748%) per month under equal (value) weights. The AG premium remains negative and significant under risk adjustments using either Carhart's (1997) four-factor model or Fama and French's (2015) five-factor model, especially when the portfolios are constructed based on equal weights.

[Insert Table 1 about here]

We also report several dimensions of firm characteristics across AG deciles in Panel B of Table 1. These characteristics include alternative asset pricing variables of SIZE, BM, PR6, and GP, the main conditioning variable of the paper, MAX, and

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

several proxies associated with overinvestment, limits-to-arbitrage, and investment frictions. In particular, higher AG firms tend to have larger market capitalizations, lower BM ratios and past returns than lower AG firms. Gross profitability displays an inverted-U shape across AG deciles. MAX, however, shows an U shape across AG deciles; that is, it is higher for lowest and highest AG firms than the rest allocated in between. This observation suggests that lowest and highest AG firms are more likely to be gambling targets to investors.

AG also exhibits some observable patterns across proxies of overinvestment, limits-to-arbitrage, and investment frictions. First, highest AG firms have higher capacity to overinvest than lowest AG firms because the difference in FCF (DEBT) between deciles 10 and 1 is significantly positive (negative). This pattern thus verifies the relation between AG and overinvestment. Second, observable from the fact that the degrees of limits-to-arbitrage are higher among firms with high and low AG ratios, the relation between limits-to-arbitrage and AG is U-shaped. Firms with high and low AG ratios have higher IVOL, CVOL, and ILLIQ, as well as lower PRICE and DVOL than those with moderate AG ratios. Finally, high and low AG firms have higher investment frictions. They tend to be younger firms and have lower total assets and lower dividend payout ratios.

Given the fact that AG is associated with proxies of existing explanations and investor gambling preference, it is important to disentangle the competing explanatory power between these potential explanations. This is the main focus of the following sections.

4 Gambling preferences and the asset growth premium

4.1 Portfolio analysis

We begin the main analyses by forming AG portfolios conditional on the proxy of investors' gambling preference, MAX. For each July of year y to June of year $y+1$, we sort individual stocks into quintile portfolios according to their values of AG calculated at the end of year $y-1$. Over the sample period, we sort all stocks independently into quintile portfolios according to their values of maximum daily return over the past month (MAX). For each of the 25 AG-MAX sorted portfolios, we calculate equally- or value-weighted returns every month from July of year y to June of year $y+1$. To observe AG premium conditional on MAX, we calculate the return difference between high and low AG portfolios within each MAX decile. According to **H1**, we expect the magnitude of negative return difference between high and low AG portfolios to be larger and more significant for high MAX decile than low MAX decile.

The results presented in Table 2 confirm the prediction of **H1**. As shown in Panel A, the AG premium is substantially negative and significant at -1.071% (-1.227%) per month for the highest MAX decile under equal (value) weights; it shrinks to -0.395% (-0.550%) per month for the 4th MAX decile and becomes insignificantly different from zero for the remaining MAX deciles. These patterns remain unchanged when returns are adjusted by either the Carhart (1997) or the Fama and French (2015) factor models.

Results reported in Panel A also has important implications to the results of Bali, Cakici, and Whitelaw (2011), who show that the pronounced negative premium between stocks with high and low MAX is robust to several cross-sectional determinants of stock returns. We show that the MAX premium is also related to a firm's AG.

In particular, the premium between high and low MAX portfolios exhibits monotonically decreasing pattern as AG increases. This finding indicates that investors not only have a preference for stocks with extreme past performance but also view high AG stocks favorably. As a result, their gambling preferences would be enhanced when lottery-like stocks experienced extreme AG in the past, leading to greater willingness to bid up the price for such stock.

Figure 1 presents graphical illustrations of the 25 portfolios formed on MAX and AG based on equally- and value-weighted returns. A dramatic finding is that only the highest AG portfolio interacting with highest MAX values exhibits remarkable underperformance. In particular, the portfolio interacting with AG5 and MAX5 generates average equally- and value-weighted returns of 0.029% and -0.187% per month, far lower than those of the portfolio interacting with AG5 and MAX1 (the corresponding returns are 1.698% and 0.938% under equal and value weights, respectively). The figure also corresponds with the 25 AG-MAX portfolio returns reported in Panel A of Table 2 that only stocks with the interaction of highest AG and highest MAX exhibit insignificant returns under equal weights and negative returns under value weights. This observation suggests that the underperformance of highest AG stocks is not a pervasive phenomenon, and that investors' gambling preference plays an important role in differentiating the subsequent performance of highest AG stocks.

[Insert Table 2 and Figure 1 about here]

In addition to single daily return, an alternative way to identify the tendency of gambling reference is to calculate the average of the N highest daily returns within the month. We adopt $N = 5$ and 10 as two alternatives with corresponding results presented in Panels B and C of Table 2.[5] The results based on MAX(5) and MAX (10)

[5]In particular, Bali, Cakici, and Whitelaw (2011) use $N = 1, 2, ..., 5$ as alternatives. We do not

are generally consistent with the observations reported in Panel A, thus suggesting that our finding is not special to the way we define investors' gambling preference.

4.2 Cross-sectional regressions

In addition to portfolio-based analyses, we also perform the Fama and MacBeth (1973) cross-sectional regressions that enable us to control for additional variables that are related to stock returns. In particular, in every month t we perform the following cross-sectional regressions separately for each MAX quintile:

$$R_{i,t} = b_0 + b_1 \mathrm{AG}_{i,t} + b_2 \mathrm{Size}_{i,t} + b_3 \mathrm{BM}_{i,t} + b_4 \mathrm{PR6}_{i,t} + b_5 \mathrm{GP}_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $R_{i,t}$ is defined as stock i's return in month t; $\mathrm{AG}_{i,t}$ is stock i's asset growth in month t; $\mathrm{Size}_{i,t}$ is stock i's market capitalization in month t; $\mathrm{BM}_{i,t}$ is stock i's book-to-market ratio in month t; $\mathrm{PR6}_{i,t}$ is stock i's past six-month return calculated in month t; $\mathrm{GP}_{i,t}$ is stock i's gross profits in month t. The independent variables are defined as in Section 3.1. We obtain estimated coefficients from Equation (2) every month and calculate average coefficients for each MAX quintile over the sample period and corresponding t-statistics that are adjusted by Newey and West's (1987) robust standard errors. According to **H1**, high MAX quintiles are expected to exhibit negative b_1 coefficients in larger magnitude and higher significance than low MAX quintiles. We report the regression results in Table 3.

[Insert Table 3 about here]

Panel A indicates that the average coefficients on AG are -0.154, -0.195, -0.128, -0.226, and -0.435 for 1st to 5th MAX quintiles. The difference in the AG coefficient between highest and lowest AG quintiles is -0.281 with a t-statistic of -2.21. This

report the results based on $N = 3, 4, 5$ to conserve space. These alternative measures provide similar results, that are available upon request. In stead, we use two slightly longer lengths ($N = 5$ and 10) to verify the robustness of our results.

finding suggests that the AG anomaly is more prevalent among stocks with higher MAX values, and that investors' gambling preference is related to the anomaly. In addition, stocks with higher MAX also reveal stronger size and BM premia, while those with lower MAX generate higher gross profitability premium. The opposite directions of MAX's impacts on BM and gross profitability anomalies are not surprising because Novy-Marx (2013) observe that the two anomalies are negatively correlated.

We also verify the effectiveness of investors' gambling preference on the AG anomaly by using MAX(5) and MAX(10) as the conditioning variables, with results presented in Panels B and C. The overall patterns remain unchanged, with the only exception that the average coefficient between highest and lowest AG quintiles is marginally significant at the 10% level for MAX(10), which is -0.268 with a t-statistic of -1.82. The evidence from cross-sectional regressions again highlights the importance of investors' gambling preference in explaining the AG premium controlling for other determinants of stock returns.

5 Gambling preferences versus alternative explanations

So far, we have documented evidence in support of our hypothesis **H1** for the AG anomaly. The next important issue is to contrast our argument with existing explanations of the AG anomaly to ensure the validity of our findings. In this section, we set up overinvestment, limits-to-arbitrage, and the q-theory with investment frictions as alternative explanations and examine the incremental explanatory power of MAX controlling for these alternatives.

5.1 The effect of gambling preferences controlling for overinvestment

Titman, Wei, and Xie (2004) propose that the negative relation between corporate investment and stock returns is induced by investors' underreactions to the overinvestment behavior of empire-building managers. Motivated by the fact that firms with higher cash flows or lower debt ratios have higher tendency to overinvest, the overinvestment argument suggests higher AG premium among stocks with higher cash flows or lower debt ratios. Before formally examining the joint impacts of investors' gambling preference and overinvestment, we first verify the explanatory ability of overinvestment proxies on the AG anomaly. To this end, we sort individual stocks into quintiles according to their values of FCF or 1/DEBT; the variable definitions are described in Section 3.3. We take an inverse for DEBT so that higher value of the variable signifies higher degree of overinvestment. We next perform the cross-sectional regressions of Equation (2) within each FCF (or 1/DEBT) quintile. If overinvestment plays and important role in explaining the AG anomaly, we expect that the negative relation between stock returns and AG is more pronounced for the highest FCF or 1/DEBT quintile. The estimation results are presented in Panel A of Table 4.

[Insert Table 4 about here]

We show that when considered alone, neither FCF nor DEBT has significant influence on the AG anomaly. This is observable from the positive difference in coefficients on AG between the 5th and 1st quintiles. This observation also implies higher AG premium for firms with lower tendency to overinvest, which is inconsistent with the prediction of the overinvestment hypothesis.

To compare the impacts of investors' gambling preference and overinvestment simultaneously, we follow Li and Zhang (2010) and Lam and Wei (2011) by performing the cross-sectional regressions separately for two-way sorted subsamples based on MAX and overinvestment proxies. In particular, we allocate individual stocks into quintiles based on MAX values and another independent sort into overinvestment tertiles, where overinvestment is proxied by FCF or 1/DEBT. We then perform the cross-sectional regressions of Equation (2) for each of the 15 portfolios interacting with MAX and overinvestment proxies. We also calculate the difference in coefficients on AG between highest and lowest MAX quintiles within each overinvestment subgroup. This examination enables us to observe the incremental impact of MAX conditional on overinvestment proxies.

Panels B and C of Table 4 present the estimation results with FCF and 1/DEBT proxying for overinvestment, respectively. The significance of the negative AG coefficient in the highest MAX quintile is not specially designated to a particular overinvestment subgroup. In particular, among stocks with highest MAX, two out of the three FCF (or 1/DEBT) subgroups have significantly negative coefficients on AG. The difference between highest and lowest MAX subgroups is significant in the high FCF tertile and the low 1/DEBT tertile. This observation indicates that the overinvestment argument does not provide uniform influence on the AG anomaly when we control for MAX. Thus investor gambling preference serves as a more powerful explanation for the AG anomaly than the overinvestment argument.

5.2 The effect of gambling preferences controlling for limits-to-arbitrage

The next task is to examine the contrast between investor gambling preference and limits-to-arbitrage in explaining the AG anomaly. Li and Zhang (2010) indicate that proxies of limits-to-arbitrage dominate q-theory with investment frictions in explain the anomaly. Lam and Wei (2011) show that proxies for limits-to-arbitrage and q-theory are highly correlated, so the two hypotheses are both supported to explain the AG anomaly. Motivated by the findings of the two studies, the robustness of our evidence to proxies of limits-to-arbitrage becomes an important issue that has yet been investigated. To address this issue, we replicate the same procedures used in Section 5.1 but replacing proxies of overinvestment with proxies of limits-to-arbitrage. As mentioned in Section 3.3, the proxies of limits-to-arbitrage include IVOL, CVOL, 1/PRICE, 1/DVOL, and ILLIQ. Again, we take inverse for PRICE and DVOL so that they are positively related to limits-to-arbitrage. We report the empirical results in Table 5.

[Insert Table 5 about here]

Panel A shows that when considered alone, IVOL and 1/PRICE provide a fair amount of support for the limits-to-arbitrage hypothesis because the 5th quintile formed based on the two proxies yields significantly negative coefficient on AG while the 1st quintile does not. This results in a significantly negative difference between the 5th and the 1st quintiles. The results based on CVOL, 1/DVOL, and ILLIQ, however, do not exhibit significant dispersion in AG coefficients between different quintiles. This evidence is quite consistent with the empirical results documented by Lam and Wei (2011), who also show that CVOL, 1/DVOL, and ILLIQ do not support the limits-to-arbitrage argument for the AG anomaly while IVOL and 1/PRICE explain a fair amount of the AG premium.

When examining the joint roles of MAX and proxies of limits-to-arbitrage, as shown in Panels B to F, we find that stocks with highest MAX values consistently generate significantly negative AG coefficients, regardless of the magnitude of limits-to-arbitrage. That is, all of the 15 coefficients for the highest MAX quintiles have significantly negative AG coefficients among low to high limits-to-arbitrage subgroups across the five proxies. It is also striking that 11 out of the 15 differences between the 5th and the 1st MAX quintiles across low to high limits-to-arbitrage subgroups are significantly negative. These observations thus suggest that the impact of investors' gambling preference on the AG anomaly is robust to the limits-to-arbitrage hypothesis.

5.3 The effect of gambling preferences controlling for investment frictions

The q-theory with investment frictions is perhaps the most promising explanation of the AG anomaly for both the U.S. and international equity markets (Lam and Wei, 2011; Titman, Wei, and Xie, 2013; Watanabe, Xu, Yao, and Yu, 2013). We thus examine whether proxies of investment frictions, including 1/AGE, 1/ASSET, 1/PAYOUT, and RATING, subsume the explanatory ability of MAX on the AG anomaly. The inverse is taken so that higher values of the variables are associated with higher investment frictions. In Panel A of Table 6, we report the results of cross-sectional regressions conditional on each of the four proxies of investment frictions. The difference in AG coefficients between highest and lowest quintiles for each proxy is negative, with RATING serving as the most powerful predictor of the AG anomaly. In particular, the coefficient is -0.105 (t-statistic = -1.41) for rated firms and is -0.353 (t-statistic = -4.75) for unrated firms, resulting a significant difference of -0.248 (t-statistic = -2.75).

[Insert Table 6 about here]

When considering the joint impacts of MAX and proxies of investment frictions, we again show in Panels B to E that stocks with highest MAX dominate the q-theory with investment frictions in explaining the AG premium. In particular, all of MAX quintile across the 11 subgroups of investment frictions exhibit significantly negative AG coefficients. The significantly negative AG coefficients for high investment frictions, however, are mostly concentrated in the highest MAX quintile across different proxies. These observations thus lead us in believing that investors' gambling preference better explains the AG anomaly than the q-theory.

5.4 Combined analyses

The comparisons between MAX and alternative explanations provided in previous subsections are conducted based on single proxy of alternative hypotheses and MAX. To have a comprehensive analysis that simultaneously consider all possible explanations, we adopt a similar approach advocated by Ali, Hwang, and Trombley (2003) by performing cross-sectional regressions that incorporate interaction terms of AG and several variables proxied for each hypothesis. The regression takes the following form:

$$\begin{aligned} R_{i,t} \;=\; & b_0 + b_1\mathrm{AG}_{i,t} + b_2\mathrm{Size}_{i,t} + b_3\mathrm{BM}_{i,t} + b_4\mathrm{PR6}_{i,t} + b_5\mathrm{GP}_{i,t} + b_6\mathrm{AG}_{i,t}\times\mathrm{MAX}_{i,t} \\ & + b_7\mathrm{AG}_{i,t}\times\mathrm{FCF}_{i,t} + b_8\mathrm{AG}_{i,t}\times\mathrm{DEBT}^{-1}_{i,t} + b_9\mathrm{AG}_{i,t}\times\mathrm{IVOL}_{i,t} \\ & + b_{10}\mathrm{AG}_{i,t}\times\mathrm{CVOL}_{i,t} + b_{11}\mathrm{AG}_{i,t}\times\mathrm{PRICE}^{-1}_{i,t} + b_{12}\mathrm{AG}_{i,t}\times\mathrm{DVOL}^{-1}_{i,t} \\ & + b_{13}\mathrm{AG}_{i,t}\times\mathrm{AGE}^{-1}_{i,t} + b_{14}\mathrm{AG}_{i,t}\times\mathrm{ASSET}^{-1}_{i,t} + b_{15}\mathrm{AG}_{i,t}\times\mathrm{PAYOUT}^{-1}_{i,t} \\ & + b_{16}\mathrm{AG}_{i,t}\times\mathrm{RATING}_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

We expect the coefficient b_6 to be significantly negative if investors' gambling preference indeed plays an important and robust role for the AG anomaly. We perform the regressions of Equation (3) every month and test the average coefficients using Newey-West (1987) robust standard errors. Table 7 gives the regression results.

[Insert Table 7 about here]

In Models (1) to (3), we incorporate interaction terms associated with overinvestment, limits-to-arbitrage, and the q-theory, respectively. We consider the full model of Equation (3) in Model (4). Confirming our prediction, the coefficients on AG $\times$ MAX are significantly negative in all of the four model specifications. In addition to the interaction term of AG and MAX, coefficients on AG $\times$ PRICE^{-1} are also persistently negative and significant in Models (2) and (4).

Throughout the paper, we adopt MAX as a proxy of investors' gambling preference because Bali, Cakici, and Whitelaw (2011) point out that MAX is a more powerful predictor of stock returns than skewness measures. To ensure that our argument regarding gambling preference is not subject to a particular measurement, we also consider alternative skewness measures to proxy for gambling preference. Following Harvey and Siddique (1999, 2000), we calculate three measures of skewness, including total skewness (TSKEW), systematic skewness (SSKEW), and idiosyncratic skewness (ISKEW). For each month t, TSKEW is computed as $\frac{1}{D_y}\sum_{d=1}^{D_y}\left(\frac{R_{i,d}-\mu_i}{\sigma_i}\right)^3$, where D_y is the number of days over past 12 months ending in month $t-1$, $R_{i,d}$ is stock i's return on day d, μ_i and σ_i are the mean and standard deviation of stock i's return over past 12 months. The calculations of SSKEW and ISKEW involve the following regression for each stock estimated over past 12 months ending in month $t-1$: $R_{i,d}-R_{f,d}=\alpha_i+\beta_i(R_{m,d}-R_{f,d})+\gamma_i(R_{m,d}-R_{f,d})^2+\varepsilon_{i,d}$, where $R_{f,d}$ is the risk-free rate on day d, $R_{m,d}$ is the market return on day d, $\varepsilon_{i,d}$ is the idiosyncratic return on day d. SSKEW is measured by γ_i from the regression, and ISKEW is defined as the skewness of daily $\varepsilon_{i,d}$ over past 12 months.

We replace MAX with TSKEW, SSKEW, and ISKEW respectively in Equation (3) and report the estimation results in Models (4) to (7) of Table 7. Coefficients on AG $\times$ TSKEW and AG $\times$ ISKEW are significant at -0.210 and -0.190 with t-statistics of

-2.83 and -2.63, respectively, while that on AG $\times$ SSKEW is insignificant. This finding confirms the robustness of our findings when investors' gambling preference is proxied by total skewness or idiosyncratic skewness (the idiosyncratic part of total skewness). When we include MAX, SSKEW, and ISKEW as interaction terms accompanied with all other proxies of alternative explanations, as presented in Model (8), we find that the coefficient on AG $\times$ MAX still remains significantly negative while that on AG $\times$ ISKEW is only marginally significant (the corresponding t-static is -1.85). This observation is important because we add new evidence to Bali, Cakici, and Whitelaw's (2011) finding that MAX not only better explains stock returns but also better accounts for the AG anomaly than skewness measures.

6 Conclusion

The reason why the AG anomaly could be pronounced has been debated in the literature. Existing studies mostly posit three lines of explanations for this anomaly, overinvestment, limits-to-arbitrage, and the q-theory. We contribute to the literature by providing a new insight into the understanding of the AG anomaly, namely investors' gambling preference. The underlying reason is that the overvaluation of high AG stocks is particularly driven by investors' trading behavior in chasing stocks with lottery-like payoffs. We thus hypothesize that the overvaluation of high AG stocks is concentrated among stocks with high MAX values but not low MAX values.

We document significant and robust evidence in confirming this hypothesis. Among the 25 AG-MAX sorted portfolios, only stocks with the interaction of highest AG and highest MAX exhibit insignificant returns under equal weights and negative returns under value weights. As a result, the AG premium is stronger by a fair amount for high MAX stocks than for low MAX stocks. Our results are quite consistent to risk-adjustments, different empirical methods, and controls of alternative explanations.

Our study has important implications. First, while existing explanations mostly attribute the AG anomaly to the biased behavior or superior ability of corporate managers or firm-level characteristic associated with limits-to-arbitrage, We provide the first study to highlight the importance of investors' preference for stocks with lottery-like payoffs in explaining the anomaly. Second, we show that investors not only have a preference for stocks with extreme past performance but also view high AG stocks favorably. Their gambling preferences are enhanced when lottery-like stocks experienced extreme AG in the past, leading to greater willingness to bid up the price for such stock. Thus, our evidence also provide important implications for the MAX anomaly.

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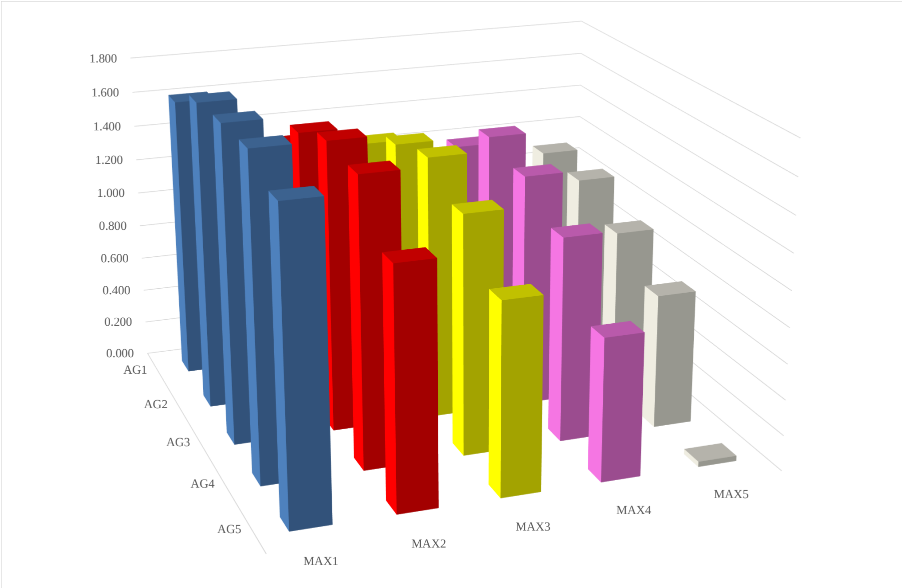
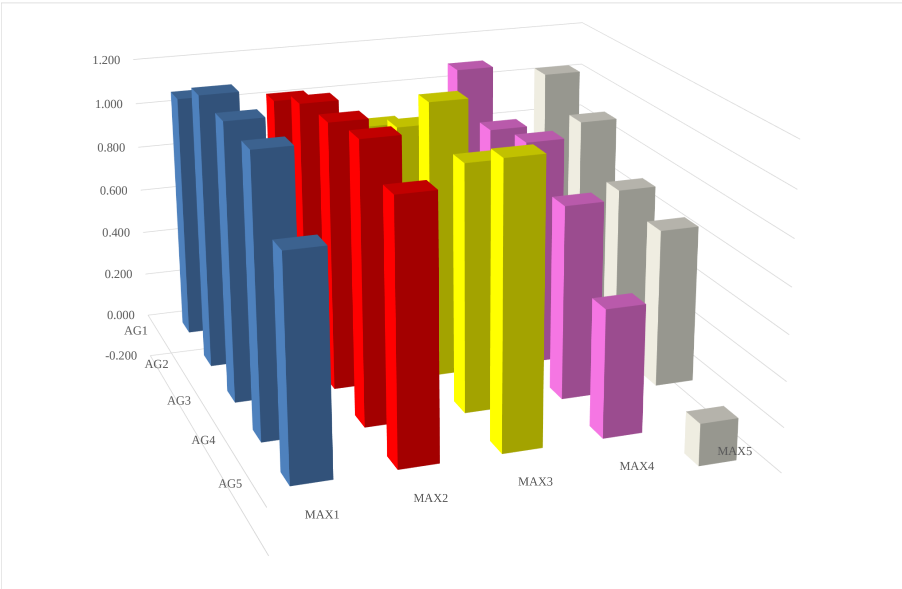


(a) Equally-weighted returns



(b) Value-weighted returns

Figure 1: Monthly returns of 25 MAX-AG sorted portfolios

Table 1: Portfolio returns and firm characteristics formed on AG

This table reports monthly returns of portfolios formed on AG based on a sample consisting of all common stocks listed on NYSE, Amex, and Nasdaq for the period from July 1963 to December 2016. From July of year y to June of year $y+1$, we define $AG_{i,y}$ as the growth rate of stock i's total assets (TA) from year $y-2$ to year $y-1$. At the end of June for each year, we allocate individual stocks into deciles based on their values of $AG_{i,y}$. The portfolios are formed starting from July to next June and are rebalanced every year. In Panel A, we calculate equally- and value-weighted monthly returns for each portfolio and define the AG premium as the difference in returns between highest and lowest deciles. In addition to raw returns, we also calculate risk-adjusted returns by obtaining intercepts from time-series regressions of returns on Carhart's (1997) four-factor model and Fama and French's (2015) five-factor model, respectively. In Panel B, we report several dimensions of firm characteristics across AG deciles, including SIZE, BM, PR6, GP, MAX, and several proxies associated with overinvestment, limits-to-arbitrage, and investment frictions. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Portfolio	1	2	3	4	5	6	7	8	9	10	10−1	Carhart α	FF5 α
Panel A: Portfolio returns across AG deciles													
EW	1.924***	1.658***	1.539***	1.437***	1.358***	1.310***	1.275***	1.102***	0.936***	0.418	-1.506***	-1.216***	-1.211***
	(4.97)	(5.56)	(6.03)	(6.26)	(6.00)	(5.63)	(5.19)	(4.16)	(3.11)	(1.18)	(-8.82)	(-7.79)	(-7.40)
VW	1.152***	1.198***	1.110***	1.036***	0.986***	0.953***	0.988***	0.907***	0.897***	0.404	-0.748***	-0.421***	-0.221*
	(4.89)	(5.49)	(6.24)	(6.37)	(5.81)	(5.64)	(5.17)	(4.03)	(3.63)	(1.29)	(-3.93)	(-2.71)	(-1.66)
Portfolio	1	2	3	4	5	6	7	8	9	10		10−1	t(10−1)
Panel B: Firm characteristics across AG deciles													
AG	-0.213	-0.069	-0.011	0.026	0.061	0.098	0.147	0.226	0.401	1.179		1.392	19.20
SIZE	0.038	0.088	0.156	0.201	0.271	0.315	0.298	0.263	0.219	0.148		0.110	11.10
BM	0.765	0.955	0.923	0.874	0.800	0.714	0.635	0.561	0.487	0.405		-0.361	-13.65
PR6	1.024	1.135	1.093	1.103	1.066	1.039	1.029	0.885	0.715	0.224		-0.800	-6.10
GP	0.269	0.317	0.324	0.329	0.349	0.368	0.391	0.391	0.365	0.282		0.013	2.23
MAX	0.077	0.058	0.048	0.044	0.042	0.044	0.046	0.051	0.056	0.067		-0.010	-8.65
FCF	-0.142	-0.006	0.025	0.035	0.040	0.043	0.042	0.035	0.018	-0.033		0.109	7.60
DEBT	0.520	0.495	0.500	0.503	0.488	0.478	0.467	0.466	0.474	0.440		-0.079	-8.07
IVOL	0.162	0.127	0.105	0.094	0.091	0.093	0.099	0.110	0.125	0.153		-0.009	-4.99
CVOL	0.144	0.076	0.056	0.049	0.046	0.048	0.052	0.060	0.072	0.111		-0.032	-8.36
PRICE	4.532	8.944	13.515	17.329	19.041	19.816	19.503	17.673	15.262	11.314		6.782	25.14
DVOL	41.635	98.818	176.258	195.011	313.564	400.259	404.541	417.271	382.706	280.927		239.292	8.59
ILLIQ	3.820	1.553	0.728	0.398	0.265	0.231	0.237	0.299	0.361	0.420		-3.401	-8.64
AGE	10.574	13.604	16.660	17.890	18.275	17.452	15.511	12.685	9.992	6.920		-3.654	-15.36
ASSET	34.618	120.554	213.861	287.536	309.651	309.048	255.384	194.502	139.657	74.878		40.260	9.93
PAYOUT	0.159	26.647	83.104	119.898	127.822	114.367	84.560	43.750	20.405	5.308		5.149	4.93

Table 2: Portfolio returns formed on AG and MAX

This table reports monthly returns of portfolios formed on AG and MAX based on a sample consisting of all common stocks listed on NYSE, Amex, and Nasdaq for the period from July 1963 to December 2016. From July of year y to June of year $y+1$, we define $AG_{i,y}$ as the growth rate of stock i's total assets (TA) from year $y-2$ to year $y-1$. At the end of June for each year, we allocate individual stocks into quintile portfolios based on their values of $AG_{i,y}$. Over the sample period, we sort all stocks independently into quintile portfolios according to their values of MAX. In Panels A to C, MAX is defined as the maximum one-, five-, and ten-day average return over the past month. We The portfolios are formed starting from July to next June and are rebalanced every year. We calculate equally- and value-weighted monthly returns for each portfolio and define the AG premium as the difference in returns between highest and lowest quintiles within each MAX quintile. In addition to raw returns, we also calculate risk-adjusted returns by obtaining intercepts from time-series regressions of returns on Carhart's (1997) four-factor model and Fama and French's (2015) five-factor model, respectively. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

AG	Equally-weighted returns					Value-weighted returns				
portfolio	1	2	3	4	5	1	2	3	4	5
Panel A: Stocks sorted by MAX										
1	1.616***	1.314***	1.269***	1.194***	1.100***	1.078***	1.031***	0.875***	1.097***	1.039***
	(7.15)	(7.62)	(7.34)	(6.10)	(4.46)	(5.64)	(7.16)	(5.60)	(6.27)	(4.88)
2	1.752***	1.533***	1.413***	1.402***	1.089***	1.224***	1.125***	0.982***	0.930***	0.924***
	(6.69)	(7.13)	(6.75)	(6.06)	(3.82)	(5.72)	(6.01)	(5.51)	(4.16)	(3.63)
3	1.784***	1.636***	1.491***	1.328***	0.941***	1.226***	1.155***	1.219***	0.988***	0.733**
	(5.64)	(6.41)	(6.01)	(5.11)	(2.90)	(4.60)	(5.22)	(5.40)	(4.02)	(2.48)
4	1.921***	1.613***	1.346***	1.155***	0.761**	1.405***	1.338***	1.061***	0.838***	0.685*
	(5.13)	(5.46)	(4.67)	(3.85)	(2.14)	(4.23)	(4.68)	(4.02)	(2.87)	(1.93)
5	1.698***	1.328***	1.070***	0.799**	0.029	0.938**	1.104***	1.254***	0.547	-0.187
	(3.83)	(3.67)	(3.17)	(2.22)	(0.07)	(2.42)	(3.13)	(3.85)	(1.59)	(-0.44)
5-1	0.082	0.014	-0.199	-0.395*	-1.071***	-0.140	0.072	0.379	-0.550**	-1.227***
	(0.27)	(0.06)	(-0.90)	(-1.74)	(-4.51)	(-0.47)	(0.24)	(1.44)	(-2.00)	(-3.84)
Carhart α	-0.076	-0.135	-0.341**	-0.449**	-0.991***	-0.311	-0.023	0.297	-0.632***	-1.231***
	(-0.29)	(-0.64)	(-2.02)	(-2.20)	(-4.56)	(-1.18)	(-0.08)	(1.27)	(-2.85)	(-4.45)
FF5 α	0.149	-0.046	-0.222	-0.264	-0.732***	-0.266	-0.079	0.376*	-0.471**	-1.090***
	(0.62)	(-0.25)	(-1.48)	(-1.49)	(-3.87)	(-1.21)	(-0.39)	(1.74)	(-2.41)	(-4.87)
Panel B: Stocks sorted by MAX(5)										
1	1.610***	1.347***	1.309***	1.293***	1.144***	1.095***	1.060***	0.961***	1.112***	1.245***
	(7.01)	(7.68)	(7.65)	(6.47)	(4.56)	(5.99)	(7.32)	(6.41)	(6.25)	(5.52)
2	1.864***	1.612***	1.456***	1.380***	1.175***	1.249***	1.191***	0.997***	0.966***	0.809***
	(6.97)	(7.74)	(7.01)	(6.16)	(4.14)	(5.72)	(6.47)	(5.47)	(4.63)	(3.38)
3	1.905***	1.583***	1.411***	1.349***	1.090***	1.284***	1.079***	1.118***	0.978***	0.928***
	(6.14)	(6.43)	(5.82)	(5.17)	(3.43)	(4.92)	(4.84)	(4.98)	(3.87)	(3.05)
4	1.993***	1.656***	1.457***	1.127***	0.688*	1.276***	1.378***	1.113***	0.648**	0.477
	(5.52)	(5.54)	(4.94)	(3.74)	(1.95)	(3.80)	(4.76)	(3.95)	(2.18)	(1.35)
5	1.528***	1.191***	0.858**	0.681*	-0.066	0.809*	0.743*	1.119***	0.431	-0.159
	(3.36)	(3.16)	(2.43)	(1.85)	(-0.16)	(1.95)	(1.92)	(2.98)	(1.16)	(-0.35)
5-1	-0.467***	-0.689***	-0.815***	-1.305***	-1.595***	0.150	-0.440**	-0.356*	-0.798***	-0.967***
	(-3.90)	(-5.36)	(-5.92)	(-8.70)	(-8.80)	(0.88)	(-2.51)	(-1.88)	(-3.53)	(-3.87)
Carhart α	-0.424***	-0.616***	-0.604***	-1.060***	-1.338***	0.243	-0.212	0.006	-0.502**	-0.720***
	(-3.89)	(-5.08)	(-4.97)	(-7.40)	(-7.93)	(1.53)	(-1.08)	(0.04)	(-2.29)	(-2.81)
FF5 α	-0.416***	-0.581***	-0.624***	-1.041***	-1.273***	0.282*	0.023	0.110	-0.414*	-0.487*
	(-3.97)	(-5.46)	(-5.05)	(-7.05)	(-6.86)	(1.84)	(0.14)	(0.78)	(-1.92)	(-1.91)
Panel C: Stocks sorted by MAX(10)										
1	1.710***	1.466***	1.421***	1.409***	1.243***	1.301***	1.194***	1.047***	1.231***	1.301***
	(7.25)	(8.05)	(7.97)	(6.70)	(4.58)	(6.99)	(8.07)	(6.81)	(6.47)	(5.43)
2	1.957***	1.602***	1.454***	1.435***	1.268***	1.186***	1.137***	0.968***	0.992***	0.904***
	(6.92)	(7.71)	(6.95)	(6.38)	(4.34)	(5.30)	(6.54)	(5.31)	(4.99)	(3.71)
3	1.903***	1.587***	1.429***	1.263***	0.971***	1.078***	1.097***	1.003***	0.882***	0.866***
	(6.19)	(6.56)	(6.08)	(4.98)	(3.17)	(4.32)	(5.12)	(4.79)	(3.61)	(3.01)
4	2.017***	1.586***	1.335***	1.154***	0.689*	1.327***	1.175***	1.045***	0.736**	0.517
	(5.51)	(5.37)	(4.69)	(3.85)	(1.94)	(3.95)	(4.32)	(3.92)	(2.51)	(1.50)
5	1.409***	1.123***	0.833**	0.573	-0.119	0.820**	0.700*	1.087***	0.390	-0.094
	(3.13)	(3.02)	(2.38)	(1.58)	(-0.30)	(2.05)	(1.82)	(3.10)	(1.06)	(-0.22)
5-1	-0.467***	-0.690***	-0.933***	-1.328***	-1.528***	0.000	-0.281	-0.212	-0.810***	-0.914***
	(-3.53)	(-5.25)	(-6.74)	(-8.71)	(-8.23)	(0.00)	(-1.53)	(-1.24)	(-3.40)	(-3.72)
Carhart α	-0.406***	-0.565***	-0.746***	-1.054***	-1.292***	0.108	-0.022	0.087	-0.491**	-0.675**
	(-3.61)	(-4.42)	(-5.67)	(-7.26)	(-7.51)	(0.63)	(-0.12)	(0.59)	(-2.08)	(-2.56)
FF5 α	-0.397***	-0.544***	-0.762***	-1.059***	-1.206***	0.129	0.153	0.205	-0.330	-0.542**
	(-3.49)	(-4.94)	(-5.99)	(-7.03)	(-6.57)	(0.80)	(0.99)	(1.47)	(-1.45)	(-2.29)

Table 3: Differences in regression coefficients of AG between high and low MAX samples

This table reports average coefficients from Fama-MacBeth cross-sectional regressions conditional on MAX based on a sample consisting of all common stocks listed on NYSE, Amex, and Nasdaq for the period from July 1963 to December 2016. In every month t, we perform the following cross-sectional regressions separately for each MAX quintile: $R_{i,t} = b_0 + b_1\mathrm{AG}_{i,t} + b_2\mathrm{Size}_{i,t} + b_3\mathrm{BM}_{i,t} + b_4\mathrm{PR6}_{i,t} + b_5\mathrm{GP}_{i,t} + \varepsilon_{i,t}$, where $R_{i,t}$ is defined as stock i's return in month t; $\mathrm{AG}_{i,t}$ is stock i's asset growth in month t; $\mathrm{Size}_{i,t}$ is stock i's market capitalization in month t; $\mathrm{BM}_{i,t}$ is stock i's book-to-market ratio in month t; $\mathrm{PR6}_{i,t}$ is stock i's past six-month return calculated in month t; $\mathrm{GP}_{i,t}$ is stock i's gross profits in month t. We obtain estimated coefficients every month and calculate average coefficients for each MAX quintile over the sample period. In Panels A to C, MAX is defined as the maximum one-, five-, and ten-day average return over the past month. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	MAX group					
Variable	1	2	3	4	5	5−1
Panel A: Stocks sorted by MAX						
Intercept	1.078***	1.165***	1.168***	1.270***	1.143***	0.065
	(6.08)	(5.35)	(4.44)	(4.20)	(2.96)	(0.23)
AG	-0.154	-0.195*	-0.128	-0.226***	-0.435***	-0.281**
	(-1.50)	(-1.93)	(-1.45)	(-2.67)	(-4.77)	(-2.21)
Size	-0.008	-0.043**	-0.169***	-0.511***	-1.759**	-1.751**
	(-0.66)	(-2.51)	(-2.80)	(-3.28)	(-2.55)	(-2.55)
BM	0.189***	0.300***	0.292***	0.376***	0.473***	0.284***
	(3.00)	(4.49)	(4.02)	(5.07)	(6.02)	(3.41)
PR6	-0.020	0.030**	0.045***	0.023*	-0.004	0.016
	(-1.39)	(2.47)	(3.50)	(1.90)	(-0.37)	(1.08)
GP	0.537***	0.683***	0.528***	0.350**	0.136	-0.401*
	(3.83)	(4.83)	(3.69)	(2.03)	(0.69)	(-1.73)
Panel B: Stocks sorted by MAX(5)						
Intercept	1.107***	1.219***	1.230***	1.288***	1.053***	-0.054
	(6.11)	(5.60)	(4.83)	(4.06)	(2.70)	(-0.19)
AG	-0.089	-0.182*	-0.129	-0.249***	-0.403***	-0.314**
	(-0.82)	(-1.67)	(-1.20)	(-3.53)	(-4.57)	(-2.28)
Size	0.004	-0.061***	-0.160***	-0.660***	-2.808***	-2.813***
	(0.19)	(-2.84)	(-2.98)	(-3.47)	(-3.66)	(-3.69)
BM	0.187***	0.266***	0.273***	0.302***	0.530***	0.343***
	(2.97)	(3.90)	(3.97)	(3.94)	(6.88)	(4.28)
PR6	-0.023	0.015	0.025**	0.033***	0.001	0.024
	(-1.57)	(1.12)	(2.04)	(2.81)	(0.08)	(1.55)
GP	0.575***	0.588***	0.491***	0.270	0.078	-0.497**
	(4.06)	(4.16)	(3.48)	(1.53)	(0.38)	(-2.19)
Panel C: Stocks sorted by MAX(10)						
Intercept	1.210***	1.217***	1.245***	1.273***	0.962**	-0.249
	(6.40)	(5.65)	(4.96)	(4.08)	(2.48)	(-0.88)
AG	-0.136	-0.147	-0.322***	-0.268***	-0.404***	-0.268*
	(-1.20)	(-1.40)	(-3.11)	(-3.17)	(-4.42)	(-1.82)
Size	0.040	-0.051***	-0.172***	-0.569***	-1.965***	-2.004***
	(1.07)	(-2.65)	(-3.23)	(-3.84)	(-3.33)	(-3.42)
BM	0.147**	0.291***	0.258***	0.331***	0.525***	0.377***
	(2.25)	(4.27)	(3.71)	(4.42)	(6.76)	(4.79)
PR6	-0.027*	-0.002	0.023*	0.027**	0.010	0.037**
	(-1.84)	(-0.13)	(1.78)	(2.14)	(0.86)	(2.48)
GP	0.518***	0.762***	0.431***	0.305*	0.042	-0.476**
	(3.42)	(5.50)	(3.11)	(1.67)	(0.20)	(-2.01)

Table 4: Differences in regression coefficients of AG between high and low MAX samples controlling for overinvestment

This table reports average coefficients from Fama-MacBeth cross-sectional regressions conditional on proxies of overinvestment based on a sample consisting of all common stocks listed on NYSE, Amex, and Nasdaq for the period from July 1963 to December 2016. In every month t, we perform the following cross-sectional regressions separately for each overinvestment quintile: $R_{i,t} = b_0 + b_1\text{AG}_{i,t} + b_2\text{Size}_{i,t} + b_3\text{BM}_{i,t} + b_4\text{PR6}_{i,t} + b_5\text{GP}_{i,t} + \varepsilon_{i,t}$, where $R_{i,t}$ is defined as stock i's return in month t; $\text{AG}_{i,t}$ is stock i's asset growth in month t; $\text{Size}_{i,t}$ is stock i's market capitalization in month t; $\text{BM}_{i,t}$ is stock i's book-to-market ratio in month t; $\text{PR6}_{i,t}$ is stock i's past six-month return calculated in month t; $\text{GP}_{i,t}$ is stock i's gross profits in month t. We obtain estimated coefficients every month and calculate average coefficients for each MAX quintile over the sample period. In Panel A, we perform the regressions separately for quintiles form on FCF or DEBT. In Panels B and C, we perform the regressions on the interactions of the 15 subgroups formed on MAX and proxies of overinvestment, FCF and DEBT, respectively. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Portfolios	Overinvestment group					
sorted by	1	2	3	4	5	5−1
Panel A: Stocks sorted by overinvestment measures						
FCF	-0.317***	-0.360***	-0.164	-0.205	-0.202*	0.115
	(-4.52)	(-3.71)	(-0.98)	(-1.64)	(-1.91)	(1.01)
1/DEBT	-0.383***	-0.345**	-0.271**	-0.329***	-0.074	0.308*
	(-5.84)	(-2.53)	(-2.08)	(-3.58)	(-0.51)	(1.96)
Overinvestment	**MAX group**					
portfolio	**1**	**2**	**3**	**4**	**5**	**5−1**
Panel B: Stocks sorted by MAX and FCF						
Low	-0.628***	-0.457***	-0.219*	-0.331**	-0.658***	-0.029
	(-3.55)	(-3.27)	(-1.73)	(-2.01)	(-3.66)	(-0.13)
Median	-0.206	0.008	-0.396	-0.462**	-0.224	-0.018
	(-0.82)	(0.03)	(-1.63)	(-2.20)	(-1.03)	(-0.06)
High	0.245	0.128	-0.142	-0.064	-0.720***	-0.964***
	(0.98)	(0.60)	(-0.58)	(-0.35)	(-3.25)	(-2.67)
Panel C: Stocks sorted by MAX and 1/DEBT						
Low	-0.233	-0.304**	-0.391**	-0.353***	-0.860***	-0.626***
	(-1.37)	(-2.16)	(-2.55)	(-2.83)	(-6.43)	(-2.96)
Median	-0.238	-0.517***	-0.147	-0.427**	-0.611***	-0.373
	(-1.05)	(-2.67)	(-0.86)	(-2.45)	(-3.06)	(-1.22)
High	0.115	-0.351	-0.134	-0.580**	-0.004	-0.120
	(0.41)	(-1.10)	(-0.59)	(-2.33)	(-0.01)	(-0.26)

Table 5: Differences in regression coefficients of AG between high and low MAX samples controlling for limits-to-arbitrage

This table reports average coefficients from Fama-MacBeth cross-sectional regressions conditional on proxies of limits-to-arbitrage based on a sample consisting of all common stocks listed on NYSE, Amex, and Nasdaq for the period from July 1963 to December 2016. In every month t, we perform the following cross-sectional regressions separately for each limits-to-arbitrage quintile: $R_{i,t} = b_0 + b_1\text{AG}_{i,t} + b_2\text{Size}_{i,t} + b_3\text{BM}_{i,t} + b_4\text{PR6}_{i,t} + b_5\text{GP}_{i,t} + \varepsilon_{i,t}$, where $R_{i,t}$ is defined as stock i's return in month t; $\text{AG}_{i,t}$ is stock i's asset growth in month t; $\text{Size}_{i,t}$ is stock i's market capitalization in month t; $\text{BM}_{i,t}$ is stock i's book-to-market ratio in month t; $\text{PR6}_{i,t}$ is stock i's past six-month return calculated in month t; $\text{GP}_{i,t}$ is stock i's gross profits in month t. We obtain estimated coefficients every month and calculate average coefficients for each MAX quintile over the sample period. In Panel A, we perform the regressions separately for quintiles form on IVOL, CVOL, 1/PRICE, 1/DVOL, and ILLIQ, respectively. In Panels B to E, we perform the regressions on the interactions of the 15 subgroups formed on MAX and each proxy of limits-to-arbitrage. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Portfolios sorted by	Limits-to-arbitrage group 1	2	3	4	5	5−1
Panel A: Stocks sorted by limits-to-arbitrage measures						
IVOL	-0.133	-0.158	-0.507***	-0.603***	-0.461***	-0.328**
	(-1.21)	(-1.45)	(-3.66)	(-5.61)	(-3.63)	(-2.02)
CVOL	-0.408***	-0.878***	-0.563***	-0.549***	-0.465***	-0.057
	(-5.02)	(-6.96)	(-5.15)	(-3.38)	(-2.61)	(-0.28)
1/PRICE	0.843***	0.073	-0.250***	-0.566***	-0.857***	-1.701***
	(7.15)	(0.76)	(-2.71)	(-5.53)	(-6.79)	(-9.05)
1/DVOL	-0.299***	-0.357***	-0.209*	-0.368***	-0.525***	-0.226
	(-3.11)	(-4.01)	(-1.84)	(-3.30)	(-3.68)	(-1.31)
ILLIQ	-0.474***	-0.361***	-0.195*	-0.300***	-0.278**	0.196
	(-3.53)	(-4.33)	(-1.83)	(-3.29)	(-2.58)	(1.14)
Limits-to-arbitrage portfolio	**MAX group 1**	**2**	**3**	**4**	**5**	**5−1**
Panel B: Stocks sorted by MAX and IVOL						
Low	-0.405**	0.156	0.125	-0.269	-0.569**	-0.164
	(-2.29)	(0.65)	(0.54)	(-1.00)	(-1.97)	(-0.50)
Median	-0.216	-0.568**	-0.444**	-0.512*	-0.703**	-0.488
	(-0.79)	(-2.43)	(-2.05)	(-1.95)	(-2.07)	(-1.11)
High	-0.338	-0.788***	-0.214	-0.405*	-1.037***	-0.700**
	(-1.58)	(-3.40)	(-1.11)	(-1.96)	(-4.28)	(-2.11)
Panel C: Stocks sorted by MAX and CVOL						
Low	-0.253	-0.275	-0.189	-0.121	-1.149***	-0.895***
	(-1.19)	(-1.43)	(-1.32)	(-0.90)	(-4.07)	(-2.81)
Median	-0.437*	-0.575*	-0.456**	-0.784***	-0.952***	-0.515
	(-1.77)	(-1.89)	(-2.42)	(-3.19)	(-2.76)	(-1.37)
High	0.212	0.213	-0.773***	-0.430	-0.757**	-0.969**
	(0.63)	(0.83)	(-3.13)	(-1.48)	(-2.18)	(-2.11)
Panel D: Stocks sorted by MAX and 1/PRICE						
Low	0.714***	0.375**	0.468***	0.094	-0.340**	-1.054***
	(4.02)	(2.13)	(2.71)	(0.65)	(-2.10)	(-4.44)
Median	0.083	0.207	-0.290	-0.706***	-1.140***	-1.223***
	(0.42)	(1.27)	(-1.60)	(-3.83)	(-5.29)	(-4.09)
High	-0.567***	-0.670***	-0.732***	-0.777***	-1.085***	-0.518*
	(-2.73)	(-3.68)	(-3.82)	(-4.01)	(-5.37)	(-1.75)
Panel E: Stocks sorted by MAX and 1/DVOL						
Low	-0.201	-0.185	-0.419**	-0.186	-0.580***	-0.379*
	(-1.19)	(-1.00)	(-2.38)	(-1.09)	(-3.93)	(-1.77)
Median	0.217	-0.264	-0.394**	-0.164	-0.415*	-0.632**
	(0.80)	(-1.31)	(-2.33)	(-0.90)	(-1.86)	(-2.02)
High	-0.333	-0.202	-0.383*	-0.525*	-0.685**	-0.352
	(-1.49)	(-0.85)	(-1.66)	(-1.91)	(-2.20)	(-0.92)
Panel F: Stocks sorted by MAX and ILLIQ						
Low	-0.097	-0.135	-0.264	-0.336*	-0.625***	-0.528**
	(-0.55)	(-0.63)	(-1.28)	(-1.89)	(-3.33)	(-1.99)
Median	0.356	-0.460**	-0.375*	-0.235	-0.793***	-1.148***
	(1.44)	(-2.17)	(-1.92)	(-1.02)	(-3.10)	(-3.23)
High	-0.388*	-0.372	-0.373	-0.916***	-1.330***	-0.942**
	(-1.70)	(-1.64)	(-1.64)	(-3.32)	(-3.51)	(-2.04)

Table 6: Differences in regression coefficients of AG between high and low MAX samples controlling for investment frictions

This table reports average coefficients from Fama-MacBeth cross-sectional regressions conditional on proxies of investment frictions based on a sample consisting of all common stocks listed on NYSE, Amex, and Nasdaq for the period from July 1963 to December 2016. In every month t, we perform the following cross-sectional regressions separately for each investment frictions quintile: $R_{i,t} = b_0 + b_1\text{AG}_{i,t} + b_2\text{Size}_{i,t} + b_3\text{BM}_{i,t} + b_4\text{PR6}_{i,t} + b_5\text{GP}_{i,t} + \varepsilon_{i,t}$, where $R_{i,t}$ is defined as stock i's return in month t; $\text{AG}_{i,t}$ is stock i's asset growth in month t; $\text{Size}_{i,t}$ is stock i's market capitalization in month t; $\text{BM}_{i,t}$ is stock i's book-to-market ratio in month t; $\text{PR6}_{i,t}$ is stock i's past six-month return calculated in month t; $\text{GP}_{i,t}$ is stock i's gross profits in month t. We obtain estimated coefficients every month and calculate average coefficients for each MAX quintile over the sample period. In Panel A, we perform the regressions separately for quintiles form on 1/AGE, 1/ASSET, 1/PAYOUT and RATING, respectively. In Panels B to E, we perform the regressions on the interactions of the 15 subgroups formed on MAX and each proxy of investment frictions. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Portfolios sorted by	Investment friction group: 1 (Yes)	2	3	4	5 (No)	5−1 (No−Yes)
Panel A: Stocks sorted by investment friction measures						
1/AGE	-0.241**	-0.480***	-0.404***	-0.484***	-0.296***	-0.055
	(-2.03)	(-4.23)	(-4.02)	(-4.72)	(-3.81)	(-0.42)
1/ASSET	-0.234**	-0.325***	-0.225**	-0.418***	-0.385***	-0.151
	(-2.38)	(-3.52)	(-2.42)	(-4.58)	(-4.20)	(-1.10)
1/PAYOUT	-0.235***	-0.464***	-0.542***	-0.258***	-0.344***	-0.109
	(-2.86)	(-3.98)	(-4.37)	(-3.16)	(-4.58)	(-1.04)
RATING	-0.105				-0.353***	-0.248***
	(-1.41)				(-4.75)	(-2.75)
Investment friction portfolio	**MAX group: 1**	**2**	**3**	**4**	**5**	**5−1**
Panel B: Stocks sorted by MAX and 1/AGE						
Low	-0.380**	-0.337*	-0.187	-0.709***	-0.975***	-0.595*
	(-2.26)	(-1.69)	(-0.99)	(-3.34)	(-3.77)	(-1.89)
Median	-0.438**	-0.250	-0.258	-0.501***	-0.988***	-0.550**
	(-2.20)	(-1.02)	(-1.21)	(-2.60)	(-5.19)	(-1.97)
High	-0.098	-0.419***	-0.269**	-0.399**	-0.503**	-0.405
	(-0.52)	(-3.00)	(-1.99)	(-2.47)	(-2.37)	(-1.48)
Panel C: Stocks sorted by MAX and 1/ASSET						
Low	-0.129	-0.099	-0.425**	-0.292*	-0.629***	-0.500**
	(-0.67)	(-0.55)	(-2.58)	(-1.85)	(-3.77)	(-2.05)
Median	-0.083	-0.267	-0.178	-0.375**	-0.580***	-0.497**
	(-0.47)	(-1.64)	(-1.08)	(-2.40)	(-3.64)	(-2.00)
High	-0.271	-0.669***	-0.102	-0.071	-0.488**	-0.216
	(-1.27)	(-2.68)	(-0.52)	(-0.41)	(-2.35)	(-0.75)
Panel D: Stocks sorted by MAX and 1/PAYOUT						
Low	-0.288*	-0.120	-0.462***	-0.468***	-0.748***	-0.460*
	(-1.70)	(-0.69)	(-2.93)	(-2.98)	(-4.08)	(-1.79)
Median	-0.396*	-0.277	-0.460**	-0.981***	-0.275*	0.121
	(-1.96)	(-1.48)	(-2.30)	(-4.56)	(-1.65)	(0.44)
High	-0.306*	-0.447***	-0.085	-0.094	-0.563***	-0.257
	(-1.84)	(-3.61)	(-0.69)	(-0.82)	(-3.27)	(-1.08)
Panel E: Stocks sorted by MAX and RATING						
RATING=Yes	0.125	-0.098	0.010	-0.044	-0.422**	-0.547**
	(0.79)	(-0.66)	(0.07)	(-0.26)	(-2.22)	(-2.20)
RATING=No	1.357	0.563	-0.053	-0.343	-0.422***	-1.778
	(1.10)	(1.21)	(-0.18)	(-1.50)	(-2.84)	(-1.44)

Table 7: Fama-MacBeth regressions jointly considering all variables

This table reports average coefficients from Fama-MacBeth cross-sectional regressions that incorporate interaction terms of AG and alternative explanations based on a sample consisting of all common stocks listed on NYSE, Amex, and Nasdaq for the period from July 1963 to December 2016. In every month t, we perform the following cross-sectional regressions:

$$\begin{aligned} R_{i,t} \quad = \quad & b_0 + b_1\mathrm{AG}_{i,t} + b_2\mathrm{Size}_{i,t} + b_3\mathrm{BM}_{i,t} + b_4\mathrm{PR6}_{i,t} + b_5\mathrm{GP}_{i,t} + b_6\mathrm{AG}_{i,t} \times \mathrm{MAX}_{i,t} + b_7\mathrm{AG}_{i,t} \times \mathrm{CF}_{i,t} \\ & + b_8\mathrm{AG}_{i,t} \times \mathrm{DEBT}_{i,t}^{-1} + b_9\mathrm{AG}_{i,t} \times \mathrm{IVOL}_{i,t} + b_{10}\mathrm{AG}_{i,t} \times \mathrm{CVOL}_{i,t} + b_{11}\mathrm{AG}_{i,t} \times \mathrm{PRICE}_{i,t}^{-1} \\ & + b_{12}\mathrm{AG}_{i,t} \times \mathrm{DVOL}_{i,t}^{-1} + b_{13}\mathrm{AG}_{i,t} \times \mathrm{AGE}_{i,t}^{-1} + b_{14}\mathrm{AG}_{i,t} \times \mathrm{ASSET}_{i,t}^{-1} + b_{15}\mathrm{AG}_{i,t} \times \mathrm{PAYOUT}_{i,t}^{-1} \\ & + b_{16}\mathrm{AG}_{i,t} \times \mathrm{RATING}_{i,t} + \varepsilon_{i,t}, \end{aligned}$$

where $R_{i,t}$ is defined as stock i's return in month t; $\mathrm{AG}_{i,t}$ is stock i's asset growth in month t; $\mathrm{Size}_{i,t}$ is stock i's market capitalization in month t; $\mathrm{BM}_{i,t}$ is stock i's book-to-market ratio in month t; $\mathrm{PR6}_{i,t}$ is stock i's past six-month return calculated in month t; $\mathrm{GP}_{i,t}$ is stock i's gross profits in month t. The conditioning variables are defined as in Tables 4 to 6. We obtain estimated coefficients every month and calculate average coefficients for each MAX quintile over the sample period. In Models (1) to (4), we include MAX as the proxy of investors' gambling preference. In Models (5) to (7), we consider three measures of skewness to proxy for investors' gambling preference. In Model (8), we include both MAX and skewness measures. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Intercept	1.181***	1.183***	1.073***	1.071***	1.069***	1.070***	1.069***	1.069***
	(4.54)	(4.69)	(4.38)	(4.46)	(4.44)	(4.45)	(4.45)	(4.46)
AG	0.017	-0.366	-0.171	0.130	-0.137	-0.147	-0.124	0.161
	(0.22)	(-1.22)	(-1.29)	(0.35)	(-0.38)	(-0.41)	(-0.34)	(0.42)
Size	-0.022*	-0.013	-0.014	-0.009	-0.008	-0.008	-0.008	-0.008
	(-1.85)	(-1.50)	(-1.58)	(-1.26)	(-1.21)	(-1.19)	(-1.23)	(-1.18)
BM	0.367***	0.375***	0.309***	0.339***	0.346***	0.346***	0.346***	0.342***
	(5.76)	(5.82)	(4.47)	(4.89)	(4.97)	(4.97)	(4.97)	(4.92)
GP	0.497***	0.469***	0.578***	0.527***	0.534***	0.540***	0.533***	0.530***
	(3.73)	(3.44)	(4.21)	(3.63)	(3.70)	(3.72)	(3.69)	(3.67)
PR6	0.014	0.012	0.015	0.007	0.008	0.007	0.009	0.008
	(1.32)	(1.09)	(1.19)	(0.53)	(0.64)	(0.57)	(0.65)	(0.58)
AG×MAX	-3.601***	-6.535***	-7.317***	-11.175***				-11.176***
	(-2.98)	(-2.67)	(-5.22)	(-4.46)				(-4.29)
AG×TSKEW					-0.210***			
					(-2.83)			
AG×SSKEW						-0.986		-32.983
						(-0.01)		(-0.44)
AG×ISKEW							-0.190***	-0.136*
							(-2.63)	(-1.85)
AG×FCF	0.513*			0.775	0.860	1.046	0.857	0.690
	(1.81)			(1.00)	(1.10)	(1.33)	(1.10)	(0.87)
AG×DEBT^{-1}	0.004			-0.032	-0.032	-0.029	-0.032	-0.027
	(0.25)			(-0.57)	(-0.57)	(-0.51)	(-0.58)	(-0.46)
AG×IVOL		13.320***		7.636**	5.060	4.102	5.162	7.216*
		(3.09)		(2.03)	(1.40)	(1.14)	(1.41)	(1.82)
AG×CVOL		1.214		1.028	0.859	0.810	0.841	0.666
		(1.51)		(0.94)	(0.80)	(0.72)	(0.78)	(0.60)
AG×PRICE^{-1}		-15.138***		-10.242***	-10.838***	-11.118***	-10.849***	-10.503***
		(-3.79)		(-4.50)	(-4.63)	(-4.68)	(-4.64)	(-4.50)
AG×DVOL^{-1}		-0.174		0.730	0.148	-0.374	0.082	0.635
		(-0.17)		(0.24)	(0.05)	(-0.13)	(0.03)	(0.21)
AG×ILLIQ		0.253*		0.094**	0.093**	0.094**	0.092**	0.100**
		(1.83)		(2.07)	(2.07)	(2.08)	(2.04)	(2.17)
AG×AGE^{-1}			1.186	0.512	0.037	0.877	-0.078	0.910
			(1.46)	(0.27)	(0.02)	(0.49)	(-0.04)	(0.50)
AG×ASSET^{-1}			0.351	3.910	4.941	3.553	4.832	3.623
			(0.14)	(0.63)	(0.80)	(0.59)	(0.79)	(0.58)
AG×PAYOUT^{-1}			0.001	0.288	0.278	0.340	0.260	0.289
			(0.00)	(1.06)	(1.04)	(1.22)	(0.98)	(1.05)
AG×RATING			-0.033	-0.037	0.008	-0.003	0.002	-0.025
			(-0.34)	(-0.28)	(0.06)	(-0.02)	(0.02)	(-0.19)