Growth Opportunity Bias

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This version: March 2019

Abstract

Growth opportunity bias (*GOB*), measured as the difference between market and fundamental values of a firm's growth opportunity, has an ability to predict future stock returns. In the portfolio sort, low-*GOB* firms earn higher returns than high-*GOB* firms, which is unexplained by the common asset pricing models. Cross-sectional regression results also confirm *GOB*'s power in predicting stock returns. Given the inability of the risk-based methods in explaining the GOB premium, we turn to behavioral approaches to gain a better understanding of the anomaly. We find that the *GOB* premium is more pronounced when investor sentiment is high or when limits-to-arbitrage is severe, which suggests that the *GOB* is more likely to capture behavioral biases than systematic risk.

JEL classification: G12; G14; G30

Keywords: Growth Opportunity Bias; Behavioral Finance; Asset Pricing; Anomaly

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1 Introduction

While it is clear that a firm's growth opportunity is a key driver of its fundamental and market valuations, it is still not so clear on how to properly measure a firm's growth opportunity, since it is the "yet-unexercised future-oriented growth option" which is not directly observable, and common proxies used to capture it are prone to errors.[1] Consequently, growth opportunities can, sometimes, be mismeasured or misjudged by investors. If investors act irrationally to a firm's growth opportunity and if the misjudgments become large and persistent, it can have a lasting impact on valuations and returns. In this study, we test whether the growth opportunity bias (GOB), i.e., the *divergence* between market and fundamental valuations of a firm's growth opportunity, predicts future stock returns.

Prior studies have, so far, shown that the difference between firms' market and fundamental valuations predicts stock returns (Lee, Myers, and Swaminathan (1999), Doukas, Kim, and Pantzalis (2010), and Bartram and Grinblatt (2018)). The difference between a firm's market and fundamental valuations is, however, likely to be driven by the divergence of its growth opportunities, as it is both unobservable and hardest to measure. If this is, indeed, the case, then the growth opportunity bias should have a reliable power in predicting stock returns.

Examining U.S. common stocks from 1977 to 2014,[2] we find an *inverse* relation between growth opportunity bias and stock returns. Firms in the lowest GOB decile portfolio significantly outperform that of the highest GOB decile by 0.510% (t = 4.55) and 0.649% (t = 3.07) per

[1]Some common proxies for estimating growth opportunities are research and development ($R\&D$), Tobin's Q, debt to equity ratio, and capital expenditure (e.g., Cao, Simin, and Zhao (2008) and Kogan and Papanikolaou (2014)).

[2]Our samples starts from 1977 due to the availability of various COMPUSTAT annual data to calculate market and fundamental values of growth opportunity (discussed in Section 2).

month for equal- and value-weighted returns, respectively. The *GOB* premium is unexplained by the Fama–French three-factor model (FF3FM), momentum-extended FF3FM, Fama–French five-factor model (FF5FM), and other commonly used asset pricing models. For instance, under the FF5FM, the return differences (alphas) between low and high *GOB* portfolios are 0.449% ($t = 3.49$) and 1.012% ($t = 4.25$) per month for equal- and value-weighted returns, respectively.

In addition to portfolio sort, we perform the Fama–MacBeth (1973) regression analysis to simultaneously control for growth opportunity bias and key firm characteristics. We show that growth opportunity bias is *negatively* related to stock returns after adjusting for size, book-to-market, momentum, return-on-assets, and asset growth. Brennan, Chordia, and Subrahmanyam (1998) argue that using the risk-adjusted returns (rather than risk loadings) as the explained variable avoids errors-in-variable problem associated with the Fama–MacBeth procedure. Following their study, we run the Fama–MacBeth regressions using the risk-adjusted returns, and we show that growth opportunity bias consistently predicts future stock returns.

We submit our results to a battery of robustness tests including using a gross-return weighting method of Asparouhova, Bessembinder, and Kalcheva (2010, 2013) to control for the potential bias caused in the rebalance method; the characteristics-adjusted returns of Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004) to control for size, book-to-market, and momentum; the double-sorted portfolios on both growth opportunity bias and market capitalization following Fama and French (2008); and additional asset pricing models such as the Pastor and Stambaugh (2003) liquidity-extended FF3FM, the Liu (2006) liquidity-augmented capital asset pricing model (LCAPM), the Hou, Xue, and Zhang (2015) q-factor model (HXZqFM), and the Stambaugh and Yuan (2017) mispricing factor model (SYmFM). The *GOB* premium stands firm to all these tests. Hence, the main finding of our study is robust and straightforward: A firm's growth opportunity bias is a strong predictor of the cross section of stock returns.

Intuitively, high *GOB* stocks are the ones that their market values of growth opportunities are much higher than the estimates of their fundamental values. It is possible that investors overreact to the growth opportunities of these stocks, which results in lower subsequent returns,[3] and, hence, driving the inverse relationship between *GOB* and stock returns. Berk, Green, and Naik (1999) argue that explanations for asset pricing anomalies fall in missing state variables in risk factors or behavioral biases. Given the inability of the risk-based methods in explaining the *GOB* premium, we investigate whether the results are driven by behavioral biases such as investor sentiment or limits-to-arbitrage. We find that the *GOB* premium survives only when investor sentiment is high or when limits-to-arbitrage is severe, which suggests that the growth opportunity bias is more likely to capture mispricing (of the non-fundamental component of stock prices) than systematic risk.

The main contribution of our study is to document the concept of growth opportunity bias (*GOB*) and its predictive power to the cross section of stock returns. Although a recent study has investigated the role of fundamental growth opportunity (*GO*) in explaining stock returns (Trigeorgis and Lambertides (2014)),[4] the *GOB* is, however, not the same as *GO*. A firm with a high *GO* is not necessarily having a high *GOB* if the market agrees with the firm's fundamental growth potential. In such a case, its *GO* is high while its *GOB* is low, and *vice versa*. Indeed, when we control for firms' fundamental values of growth opportunities, the *GOB*

[3]Cooper, Gulen, and Schill (2008) find evidence that investors tend to overreact to firms' past growth rates.

[4]The main objective of Trigeorgis and Lambertides (2014) is to develop an extended asset pricing model (on the basis of Fama and French (1992) model) that incorporates growth option as well as distress/leverage variables.

premium stands firm.[5] Thus, *GO* captures a firm's growth potential, while *GOB* is likely to pick up the *disagreement* between markets and fundamentals.[6] Thus, the information content of *GOB* is related to market misperceptions of firms' future growth opportunities.

We expect the *GOB* to be widely used both in academic and in practice. Apart from forming trading strategies (such as long low-*GOB* and short high-*GOB* stocks) to exploit the anomaly, *GOB* can be used as proxies of investor behavioral biases (e.g., high *GOB* could indicate over-reaction) or measures of limits-to-arbitrage (e.g., high *GOB* could suggest severe limits-to-arbitrage). *GOB* also has the potential to be broadly used in corporate decision-making. For example, managers often consider acquiring other firms with high growth potential in order to maintain their own growth momentum (Levine (2017)). *GOB* can be used as a tool to evaluate their target companies, since a high *GOB* may well suggest investors overreacting to a target's growth potential, topping it up with a high takeover premium can be a particularly expensive deal for the acquirer. Or, for instance, when a firm's *GOB* is high, its cost of equity is low. *GOB* can, thus, be used as a timing tool for firms to tap the capital markets.[7]

The remainder of the paper is organized as follows. Section 2 describes the data and sample. Section 3 presents the empirical results, performs robustness tests, and seeks explanations of the results. Section 4 concludes the paper.

[5] See Table 6.

[6] Banerjee and Kremer (2010) and Banerjee (2011) provide theoretical foundations on how disagreement affects stock returns.

[7] Managers have strong incentives to time the market and issue overvalued equity to finance their investment in order to take advantage of the mispricing of the non-fundamental component of stock prices, see Baker, Stein, and Wurgler (2003) and Polk and Sapienza (2009).

2 Data and sample

We collect stock returns data from the Center for Research in Security Prices (CRSP). Our sample period is from July 1977 to June 2014, which covers NYSE/AMEX/NASDAQ ordinary common stocks.[8] We exclude regulated and financial firms, which have four-digit standard industrial classification (SIC) code between 4900–4999 and 6000–6999. We collect data of monthly stock returns, daily returns, daily trading volumes, daily prices per share from CRSP.[9] We measure monthly market capitalizations of sample stocks using price per share and the number of shares outstanding from CRSP. With COMPUSTAT annual data, we follow Davis, Fama, and French (2000) to calculate a firm's book value of equity. We also calculate the return-on-assets (ROA) following Lewellen (2015) and Bessembinder, Cooper, and Zhang (2018) and the total asset growth rate (AG) following Cooper, Gulen, and Schill (2008).

The key variable of our study is the growth opportunity bias (GOB), the difference between a firm's market value of growth opportunity and fundamental value of growth opportunity. We estimate the market value of growth opportunity (MGO) following Trigeorgis and Lambertides (2014), which is the percentage of a firm's market value arising from its future growth opportunities ($PVGO/MV$) given

$$MV_{i,t} = \frac{CF_{i,t}}{k_i} + PVGO_{i,t}, \tag{1}$$

[8]We identify ordinary common stocks as those with CRSP share codes 10 and 11.

[9]We make adjustments to delisting returns. If a delisted stock's delisting return is missing, we follow Shumway (1997) and Shumway and Warther (1999) and assume a delisting return of -1 for delisting due to liquidation (CRSP delisting codes 400–490), -0.33 for performance related delisting (CRSP codes 500 and 520–584), and zero otherwise.

where $MV_{i,t}$ is the market value of firm i at time t, $CF_{i,t}$ is the operating cash flow of firm i at time t, and k_i is the firm's weighted average cost of capital (WACC). CF is measured as net cash flow from operating activities (COMPUSTAT item 308).[10] Following Trigeorgis and Lambertides (2014), we estimate the cost of equity by using the market model and setting beta equal to 1 for all firms and estimating the cost of equity as the average return of the Standard & Poor's ($S\&P$) 500 index over the previous 60-month period, and estimate the cost of debt to be four units below the corresponding cost of equity.[11]

Trigeorgis and Lambertides (2014) also identify eight key variables which determine the fundamental value of growth opportunity (FGO). We follow their approach in our estimation of FGO.

$$
\begin{aligned}
FGO_{i,t} &= \gamma_{0,t} + \gamma_{1,t} firm\ specific\ volatility_{i,t} + \gamma_{2,t} managerial\ flexibility_{i,t} \\
&+ \gamma_{3,t} organizational\ flexibility_{i,t} + \gamma_{4,t} financial\ flexibility_{i,t} \\
&+ \gamma_{5,t} cash\ flow\ coverage_{i,t} + \gamma_{6,t} R\&D\ intensity_{i,t} \\
&+ \gamma_{7,t} cumulative\ growth_{i,t} + \gamma_{8,t} market\ power_{i,t} \\
&+ +\gamma_{9,t} INDdummy_{i,t} + \gamma_{10,t} Fix_{i,t} + \gamma_{11,t} Interation_{i,t} + \varepsilon_{i,t}, \qquad (2)
\end{aligned}
$$

Firm-specific volatility is measured by the standard deviations of residuals of the regression of the monthly stock returns in excess of risk-free rate on the Fama–French (1993) three factors

[10] Similar to Trigeorgis and Lambertides (2014), for years prior to 1988, we follow Xie (2001) in estimating cash flow from operations as funds from operations (item 110) - change in current assets (item 4) + change in cash and cash equivalents (item 1) + change in current liabilities (item 5) - change in short-term debt (item 34). Funds from operations are available from COMPUSTAT since 1971 (Xie, 2001).

[11] Cao, Simin, and Zhao (2008) show that the estimation of $PVGO$ is not sensitive to alternative approximations of the discount rate.

over the prior 36 months (e.g., Bali and Cakici, 2008). Managerial flexibility is proxied by the skewness of monthly stock returns over the prior 36 months. Organizational flexibility is the ratio of its selling, general, and administrative (SGA) expenses to sales. Financial flexibility is debt-to-assets (DV) ratio, i.e., the book value of total liabilities (D) divided by the market value of the firm's assets (V). Cash flow coverage (CFC) is the amount of operating cash and equivalents maintained by the firm.[12] $R\&D$ intensity is the average $R\&D$ expenses over the recent 3-year period as a percentage of total assets. Missing $R\&D$ observations are set to 0. Cumulative growth is the percentage change in the firm's sales over the recent 3-year period. Market power is the square root of the firm's Herfindahl-Hirschman Index (HHI) if the firm has above-average Tobin's q, and 0 if the firm has below-average q. We use the two-digit SIC code for industry-level dummy variables. We also use fixed effects to take into account time variation, unobserved heterogeneity and variation (e.g., in volatility) at the firm level, and the economy-wide variation effects (such as in interest rates) or other unobserved factors. Interaction effects between skewness and leverage are also used.[13] We estimate Equation (2) over the previous 5-year period to obtain average coefficients from the time-series cross-sectional regressions for the above option-motivated variables for each firm. We then use current data on these variables for the estimation of fundamental value of growth opportunity.

Table 1 provides descriptive statistics for the main variables used in our study. The market and fundamental values of growth opportunity are, on average, at 0.493 and 0.397, which suggest

[12] $CFC_t = \frac{Cash\ Flow\ From\ Operations_t + Cash\ \&Cash\ Equivalentst_{t-1}}{Interest\ Expense_t + PreferredDividends_t}$. Missing interest expense and missing preferred dividends are set to 0.

[13] We winsorize the top and bottom 1% of observations for the estimations of market and fundamental value of growth opportunity.

that, on average, 49.3% or 39.7% of firm value comes from unexercised market or fundamental values of growth opportunity, resulting in an average *GOB* of 9.5%.

[Table 1 about here]

3 Empirical results

3.1 Results on portfolio sorts

To perform the portfolio analysis, we form portfolios with NYSE breakpoints at the end of June of each year and hold the portfolios for the subsequent 12 months. We calculate the monthly portfolio returns over the 12-month holding period based on the decomposed buy-and-hold method of Liu and Strong (2008):

$$R_{p,\tau} = \sum_{i=1}^{N} \frac{w_i \prod_{t=1}^{\tau-1}(1 + R_{i,t})}{\sum_{j=1}^{N} w_j \prod_{t=1}^{\tau-1}(1 + R_{j,t})} R_{i,\tau}, \quad \tau = 2, \ldots, 12; \quad R_{p,1} = \sum_{i=1}^{N} w_i R_{i,1}, \tag{3}$$

where $R_{p,\tau}$ is the month-τ return of the portfolio in the 12-month holding period, $R_{i,t}$ is the month-t return of stock i, N is the number of stocks in the portfolio, and w_i is the portfolio weight in stock i (we use equal, value, and gross-return weightings in our study). If a stock is delisted in the 12-month holding period, we assume that the returns of the stock over the remaining holding period are equal to zero. With equation (3), the calculations of the decomposed buy-and-hold returns do not involve rebalancing the portfolio weights and constituents over the 12-month holding period.

In addition to the monthly raw returns, we also measure portfolio performance based on several commonly used asset pricing models including the Fama–French (1993) three-factor model

(FF3FM), the Carhart (1997) momentum-extended FF3FM, and the Fama–French (2015) five-factor model (FF5FM). Specifically, we run the following time-series regressions:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}, \tag{4}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}, \tag{5}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}, \tag{6}$$

where $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French (FF) size factor, $f_{HML,t}$ is the month-t value of the FF book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the FF profitability factor, and $f_{CMA,t}$ is the month-t value of the FF investment factor.[14]

Table 2 Panel A reports the equal-weighed portfolio results. For raw returns, we observe an economically and statistically significant *GOB* premium. Stocks in the low-*GOB* decile earn an average return of 1.690% per month, while stocks in the high-*GOB* decile earn an average returns of 1.179% per month, generating a spread of 0.510% ($t = 4.55$) per month. Commonly used asset pricing models such as the FF3FM, the momentum-extended FF3FM, and the FF5FM are unable to explain the *GOB* premium. After adjusting for the FF5FM, for example, the *GOB* premium is 0.449% ($t = 3.49$) per month. Importantly, all *GOB* premiums, both before and after risk adjustment, have t-statistics above 3, the t-cutoff point recommended by Harvey, Liu, and Zhu (2016).[15]

[14] We obtain the one-month T-Bill rates, excess market returns, size, book-to-market, momentum, profitability, and investment factors from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[15] Harvey, Liu, and Zhu (2016) propose t cutoff values of 2.78 and 3.39, and argue that a newly discovered factor should have a t-statistic above 3. Hou, Xue, and Zhang (2018) replicate a total of 452 documented anomalies and show that imposing a t cutoff value of 2.78 would raise the proportion of insignificant anomalies to 82%.

[Table 2 about here]

Panel B presents the value-weighted results. The *GOB* premiums remain highly significant before and after risk adjustment. The raw *GOB* premium is 0.649% ($t = 3.07$) per month, and it is 0.807% ($t = 3.65$) under the FF3FM, 0.613% ($t = 2.76$) under the momentum-extended FF3FM, and 1.012% ($t = 4.25$) under the FF5FM, respectively.

3.2 Robustness on portfolio sorts

We next conduct various robustness tests to check our portfolio results. First, following Asparouhova, Bessembinder, and Kalcheva (2010) and Asparouhova, Bessembinder, and Kalcheva (2013), we use the gross-return-weighted returns to control for some potential biases caused by microstructure noise,[16] which is calculated as:

$$R_{P\tau}^{rw} = \sum_{i=1}^{N} \frac{(1+R)_{i,\tau-1}}{\sum_{j=1}^{N}(1+R)_{j,\tau-1}} R_{i\tau}. \tag{7}$$

Table 3 reports the gross-return-weighed stock returns for the decile portfolios. It shows a similar pattern to the equal- and value-weighted results in Table 2. The raw return difference between the gross-return-weighed low-*GOB* decile and the high-*GOB* decile is 0.526% ($t = 4.73$) per month. Using the benchmark models of the FF3FM, the momentum-extended FF3FM, and the FF5FM, the low-*GOB* portfolio still significantly outperforms the high-*GOB* portfolio by 0.524%, 0.434%, and 0.505% per month, respectively. All of them are highly significant with t-statistics above 3.

[16] For example, in many cases, buy orders are executed at a higher price than the true value of the assets, while sell orders are executed at a lower price than the true value of the assets. Large orders from institutional investors are often executed at prices beyond the range of quotations.

[Table 3 about here]

Second, instead of using asset pricing models as our benchmarks, we use the characteristics-adjusted returns to test the *GOB* premium. Following Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) and Wermers (2004), the characteristics-adjusted returns are the difference between individual firm's returns and the DGTW benchmark portfolio returns.[17] Results in Table 4 show that, after adjusting for the DGTW characteristics, the outperformance of low-*GOB* decile relative to high-*GOB* decile remains highly significant at 0.386% ($t = 3.72$) and 0.588% ($t = 3.96$) per month for equal- and value-weighted methods, respectively.

[Table 4 about here]

Third, we test the *GOB* premium across different size groups. This is important because Fama and French (2008) argue that the extreme returns associated with small stocks lack practical and economic sense. Specifically, using NYSE breakpoints, we first sort stocks into three size groups and then ten *GOB* groups (3×10). Following Fama and French (2008), we define stocks below the 20% of market capitalization of NYSE stocks as "Micro"; stocks above the 20% but below 50% of market capitalization of NYSE stocks as "Small"; and stocks above the 50% of market capitalization of NYSE stocks as "Large".

Table 5 reports the returns of the *GOB* portfolios across each size group. As we can see, the *GOB* premium remains highly significant across all three size subsamples. Before any risk adjustment, the *GOB* premiums of the micro-size subsample are 0.591% ($t = 3.57$) and 0.650% ($t = 4.16$) per month for equal- and value-weighted portfolios, and the corresponding figures are 0.497% ($t = 2.97$) and 0.444% ($t = 2.40$) for the small-size subsample, and 0.364% ($t = 2.65$) and

[17] The DGTW benchmarks are available at http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

0.444% ($t = 2.30$) for the large-size subsample. The *GOB* premiums of different size subsamples are also robust to the FF3FM, the momentum-extended FF3FM, and the FF5FM.

[Table 5 about here]

Forth, we control for the fundamental value of growth opportunity (*FGO*) to test whether the *GOB* premium can be explained by the fundamentals of growth opportunity. Specifically, following Bali, Cakici, and Whitelaw (2011), we control for *FGO* by first forming decile portfolios sorted by *FGO* using NYSE breakpoints. Then, within each *FGO* decile, we sort stocks into decile portfolios based on *GOB* using NYSE breakpoints.

Table 6 reports the results. Following Bali, Cakici, and Whitelaw (2011), for each *GOB* group, returns are averaged across ten *FGO* portfolios. Low-*GOB* decile (high-*GOB* decile) contains stocks with the lowest (highest) *GOB* averaged across the ten *FGO* groups. This procedure creates *GOB* portfolios with similar levels of *FGO*, and, thus, controls for differences in *FGO*. As can be seen, the *GOB* premiums remain highly significant after controlling for the fundamental value of growth opportunity.[18]

[Table 6 about here]

Finally, we measure portfolio performance based on additional asset pricing models including the Pastor and Stambaugh (2003) liquidity-extended FF3FM, the Liu (2006) liquidity-augmented capital asset pricing model (LCAPM), the Hou, Xue, and Zhang (2015) q-factor

[18] In untabulated results, we also conduct Fama–Macbeth (1973) regressions by controlling for *FGO*, and *GOB* remains significant.

model (HXZqFM), and the Stambaugh and Yuan (2017) mispricing factor model (SYmFM). Specifically, we run the following time-series regressions:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,p} f_{PSF,t} + \varepsilon_{i,t}, \tag{8}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}, \tag{9}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,r} f_{ROA,t} + \beta_{i,c} f_{I/A,t} + \varepsilon_{i,t}, \tag{10}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,ssy} f_{SMBSY,t} + \beta_{i,h} f_{MGMT,t} + \beta_{i,r} f_{PERF,t} + \varepsilon_{i,t}, \tag{11}$$

where $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French (FF) size factor, $f_{HML,t}$ is the month-t value of the FF book-to-market factor, $f_{PSF,t}$ is the month-t value of the Pastor–Stambaugh (PS) traded liquidity factor, $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor, $f_{ME,t}$ is the month-t value of the Hou, Xue, and Zhang (2015) (HXZ) size factor, $f_{ROA,t}$ is the month-t value of the HXZ profitability factor, $f_{I/A,t}$ is the month-t value of the HXZ investment factor,[19] $f_{SMBSY,t}$ is the month-t value of the Stambaugh–Yuan (SY) size factor, $f_{MGMT,t}$ is the month-t value of the SY management factor., and $f_{PERF,t}$ is the month-t value of the SY performance factor.[20]

Table 7 reports the alphas of the *GOB* portfolios under those additional asset pricing models. The *GOB* premium is, again, unexplained by these additional models. For instance, under the HXZ q-factor model (HXZqFM), the *GOB* premiums are 0.417% ($t = 3.16$) and 1.015% ($t = 3.82$) per month for equal- and value-weighted portfolios, respectively.

[19] We thank Lu Zhang for sharing with us their size, profitability, and investment factors.

[20] We obtain Stambaugh–Yuan size, management, and performance factors from Robert Stambaugh's website: http://finance.wharton.upenn.edu/ stambaug/.

[Table 7 about here]

3.3 Cross-sectional regression results

3.3.1 Fama–Macbeth regressions

To further test the return predictability of growth opportunity bias, we, in this subsection, run Fama–Macbeth (1973) regressions as follows:

$$R_{i,t+m} - R_{f,t+m} = \gamma_0 + \gamma_1 GOB_{i,t} + \epsilon_{i,t+1}, \tag{12}$$

$$R_{i,t+m} - R_{f,t+m} = \gamma_0 + \gamma_1 GOB_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} + \gamma_4 MOM_{i,t} + \epsilon_{i,t+1}, \tag{13}$$

$$\begin{aligned} R_{i,t+m} - R_{f,t+m} &= \gamma_0 + \gamma_1 GOB_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} \\ &+ \gamma_4 MOM_{i,t} + \gamma_5 ROA_{i,t} + \gamma_6 AG_{i,t} + \epsilon_{i,t+1}, \end{aligned} \tag{14}$$

where $R_{i,t+m}$ is stock i's return (Ret_1) in month $t+m$ ($m = 1, 2, ..., 12$), $R_{f,t+m}$ is the risk-free rate for month $t+m$, $GOB_{i,t}$ is firm i's growth opportunity bias, $ln(MV)_{i,t}$ is the natural logarithm of firm i's market capitalization, $MOM_{i,t}$ is the buy-and-hold return of stock i over month $t-6$ to month $t-1$, $ln(B/M)_{i,t}$ is the natural logarithm of firm i's book-to-market ratio, $ROA_{i,t}$ is firm i's return-on-assets, and $AG_{i,t}$ is firm i's asset growth rate. $GOB_{i,t}$, $ln(MV)_{i,t}$, $ln(B/M)_{i,t}$, $ROA_{i,t}$, and $AG_{i,t}$ are measured at the end of June of year t.

Table 8 Panel A presents the conventional Fama–MacBeth regression results. Consistent with the results based on portfolio sorts, the univariate regression exhibits significant return predictability of growth opportunity bias: high GOB predicts low returns for the next 12 months. After controlling for key firm characteristics such as size, book-to-market, momentum, return-on-assets, and asset growth, the predictive power of GOB remains highly significant ($t > 3$). As to other characteristics, MV and AG are negatively related to subsequent returns, while B/M, MOM, and ROA are positively related to subsequent returns, in line with previous studies.[21]

Brennan, Chordia, and Subrahmanyam (1998) argue that the standard Fama–Macbeth (1973) procedure as in Eqs. (12), (13), and (14) may affect statistical inference when the factor loadings are measured with errors. They recommend the use of risk-adjusted returns as the dependent variables to address the errors-in-variable problem associated with the Fama–Macbeth regressions. We follow their approach and calculate the risk-adjusted returns based on the following equation (Chordia, Huh, and Subrahmanyam (2009)):

$$R^*_{i,t} = R_{i,t} - R_{f,t} - \beta_{i,m} f_{MKT,t} - \beta_{i,s} f_{SMB,t} - \beta_{i,h} f_{HML,t}, \tag{15}$$

where $R^*_{i,t+1}$ is the monthly percentage risk-adjusted returns between July of year t and June of year $t+1$. We calculate the risk-adjusted returns based on the Fama and French (1993) three-factor model, which are the sum of the constant terms ($\alpha_{i,t}$) and the residuals ($\varepsilon_{i,t}$) from the time-series regression of excess returns on the Fama–French three factors using the 36-month rolling window.[22] We run the Fama-Macbeth regressions using Eqs. (12) to (14) but with the risk-adjusted returns $R^*_{i,t}$ as the dependent variable to test the robustness of the regression results. Panel B reports the risk-adjusted results which largely mirror the findings in Panel A.

[Table 8 about here]

Fama and French (2008) argue that microcap stocks which account for about 60.7% of the total number of stocks, though represent only 3.21% of the total market capitalization, can af-

[21]See, for example, Fama and French (1993), Jegadeesh and Titman (1993), Cooper, Gulen, and Schill (2008), and Lewellen (2015).

[22]The results (untabulated) are qualitatively similar based on the Fama and French (2015) five-factor models risk-adjusted returns.

fect portfolio returns. Hou, Xue, and Zhang (2018) argue that ordinary least squares can be dominated by microcaps because of their high proportion in total number of stocks. Moreover, premiums found in microcap stocks are likely to be unprofitable in practice due to high transaction costs in trading those stockes (Novy-Marx and Velikov, 2016).

Following Fama and French (2008), we define stocks with market capitalization below the 20% of NYSE stocks as microcaps. We examine the potential impact of the microcap stocks on the relation between growth opportunity bias and stock returns by excluding the microcaps in Fama–MacBeth regressions, as in Green, Hand, and Zhang (2017). Table 9 reports the results. It shows that the relation between growth opportunity bias and future stock returns remains intact after excluding the microcap stocks.[23]

[Table 9 about here]

Recently, Lewellen (2015) and Bessembinder, Cooper, and Zhang (2018) show the importance of 14 firm characteristics in the cross-sectional stock returns. Following their studies, we conduct further test by controlling these additional variables:

(i) *Beta*. Market beta is estimated using daily excess stock returns and excess market returns over the preceding 12 months.

(ii) *Accruals*. We follow Sloan (1996) to measure operating accruals, OA, as changes in noncash working capital minus depreciation, in which the noncash working capital is changes in noncash current assets minus changes in current liabilities less short-term debt and taxes payable. In particular, $OA = (dCA - dCASH) - (dCL - dSTD - dTP) - DP$, where dCA is

[23] We also form portfolios with all-but-micro breakpoints (Hou, Xue, and Zhang (2018)) at the end of June of each year and hold the portfolios for the subsequent 12 months. The results (untabulated) are qualitatively similar to those reported in Table 2.

the change in current assets (COMPUSTAT item ACT), $dCASH$ is the change in cash or cash equivalents (item CHE), dCL is the change in current liabilities (item LCT), $dSTD$ is the change in debt included in current liabilities (item DLC), dTP is the change in income taxes payable (item TXP), and DP is depreciation and amortization (item DP). Missing changes in TXP are set to zero. Following Sloan (1996), accruals are scaled by the mean of current and prior years total assets.

(iii) *Dividend*. Dividends per share over the prior 12 months divided by the price at the end of the previous month.

(iv) *Log return*. Natural log of buy-and-hold stock returns over months (-36, -13).

(v) *IVOL* (idiosyncratic risk). The standard deviations of residuals from regressing daily stock returns against the FF3FM over the prior 12 months (with a minimum of 100 days).

(vi) *Illiquidity*. The average daily ratio of absolute stock return to dollar trading volume during the prior 12 months, as defined in Amihud (2002)

(vii) *Turnover*. Average monthly turnover (shares traded divided by shares outstanding) during the prior 12 months

(viii) *Leverage*. Debt in current liabilities (item DLC) plus long-term debt (item $DLTT$), divided by market capitalization.

(ix) *Sales*. Sales (item $SALE$) divided by market capitalization.

Table 10 shows that GOB continues to predict cross-sectional stock returns after controlling for all these additional variables. The slope coefficients on GOB are -0.041 ($t = -2.51$) and -0.032 ($t = -2.14$) for raw returns and risk-adjusted returns, respectively.

[Table 10 about here]

3.4 Behavioral explanations on growth opportunity bias premium

Our analysis, so far, shows that firms with low *GOB* earn higher future returns than those with high *GOB*, and the *GOB* premium is unexplained by the risk-based methods. Could the *GOB* premium be driven by investors' behavioral biases?

There are usually two types of investors competing in the stock markets: irrational investors who are prone to sentiment, and rational arbitrageurs (DeLong, Shleifer, Summers, and Waldmann, 1990). Irrational investors are more likely to overact to firms' growth opportunities which results in large *GOB*s, especially in high sentiment periods. But such irrationality-induced anomalies could not survive unless rational arbitrage is limited (Brav and Heaton, 2002). Hence, asset pricing anomalies, if any, could arise from a combination of two aspects: a change in investor sentiment; and limits to arbitrage (Baker and Wurgler, 2007; Jacobs, 2015). In this subsection, we study whether investor sentiment and limits-to-arbitrage help explain the *GOB* premium.

3.4.1 Investor sentiment and growth opportunity bias premium

Prior studies show that investor sentiment plays a significant role in explaining asset pricing anomalies (e.g., Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; Baker, Wurgler, and Yuan, 2012; Hribar and McInnis, 2012; Seybert and Yang, 2012; Stambaugh, Yu, and Yuan, 2012, 2014; Firth, Wang, and Wong, 2015;). Generally speaking, during high-sentiment periods, the optimistic views tend to be overly optimistic and stocks are likely to be overpriced; during low-sentiment periods, the optimistic views tend to be more realistic and stocks are likely to be more correctly priced. Consequently, anomalies should be more pronounced during high-sentiment periods.

We conjecture that if *GOB* captures behavioral biases, then the *GOB* premium should be more pronounced in high-sentiment periods. As all else being equal, a high-*GOB* stock has a high proportion of its market value estimated from its yet-unexercised growth opportunities (i.e., high *PVGO*). Given that *PVGO* is positively correlated with aggregate idiosyncratic volatility (Cao, Simin, and Zhao, 2008), and stocks with high volatility are usually those with strong speculative appeal (Baker and Wurgler, 2007), it is reasonable to expect that the *GOB* premium is more pronounced in periods of high investor sentiment when the "propensity to speculate" is high, since speculative stocks (high-*GOB* stocks in our case) are more sensitive to the sentiment effect (Baker and Wurgler, 2007) and a larger proportion of unsophisticated/irrational investors participant in high sentiment period (Yu and Yuan, 2011; Antoniou, Doukas, and Subrahmanyam, 2015).

We, thus, examine the performance of *GOB* portfolios during high and low sentiment periods. We use two common sentiment measures in our study: the University of Michigan consumer sentiment index and the Baker and Wurgler (2006) sentiment index.[24] Table 11 reports the *GOB* premiums for high- and low-sentiment periods. Panel A reports results based on the University of Michigan sentiment index. As can be seen, for both equal- and value-weighted results, the *GOB* premiums are only significant in high-sentiment periods. Using the FF5FM, for example, the *GOB* premiums in high-sentiment periods are 0.731% ($t = 4.38$) and 1.521% ($t = 4.93$) per month for equal- and value-weighted returns, respectively. However, the corresponding *GOB* premiums in low-sentiment periods are 0.069% ($t = 0.40$) and 0.383% ($t = 1.28$) per month,

[24] The Baker and Wurgler's sentiment index is obtained from Jeffrey Wurglers NYU webpage: http://people.stern.nyu.edu/jwurgler/ The University of Michigan sentiment index is downloaded from the University of Michigan Surveys of Consumers website: http://www.sca.isr.umich.edu/

respectively. Panel B presents results based on Baker and Wurgler (2006) sentiment index. It, again, shows that the *GOB* premiums only survive in high-sentiment periods. Overall, our results suggest that investor sentiment is a strong driving force of the *GOB* premium.

[Table 11 about here]

3.4.2 Limits-to-arbitrage and growth opportunity bias premium

We now turn to examine whether the *GOB* premium is also driven by limits-to-arbitrage. Prior studies show that limits-to-arbitrage can prevent the effectiveness of rational arbitrageurs to "undo the dislocations" caused by irrational investors (e.g., Shleifer and Vishny, 1997; Hirshleifer, 2001; Brav and Heaton, 2002; Barberis and Thaler, 2003; Doukas, Kim, and Pantzalis, 2010; Brav, Heaton, and Li, 2010). Given arbitrage is risky, costly, and limited,[25] if the *GOB* premium is, indeed, driven by behavioral biases, it should be more pronounced for stocks with high limits-to-arbitrage.

We postulate that if the relation between *GOB* and stock returns is related to limits-to-arbitrage, it should be more pronounced when arbitrage costs are high than when the costs are low. To test this, we first sort stocks into five arbitrage costs groups; For each group, we then sort stocks into five *GOB* portfolios.[26] We use three arbitrage costs measures in our study:

[25]A large body of literature have examined the limits-to-arbitrage explanation for various asset pricing anomalies. For example, Ali, Hwang, and Trombley (2003) find that the book-to-market effect is concentrated in firms with high transaction costs and large idiosyncratic volatility. Mashruwala, Rajgopal, and Shevlin (2006) show that great idiosyncratic volatility, high transaction costs, and short-sale constraints prevent rational traders from exploiting the accrual anomaly. Li and Zhang (2010) and Lipson, Mortal, and Schill (2012) highlight the limits-to-arbitrage explanation for the asset growth anomaly. McLean (2010) reports that the long-term reversal anomaly is related to limits-to-arbitrage. Mclean and Pontiff (2016) study 97 anomalies and find that mispricing accounts for the predictability of characteristics on the cross-sectional stock returns. Li and Luo (2016) examine whether the relation between firms' cash holdings and stock returns is related to the limits-to-arbitrage.

[26]For some arbitrage costs measures, we have insufficient number of stocks when we independently sort stocks to five arbitrage costs groups and five growth opportunity bias groups, both using NYSE breakpoints.

(i) The negative dollar volume measure of Brennan, Chordia, and Subrahmanyam (1998), DTV, defined as the daily dollar volume averaged over the prior 12 months. To be consistent with other arbitrage costs proxies, we use negative dollar volume so that large DTV indicates high arbitrage costs.

(ii) The price impact measure of Amihud (2002), RV, defined as the daily absolute-return-to-dollar-volume ratio averaged over the prior 12 months.

(iii) The bid-ask spread estimate of Corwin and Schultz (2012), CS. For each month, they estimate the bid-ask spread using daily high and low prices in that month. The CS measure is the average of the Corwin and Schultz (2012) estimates over the previous 12 months.[27]

Table 12 reports the results. As can be seen, the GOB premium is more pronounced when the limits-to-arbitrage (LA) is high. For example, using the dollar volume (DTV) measure (Panel A), the GOB premiums for high-LA stocks are 0.543% ($t = 4.09$) and 0.577% ($t = 4.59$) per month for equal- and value-weighted returns, respectively. However, the corresponding GOB premiums for low-LA stocks are 0.283% ($t = 1.65$) and 0.220% ($t = 1.29$) per month, respectively. Overall, our results in Tables 11 and 12 show that investor sentiment and limits-to-arbitrage provide better explanations to the GOB premium.

[Table 12 about here]

[27]We thank Shane Corwin for sharing with us their high-low-price-based bid-ask spread estimates.

4 Conclusion

Given the "yet-unexercised future-oriented growth option" of a firm is not directly observable, investors may, sometimes, misjudge a firm's growth potential that leads to a growth opportunity bias (GOB): the divergence between market and fundamental valuations of growth opportunity. We conjecture that the growth opportunity bias has an ability to predict future stock returns as it is likely to capture the behavioral biases of investors.

Examining U.S. common stocks from 1977 to 2014, we find an inverse relation between growth opportunity bias and future stock returns. In the portfolio sort, firms with low GOB earn higher future returns than firms with high GOB. The GOB premium is not explained by the commonly used asset pricing models. Further, cross-sectional regression results also confirm GOB's ability in predicting future returns after controlling for key firm characteristics such as size, book-to-market, return-on-assets, and asset growth.

Given the inability of the risk-based methods in explaining the GOB premium, we turn to behavioural aspects to seek a better understanding of the anomaly. We find that the GOB premium is more pronounced when investor sentiment is high and when limits-to-arbitrage is severe, which suggests that the GOB is more likely to capture behavioural biases than systematic risk.

We expect the GOB to be widely used both in academic and in practice. Apart from forming trading strategies to exploit the anomaly, GOB can be used as proxies of investor behavioral biases or measures of limits-to-arbitrage. It can also be used broadly in corporate decision-making. For example, managers often consider acquiring other firms with high growth potential to maintain their own growth momentum. *GOB* can be used as a tool to evaluate their target companies, since a high *GOB* is likely to indicate investors overreacting to a target's growth potential, topping it up with a high takeover premium can be a particularly expensive deal. Or, when a firm's *GOB* is high, its cost of equity is low. *GOB* can, thus, be used as a timing tool for firms to tap the capital markets. The relation between *GOB* and corporate financing and investment decision-making is another avenue for future research.

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Table 1 Descriptive statistics

This table reports descriptive statistics for the following variables. Market value of growth opportunity (MGO) is the percentage of a firm's value from future growth opportunities ($PVGO/MV$), estimated by subtracting from the current firm market value (MV) the perpetual discounted stream of firm cash flows under a no-growth policy based on equation (1). Fundamental value of growth opportunity (FGO) is the corresponding estimated value from the model of equation (2). Firm-specific volatility is measured by the standard deviations of residuals of the regression of the monthly stock returns in excess of risk-free rate on the Fama–French (1993) three factors over the prior 36 months. Managerial flexibility is proxied by the skewness of monthly stock returns over the prior 36 months. Organizational flexibility is the ratio of its selling, general, and administrative (SGA) expenses to sales. Financial flexibility is debt-to-assets (DV) ratio, i.e., the book value of total liabilities (D) divided by the market value of the firm's assets (V). Cash flow coverage (CFC is the amount of operating cash and equivalents maintained by the firm. $R\&D$ intensity is the average $R\&D$ expenses over the recent 3-year period as a percentage of total assets. Missing $R\&D$ observations are set to 0. Cumulative growth is the percentage change in the firm's sales over the recent 3-year period. Market power is the square root of the firm's Herfindahl-Hirschman Index (HHI) if the firm has above-average Tobin's q, and 0 if the firm has below-average q. Growth opportunity bias (GOB) is the difference between a firm's market value of growth opportunity and fundamental value of growth opportunity. Market capitalization ($MV(\$m)$) is the product of price and shares outstanding measured in millions of dollars. Book-to-market ratio (B/M) is the ratio of book value of equity to market value of equity. Book equity is total assets minus liabilities, plus balance sheet deferred taxes and investment tax credit if available, minus preferred stock liquidating value if available, or redemption value if available, or carrying value. Market equity is the product of price and shares outstanding. Return-on-assets (ROA) is income before extraordinary items divided by average total assets. Total asset growth (AG) is the growth rate of total assets. The cross-sectional averages for each variable are calculated over NYSE/AMEX/NASDAQ stocks from 1977 to 2013. The reported mean, standard deviation, minimum, Q1 (bottom 25%), median, Q3 (top 25%), and maximum are based on these time-series cross-sectional averages.

	GOB	MGO	FGO	$MV(\$m)$	B/M	ROA	AG
Mean	0.095	0.493	0.397	1995.512	0.906	0.016	0.143
Stdev	8.796	7.974	3.699	11663.539	1.638	0.151	0.555
Min	-58.704	-48.342	-10.602	0.180	0.000	-3.714	-0.959
Q1	-1.220	-0.696	-0.670	24.200	0.350	-0.000	-0.024
Medium	0.325	0.441	0.377	112.631	0.626	0.043	0.068
Q3	2.311	1.451	1.079	645.375	1.080	0.082	0.186
Max	48.478	37.876	11.798	472518.688	191.497	1.227	48.409
N	85101						

Table 2

Performance of the growth opportunity bias decile portfolios

Using NYSE breakpoints, we form equal- and value-weighted decile portfolios at the end of June each year and hold them for the subsequent 12 months. The row labelled Raw shows the raw mean returns measured on a monthly basis. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, and $f_{CMA,t}$ is the month-t value of the Fama–French investment factor. The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks. The testing period is 7/1977–6/2014 (444 months). Numbers in parentheses are t-statistics.

	Low-GOB	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*High-GOB*	*L−H*
Panel A: Equally weighted											
Raw (%)	1.690	1.595	1.471	1.447	1.357	1.334	1.258	1.188	1.194	1.179	0.510
	(5.69)	(5.87)	(5.66)	(5.60)	(5.33)	(5.12)	(4.84)	(4.55)	(4.42)	(3.83)	(4.55)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$											
$\alpha_{i,t}$	0.330	0.282	0.184	0.187	0.102	0.108	0.026	-0.074	-0.101	-0.178	0.508
	(3.12)	(3.69)	(2.46)	(2.95)	(1.48)	(1.58)	(0.36)	(-0.94)	(-1.17)	(-1.32)	(4.33)
$\beta_{i,mkt}$	0.972	0.985	0.988	0.960	0.995	0.969	0.955	1.009	0.991	0.970	0.001
	(33.04)	(49.94)	(44.84)	(54.08)	(58.40)	(53.91)	(48.99)	(41.58)	(38.80)	(24.45)	(0.05)
$\hat{\beta}_{i,s}$	1.111	0.903	0.772	0.815	0.685	0.769	0.794	0.702	0.844	1.126	-0.015
	(21.51)	(23.65)	(18.46)	(24.45)	(17.41)	(23.85)	(20.07)	(13.89)	(18.67)	(18.38)	(-0.27)
$\hat{\beta}_{i,h}$	0.304	0.282	0.288	0.218	0.227	0.122	0.151	0.210	0.251	0.288	0.016
	(5.67)	(8.29)	(7.51)	(7.07)	(6.92)	(3.71)	(4.00)	(5.33)	(5.62)	(3.92)	(0.32)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$											
$\alpha_{i,t}$	0.328	0.270	0.220	0.192	0.139	0.110	0.047	-0.020	-0.053	-0.080	0.408
	(2.88)	(3.40)	(2.86)	(2.99)	(2.00)	(1.57)	(0.64)	(-0.25)	(-0.61)	(-0.56)	(3.45)
$\beta_{i,mkt}$	0.972	0.987	0.980	0.959	0.987	0.968	0.951	0.998	0.981	0.949	0.023
	(31.99)	(49.28)	(43.50)	(53.02)	(56.29)	(54.48)	(49.03)	(43.03)	(41.55)	(25.31)	(0.79)
$\hat{\beta}_{i,s}$	1.111	0.901	0.776	0.815	0.689	0.769	0.796	0.707	0.848	1.136	-0.025
	(21.54)	(23.49)	(19.27)	(24.45)	(18.45)	(23.96)	(20.05)	(14.70)	(19.57)	(19.70)	(-0.51)
$\hat{\beta}_{i,h}$	0.305	0.287	0.273	0.216	0.212	0.121	0.142	0.188	0.231	0.248	0.057
	(5.49)	(8.30)	(7.10)	(7.04)	(6.42)	(3.46)	(3.69)	(4.88)	(5.46)	(3.41)	(1.25)
$\hat{\beta}_{i,w}$	0.002	0.015	-0.043	-0.005	-0.043	-0.003	-0.024	-0.064	-0.055	-0.116	0.118
	(0.07)	(0.66)	(-1.66)	(-0.31)	(-1.96)	(-0.17)	(-1.21)	(-3.00)	(-1.94)	(-2.64)	(4.30)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$											
$\alpha_{i,t}$	0.413	0.262	0.156	0.165	0.059	0.100	-0.035	-0.129	-0.100	-0.036	0.449
	(3.80)	(3.34)	(2.06)	(2.59)	(0.82)	(1.44)	(-0.49)	(-1.68)	(-1.21)	(-0.26)	(3.49)
$\beta_{i,mkt}$	0.968	0.988	0.991	0.969	1.002	0.973	0.970	1.018	0.985	0.948	0.020
	(32.36)	(49.23)	(44.83)	(54.71)	(57.78)	(55.12)	(52.57)	(43.20)	(42.57)	(26.09)	(0.62)
$\hat{\beta}_{i,s}$	1.034	0.927	0.808	0.818	0.725	0.775	0.828	0.751	0.884	1.055	-0.020
	(21.35)	(26.36)	(21.92)	(28.33)	(23.10)	(25.38)	(23.37)	(18.35)	(21.79)	(16.53)	(-0.38)
$\hat{\beta}_{i,h}$	0.096	0.130	0.154	0.038	0.100	-0.028	-0.039	0.068	0.144	0.143	-0.046
	(1.56)	(3.06)	(3.93)	(1.05)	(2.76)	(-0.72)	(-0.88)	(1.27)	(2.50)	(1.56)	(-0.60)
$\hat{\beta}_{i,r}$	-0.217	0.068	0.072	0.009	0.101	-0.001	0.083	0.107	0.050	-0.291	0.074
	(-3.35)	(1.79)	(1.80)	(0.21)	(2.52)	(-0.01)	(2.04)	(2.25)	(1.08)	(-4.16)	(1.02)
$\hat{\beta}_{i,c}$	0.222	0.084	0.082	0.190	0.084	0.138	0.205	0.116	0.007	0.097	0.126
	(2.47)	(1.33)	(1.47)	(3.87)	(1.51)	(2.52)	(3.73)	(1.67)	(0.11)	(0.87)	(1.18)

(continued)

	Low-GOB	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	High-GOB	$L-H$
	Panel B: Value weighted										
Raw (%)	1.540	1.216	1.219	1.220	1.196	0.991	1.127	0.982	0.956	0.891	0.649
	(5.20)	(4.98)	(5.25)	(5.22)	(5.27)	(4.45)	(4.95)	(4.10)	(3.82)	(3.11)	(3.07)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.435	0.140	0.185	0.248	0.225	-0.009	0.116	-0.119	-0.241	-0.372	0.807
	(2.85)	(1.18)	(2.11)	(2.59)	(2.49)	(-0.11)	(1.30)	(-1.08)	(-2.32)	(-2.57)	(3.65)
$\beta_{i,mkt}$	1.032	1.011	1.007	0.988	0.971	0.983	0.971	1.030	1.078	1.134	-0.102
	(26.36)	(31.64)	(45.55)	(36.95)	(38.24)	(46.95)	(47.06)	(34.38)	(31.54)	(24.46)	(-1.46)
$\hat{\beta}_{i,s}$	0.473	0.083	-0.004	-0.083	-0.081	-0.106	0.028	0.024	0.192	0.399	0.074
	(5.83)	(1.47)	(-0.10)	(-1.93)	(-2.06)	(-2.57)	(0.65)	(0.38)	(3.97)	(4.99)	(0.56)
$\hat{\beta}_{i,h}$	-0.200	0.056	-0.011	-0.123	-0.093	0.003	-0.038	0.146	0.242	0.182	-0.382
	(-2.47)	(0.94)	(-0.25)	(-3.02)	(-1.85)	(0.06)	(-0.97)	(2.45)	(4.42)	(2.22)	(-2.98)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.367	0.072	0.215	0.206	0.232	0.007	0.150	-0.069	-0.183	-0.245	0.613
	(2.38)	(0.59)	(2.36)	(2.19)	(2.30)	(0.08)	(1.59)	(-0.62)	(-1.66)	(-1.66)	(2.76)
$\beta_{i,mkt}$	1.047	1.026	1.001	0.997	0.970	0.979	0.964	1.020	1.065	1.107	-0.060
	(28.36)	(32.18)	(45.05)	(37.76)	(37.41)	(45.66)	(45.30)	(34.50)	(33.46)	(25.71)	(-0.98)
$\hat{\beta}_{i,s}$	0.466	0.076	-0.001	-0.087	-0.080	-0.104	0.032	0.029	0.198	0.412	0.054
	(5.92)	(1.36)	(-0.02)	(-2.01)	(-1.99)	(-2.57)	(0.76)	(0.49)	(4.40)	(5.96)	(0.45)
$\hat{\beta}_{i,h}$	-0.173	0.084	-0.023	-0.106	-0.096	-0.004	-0.052	0.125	0.218	0.131	-0.303
	(-2.40)	(1.39)	(-0.52)	(-2.72)	(-1.77)	(-0.10)	(-1.26)	(2.09)	(4.00)	(1.89)	(-2.98)
$\hat{\beta}_{i,w}$	0.079	0.080	-0.036	0.049	-0.008	-0.019	-0.040	-0.059	-0.069	-0.149	0.228
	(1.48)	(2.25)	(-1.32)	(1.80)	(-0.17)	(-0.78)	(-1.32)	(-1.63)	(-1.86)	(-2.98)	(2.81)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.601	0.091	0.178	0.160	0.145	-0.109	0.038	-0.355	-0.312	-0.411	1.012
	(3.59)	(0.72)	(1.98)	(1.61)	(1.49)	(-1.21)	(0.38)	(-3.23)	(-2.87)	(-2.64)	(4.25)
$\beta_{i,mkt}$	1.011	1.018	1.008	1.004	0.997	1.007	0.986	1.068	1.080	1.132	-0.122
	(27.27)	(31.41)	(43.13)	(39.25)	(40.05)	(48.16)	(44.68)	(37.01)	(30.88)	(26.37)	(-1.94)
$\hat{\beta}_{i,s}$	0.350	0.120	0.003	-0.037	-0.086	-0.078	0.069	0.178	0.280	0.465	-0.115
	(5.16)	(2.17)	(0.06)	(-0.85)	(-2.05)	(-1.94)	(1.77)	(3.77)	(6.04)	(6.99)	(-1.13)
$\hat{\beta}_{i,h}$	-0.237	0.040	-0.008	-0.158	-0.186	-0.071	-0.091	0.031	0.225	0.144	-0.382
	(-2.38)	(0.52)	(-0.15)	(-3.20)	(-4.00)	(-1.44)	(-1.95)	(0.48)	(3.52)	(1.41)	(-2.37)
$\hat{\beta}_{i,r}$	-0.346	0.125	0.022	0.152	0.064	0.127	0.130	0.427	0.186	0.135	-0.481
	(-3.68)	(1.84)	(0.36)	(2.60)	(1.06)	(2.02)	(2.41)	(7.10)	(2.78)	(1.43)	(-3.25)
$\hat{\beta}_{i,c}$	0.030	-0.016	-0.012	0.070	0.220	0.170	0.085	0.170	-0.050	-0.050	0.080
	(0.24)	(-0.16)	(-0.14)	(0.85)	(2.51)	(2.37)	(1.05)	(2.15)	(-0.61)	(-0.38)	(0.40)

Table 3

Robustness test on gross-return-weighted returns

Using NYSE breakpoints, we form gross-return-weighted decile portfolios at the end of June each year and hold them for the subsequent 12 months. The row labelled Raw shows the raw mean returns measured on a monthly basis. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, and $f_{CMA,t}$ is the month-t value of the Fama–French investment factor. The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks. The testing period is 7/1977–6/2014 (444 months). Numbers in parentheses are t-statistics.

	Low-GOB	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	High-GOB	$L-H$
Raw (%)	1.670	1.506	1.459	1.403	1.323	1.293	1.202	1.181	1.172	1.143	0.526
	(5.55)	(5.56)	(5.47)	(5.41)	(5.12)	(4.98)	(4.68)	(4.46)	(4.29)	(3.64)	(4.73)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.288	0.186	0.147	0.122	0.052	0.035	-0.044	-0.104	-0.140	-0.236	0.524
	(2.45)	(2.22)	(1.76)	(1.65)	(0.66)	(0.46)	(-0.52)	(-1.15)	(-1.46)	(-1.53)	(4.42)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \beta_{i,wml} f_{wml,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.430	0.265	0.274	0.238	0.186	0.153	0.081	0.041	0.011	-0.004	0.434
	(3.20)	(2.95)	(3.03)	(3.07)	(2.39)	(1.89)	(0.98)	(0.48)	(0.11)	(-0.02)	(3.49)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \beta_{i,rmw} f_{rmw,t} + \beta_{i,cma} f_{cma,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.426	0.202	0.152	0.109	0.032	0.029	-0.098	-0.149	-0.115	-0.079	0.505
	(3.16)	(2.23)	(1.67)	(1.39)	(0.36)	(0.35)	(-1.16)	(-1.61)	(-1.15)	(-0.48)	(3.97)

Table 4
Robustness test on characteristics-adjusted returns

Using NYSE breakpoints, we form equal- and value-weighted decile portfolios at the end of June each year and hold them for the subsequent 12 months. This table reports the characteristics-adjusted portfolio returns per month. Following Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) and Wermers (2004), the characteristics-adjusted returns are the difference between individual firm's returns and the DGTW benchmark portfolio returns. The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks. The testing period is 7/1977–6/2013 (444 months). Numbers in parentheses are t-statistics.

Low-GOB	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	High-GOB	$L-H$
Panel A: characteristics-adjusted returns (%) per month of equal-weighted decile portfolios										
0.285	0.277	0.176	0.148	0.126	0.101	0.037	0.003	-0.054	-0.100	0.386
(3.76)	(4.28)	(2.81)	(2.74)	(2.18)	(1.73)	(0.64)	(0.05)	(-0.86)	(-1.00)	(3.72)
Panel B: characteristics-adjusted returns (%) per month of value-weighted decile portfolios										
0.304	0.071	0.121	0.089	0.126	-0.057	0.052	-0.086	-0.173	-0.284	0.588
(2.64)	(0.84)	(1.69)	(1.27)	(1.85)	(-0.88)	(0.69)	(-1.19)	(-2.21)	(-2.73)	(3.96)

Table 5
Robustness test on growth opportunity bias and size

Using NYSE breakpoints, we divide the sample of NYSE/AMEX/NASDAQ non-financial and non-regulated stocks into three MV and then ten GOB-based sub-samples within each MV group at the end of June each year starting from 1977. We hold the portfolios for the subsequent 12 months. Stocks below the 20% of market capitalization of NYSE stocks are defined as "Micro". Stocks above the 20% but below 50% of market capitalization of NYSE stocks are defined as "Small". Stocks above the 50% of market capitalization of NYSE stocks are defined as "Large". The row labelled Raw shows the raw mean returns measured on a monthly basis. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, and $f_{CMA,t}$ is the month-t value of the Fama–French investment factor. The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks. The testing period is 7/1977–6/2014 (444 months). Numbers in parentheses are t-statistics.

	Panel A: Equal-weighted				Panel B: Value-weighted			
	Low-GOB	$D5$	High-GOB	$L-H$	Low-GOB	$D5$	High-GOB	$L-H$
Micro(Raw (%))	1.825	1.638	1.234	0.591	1.747	1.469	1.097	0.650
	(5.72)	(5.53)	(3.63)	(3.57)	(5.22)	(4.91)	(3.26)	(4.16)
Small(Raw (%))	1.381	1.297	0.884	0.497	1.367	1.321	0.924	0.444
	(4.38)	(4.62)	(2.78)	(2.97)	(4.24)	(4.71)	(2.90)	(2.40)
Big(Raw (%))	1.367	1.223	1.002	0.364	1.323	1.058	0.879	0.444
	(4.91)	(5.13)	(3.71)	(2.65)	(5.07)	(4.50)	(3.23)	(2.30)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}$							
Micro($\alpha_{i,t}$)	0.850	0.710	0.323	0.527	0.680	0.516	0.060	0.620
	(5.76)	(5.93)	(1.68)	(3.22)	(5.33)	(5.04)	(0.36)	(3.74)
Small($\alpha_{i,t}$)	0.376	0.388	-0.171	0.547	0.368	0.429	-0.138	0.506
	(3.23)	(4.05)	(-1.20)	(3.10)	(2.95)	(4.20)	(-0.96)	(2.70)
Big($\alpha_{i,t}$)	0.566	0.521	0.161	0.404	0.701	0.524	0.056	0.645
	(5.04)	(6.91)	(1.35)	(2.88)	(4.80)	(4.88)	(0.48)	(3.30)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$							
Micro($\alpha_{i,t}$)	0.858	0.752	0.452	0.406	0.708	0.542	0.192	0.516
	(5.31)	(5.96)	(2.18)	(2.36)	(4.67)	(5.04)	(1.05)	(3.04)
Small($\alpha_{i,t}$)	0.335	0.394	-0.063	0.398	0.333	0.424	-0.055	0.388
	(2.94)	(3.85)	(-0.45)	(2.36)	(2.64)	(3.94)	(-0.38)	(2.06)
Big($\alpha_{i,t}$)	0.581	0.561	0.220	0.361	0.630	0.595	0.145	0.485
	(5.13)	(7.42)	(1.85)	(2.60)	(4.15)	(5.31)	(1.24)	(2.42)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$							
Micro($\alpha_{i,t}$)	0.992	0.776	0.604	0.388	0.790	0.535	0.231	0.559
	(6.68)	(5.86)	(3.02)	(2.19)	(5.49)	(4.91)	(1.32)	(3.30)
Small($\alpha_{i,t}$)	0.397	0.341	-0.249	0.646	0.404	0.380	-0.248	0.652
	(3.24)	(3.61)	(-1.73)	(3.38)	(3.13)	(3.78)	(-1.74)	(3.29)
Big($\alpha_{i,t}$)	0.604	0.423	0.056	0.548	0.742	0.500	0.043	0.699
	(5.02)	(5.48)	(0.46)	(3.44)	(4.78)	(4.23)	(0.34)	(3.19)

Table 6

Robustness test on growth opportunity bias controlling for fundamental value of growth opportunity

Using NYSE breakpoints, we form equal- and value-weighted decile portfolios at the end of June each year and hold them for the subsequent 12 months based on the fundamental value of growth opportunity (FGO). Then, we form equal- and value-weighted decile portfolios at the end of June each year and hold them for the subsequent 12 months based on the growth opportunity bias GOB within each FGO decile portfolios. This table reports the average performance of decile GOB portfolios across the five control FGO deciles. The row labelled Raw shows the raw mean returns measured on a monthly basis. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, and $f_{CMA,t}$ is the month-t value of the Fama–French investment factor. The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks. The testing period is 7/1977–6/2014 (444 months). Numbers in parentheses are t-statistics.

	Low-GOB	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	High-GOB	$L-H$
	Panel A: equal-weighted decile portfolios										
Raw (%)	1.749	1.632	1.541	1.419	1.519	1.304	1.260	1.263	1.217	1.079	0.670
	(6.52)	(6.29)	(6.13)	(5.74)	(6.17)	(5.28)	(5.13)	(4.99)	(4.59)	(3.86)	(6.69)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.370	0.278	0.218	0.141	0.246	0.037	0.014	0.023	-0.036	-0.216	0.586
	(3.97)	(3.29)	(2.75)	(1.80)	(3.45)	(0.53)	(0.20)	(0.29)	(-0.46)	(-1.90)	(6.08)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \beta_{i,wml} f_{wml,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.384	0.315	0.242	0.168	0.263	0.080	0.077	0.061	0.002	-0.136	0.520
	(4.03)	(3.61)	(2.85)	(2.11)	(3.52)	(1.14)	(1.04)	(0.74)	(0.03)	(-1.15)	(5.08)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \beta_{i,rmw} f_{rmw,t} + \beta_{i,cma} f_{cma,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.307	0.171	0.126	-0.013	0.157	-0.068	-0.080	-0.046	-0.071	-0.175	0.482
	(3.35)	(2.12)	(1.60)	(-0.17)	(2.28)	(-1.03)	(-1.14)	(-0.58)	(-0.93)	(-1.43)	(4.51)
	Panel B: value-weighted decile portfolios										
Raw (%)	1.375	1.561	1.316	1.243	1.292	1.112	1.107	1.083	0.949	0.855	0.520
	(5.03)	(6.10)	(5.56)	(5.39)	(5.66)	(4.85)	(4.79)	(4.43)	(3.68)	(2.91)	(3.82)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.013	0.254	0.114	0.091	0.162	0.001	0.013	-0.034	-0.210	-0.413	0.426
	(0.13)	(2.61)	(1.39)	(1.04)	(2.01)	(0.01)	(0.16)	(-0.34)	(-2.24)	(-3.41)	(3.31)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \beta_{i,wml} f_{wml,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.024	0.296	0.110	0.089	0.206	0.059	0.086	0.026	-0.132	-0.293	0.317
	(0.25)	(2.98)	(1.33)	(1.03)	(2.47)	(0.75)	(1.06)	(0.25)	(-1.43)	(-2.42)	(2.46)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \beta_{i,rmw} f_{rmw,t} + \beta_{i,cma} f_{cma,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	-0.076	0.162	-0.039	-0.160	0.016	-0.122	-0.140	-0.164	-0.268	-0.390	0.314
	(-0.75)	(1.65)	(-0.48)	(-1.92)	(0.20)	(-1.54)	(-1.64)	(-1.72)	(-2.82)	(-3.04)	(2.12)

Table 7

Performance of the growth opportunity bias decile portfolios: additional asset pricing models

The models used are the Pastor and Stambaugh (2003) liquidity-extended FF3FM, the Liu (2006) liquidity-augmented capital asset pricing model (LCAPM), the Hou, Xue, and Zhang (2015) q-factor model (HXZqFM), and the Stambaugh and Yuan (2017) mispricing factor model (SYmFM), respectively. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor, $f_{PSF,t}$ is the month-t value of the Pastor and Stambaugh (2003) traded liquidity factor, $f_{ME,t}$ is the month-t value of the HXZ (i.e., Hou, Xue, and Zhang, 2015) size factor, $f_{ROA,t}$ is the month-t value of the HXZ profitability factor, and $f_{I/A,t}$ is the month-t value of the HXZ investment factor, $f_{SMBSY,t}$ is the month-t value of the SY (Stambaugh and Yuan, 2017) size factor, $f_{MGMT,t}$ is the month-t value of the SY firms' managements factor, $f_{PERF,t}$ is the month-t value of the SY firms' performance factor. The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks with daily trading volumes available in the 12 months prior to portfolio formation. The testing period is 7/1977–6/2014 (444 months). Numbers in parentheses are t-statistics.

	Low-GOB	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	High-GOB	$L-H$
Panel A: equal-weighted decile portfolios											
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,p}f_{PSF,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.331	0.209	0.158	0.167	0.116	0.058	0.107	0.037	-0.135	-0.132	0.463
	(2.96)	(2.27)	(2.21)	(2.43)	(1.65)	(0.85)	(1.45)	(0.46)	(-1.34)	(-1.01)	(3.21)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,l}f_{LF,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.521	0.337	0.324	0.295	0.247	0.209	0.215	0.112	-0.038	-0.023	0.544
	(2.54)	(2.06)	(2.26)	(2.14)	(1.55)	(1.42)	(1.57)	(0.84)	(-0.20)	(-0.09)	(3.14)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{ME,t}+\beta_{i,r}f_{ROA,t}+\beta_{i,c}f_{I/A,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.536	0.360	0.254	0.225	0.134	0.165	0.065	-0.044	-0.029	0.119	0.417
	(4.32)	(3.76)	(2.64)	(3.14)	(1.52)	(2.24)	(0.84)	(-0.53)	(-0.33)	(0.80)	(3.16)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,ssy}f_{SMBSY,t}+\beta_{i,mgmt}f_{MGMT,t}+\beta_{i,perf}f_{PERF,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.331	0.240	0.195	0.152	0.088	0.045	-0.025	-0.075	-0.080	0.018	0.313
	(2.37)	(2.48)	(1.97)	(1.92)	(1.09)	(0.55)	(-0.28)	(-0.90)	(-0.82)	(0.11)	(2.33)
Panel B: value weighted decile portfolios											
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,p}f_{PSF,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.381	0.142	0.195	0.221	0.193	-0.024	0.069	-0.149	-0.224	-0.379	0.760
	(2.38)	(1.22)	(2.24)	(2.28)	(2.09)	(-0.29)	(0.80)	(-1.37)	(-2.10)	(-2.64)	(3.27)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,l}f_{LF,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.719	0.125	0.203	0.270	0.194	-0.044	0.157	-0.060	-0.090	-0.226	0.944
	(3.60)	(0.96)	(2.06)	(2.49)	(1.83)	(-0.47)	(1.62)	(-0.49)	(-0.71)	(-1.27)	(3.37)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{ME,t}+\beta_{i,r}f_{ROA,t}+\beta_{i,c}f_{I/A,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.700	0.111	0.264	0.157	0.182	-0.110	0.137	-0.300	-0.303	-0.314	1.015
	(3.92)	(0.82)	(2.64)	(1.47)	(1.52)	(-1.19)	(1.26)	(-2.57)	(-2.56)	(-1.81)	(3.82)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,ssy}f_{SMBSY,t}+\beta_{i,mgmt}f_{MGMT,t}+\beta_{i,perf}f_{PERF,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.469	0.019	0.209	0.156	0.198	-0.112	0.062	-0.229	-0.239	-0.201	0.670
	(2.82)	(0.15)	(2.13)	(1.54)	(1.65)	(-1.32)	(0.58)	(-1.99)	(-1.94)	(-1.26)	(2.85)

Table 8
Fama–MacBeth (1973) regressions

We run the following regression each month over each 12-month period from July $(t+1)$ to next June $(t+12)$:

$$
\begin{aligned}
R^*_{i,t+m} &= \gamma_0 + \gamma_1 GOB_{i,t} + \epsilon_{i,t+1}, \\
R^*_{i,t+m} &= \gamma_0 + \gamma_1 GOB_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} + \gamma_4 MOM_{i,t} + \epsilon_{i,t+1}, \\
R^*_{i,t+m} &= \gamma_0 + \gamma_1 GOB_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} + \gamma_4 MOM_{i,t} + \gamma_5 ROA_{i,t} + \gamma_6 AG_{i,t} + \epsilon_{i,t+1},
\end{aligned}
$$

where $R^*_{i,t+m}$ is stock i's return in month $t+m$ in excess of risk-free rate in month $t+m$ $(m = 1, 2, ..., 12)$, or stock i's risk-adjusted returns based on rolling regression. $GOB_{i,t}$ is firm i's growth opportunity bias, $ln(MV)_{i,t}$ is the natural logarithm of firm i's market capitalization, $MOM_{i,t}$ is the buy-and-hold return of stock i over month $t-6$ to month $t-1$, $ln(B/M)_{i,t}$ is the natural logarithm of firm i's book-to-market ratio, $ROA_{i,t}$ is firm i's return-on-assets, and $AG_{i,t}$ is firm i's asset growth rate. $GOB_{i,t}$, $ln(MV)_{i,t}$, $ln(B/M)_{i,t}$, $ROA_{i,t}$, and $AG_{i,t}$ are measured at the end of June of year t. We calculate the risk-adjusted returns based on the Fama–French (1993) three-factor model, which are the sum of the constant terms and the residuals from the time-series regression of the excess returns on the Fama–French three factors using the 36-month rolling window. Numbers in parentheses are t-statistics.

Constant	GOB	$ln(MV)$	$ln(B/M)$	MOM	ROA	AG
			Panel A: raw returns			
0.916	-0.066					
(3.25)	(-3.60)					
1.475	-0.057	-0.097	0.259	0.355		
(3.88)	(-3.39)	(-2.25)	(3.71)	(3.11)		
1.605	-0.055	-0.115	0.204	0.295	1.135	-0.528
(4.53)	(-3.55)	(-3.04)	(3.19)	(2.68)	(2.80)	(-8.68)
			Panel B: risk-adjusted returns			
-0.012	-0.053					
(-0.14)	(-3.33)					
0.415	-0.053	-0.077	0.072	0.160		
(1.95)	(-3.63)	(-2.46)	(1.58)	(1.20)		
0.616	-0.046	-0.115	0.027	0.131	2.144	-0.414
(3.14)	(-3.32)	(-4.23)	(0.63)	(1.00)	(6.38)	(-7.83)

Table 9

Fama–MacBeth (1973) regressions excluding the microcap stocks

We run the following regression each month over each 12-month period from July $(t+1)$ to next June $(t+12)$ excluding microcap stocks:

$$
\begin{aligned}
R^*_{i,t+m} &= \gamma_0 + \gamma_1 GOB_{i,t} + \epsilon_{i,t+1}, \\
R^*_{i,t+m} &= \gamma_0 + \gamma_1 GOB_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} + \gamma_4 MOM_{i,t} + \epsilon_{i,t+1}, \\
R^*_{i,t+m} &= \gamma_0 + \gamma_1 GOB_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} + \gamma_4 MOM_{i,t} + \gamma_5 ROA_{i,t} + \gamma_6 AG_{i,t} + \epsilon_{i,t+1},
\end{aligned}
$$

where $R^*_{i,t+m}$ is stock i's return in month $t+m$ in excess of risk-free rate in month $t+m$ $(m = 1, 2, ..., 12)$, or stock i's risk-adjusted returns based on rolling regressions. $GOB_{i,t}$ is firm i's growth opportunity bias, $ln(MV)_{i,t}$ is the natural logarithm of firm i's market capitalization, $MOM_{i,t}$ is the buy-and-hold return of stock i over month $t-6$ to month $t-1$, $ln(B/M)_{i,t}$ is the natural logarithm of firm i's book-to-market ratio, $AG_{i,t}$ is firm i's asset growth rate, and $ROA_{i,t}$ is firm i's return-on-assets. $GOB_{i,t}$, $ln(MV)_{i,t}$, $ln(B/M)_{i,t}$, $ROA_{i,t}$, and $AG_{i,t}$ are measured at the end of June of year t. We calculate the risk-adjusted returns based on the Fama–French (1993) three-factor model, which are the sum of the constant terms and the residuals from the time-series regression of the excess returns on the Fama–French three factors using the 36-month rolling window. Stocks below the 20% of market capitalization of NYSE stocks are defined as microcap stocks. Numbers in parentheses are t-statistics.

Constant	GOB	$ln(MV)$	$ln(B/M)$	MOM	ROA	AG
			Panel A: raw returns			
0.653	-0.162					
(2.23)	(-3.39)					
0.844	-0.143	-0.018	0.185	0.529		
(1.78)	(-4.08)	(-0.42)	(2.51)	(3.24)		
1.022	-0.147	-0.037	0.161	0.528	1.479	-0.437
(2.23)	(-5.26)	(-0.92)	(2.25)	(3.32)	(2.72)	(-5.66)
			Panel B: risk-adjusted returns			
-0.242	-0.127					
(-2.56)	(-4.26)					
-0.514	-0.122	0.035	-0.047	0.327		
(-3.35)	(-4.51)	(2.11)	(-1.09)	(2.00)		
-0.311	-0.116	0.009	-0.025	0.385	2.624	-0.344
(-2.21)	(-5.00)	(0.53)	(-0.57)	(2.39)	(5.86)	(-5.25)

Table 10

Fama–MacBeth (1973) regressions with additional control variables

We run the following regression each month over each 12-month period from July $(t+1)$ to next June $(t+12)$:

$$R^*_{i,t+m} = \gamma_0 + \gamma_1 GOB_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} + \gamma_4 MOM_{i,t} + \gamma_5 ROA_{i,t} + \gamma_6 AG_{i,t} + Controls + \epsilon_{i,t+1},$$

where $R^*_{i,t+m}$ is stock i's return in month $t+m$ in excess of risk-free rate in month $t+m$ $(m = 1, 2, ..., 12)$, or stock i's risk-adjusted returns based on rolling regressions. $GOB_{i,t}$ is firm i's growth opportunity bias, $ln(MV)_{i,t}$ is the natural logarithm of firm i's market capitalization, $MOM_{i,t}$ is the buy-and-hold return of stock i over month $t-6$ to month $t-1$, $ln(B/M)_{i,t}$ is the natural logarithm of firm i's book-to-market ratio, $ROA_{i,t}$ is firm i's return-on-assets, and $AG_{i,t}$ is firm i's asset growth rate. $GOB_{i,t}$, $ln(MV)_{i,t}$, $ln(B/M)_{i,t}$, $ROA_{i,t}$, and $AG_{i,t}$ are measured at the end of June of year t. *Controls* include *Beta*, *Accruals*, *Dividend*, *Log return*, *IVOL* (idiosyncratic risk), *Illiquidity*, *Turnover*, *Leverage*, and *Sales*.We calculate the risk-adjusted returns based on the Fama–French (1993) three-factor model, which are the sum of the constant terms and the residuals from the time-series regression of the excess returns on the Fama–French three factors using the 36-month rolling window. Numbers in parentheses are t-statistics.

Constant	*GOB*	*ln(MV)*	*ln(B/M)*	*MOM*	*ROA*	*AG*	*Beta*	*Accruals*	*Dividend*	*Log return*	*IVOL*	*Illiquidity*	*Turnover*	*Leverage*	*Sales*
Panel A: raw returns															
1.856	-0.041	-0.134	0.063	0.279	1.031	-0.356	0.253	-1.343	0.220	-0.201	-15.502	0.017	-0.520	-0.084	0.004
(6.95)	(-2.51)	(-4.32)	(1.29)	(2.49)	(2.95)	(-5.72)	(1.63)	(-4.42)	(0.23)	(-3.01)	(-3.31)	(4.56)	(-3.51)	(-3.05)	(0.55)
Panel B: risk-adjusted returns															
1.151	-0.032	-0.114	-0.009	0.189	1.199	-0.305	-0.056	-1.073	0.907	0.141	-18.717	0.017	-0.415	-0.094	0.002
(6.70)	(-2.14)	(-5.49)	(-0.20)	(1.40)	(3.63)	(-5.04)	(-0.65)	(-3.70)	(1.18)	(1.88)	(-4.70)	(5.16)	(-3.13)	(-3.68)	(0.28)

Table 11

Investor sentiment and growth opportunity bias

Using NYSE breakpoints, we form equal- and value-weighted decile portfolios at the end of June each year and hold them for the subsequent 12 months. We use the University of Michigan sentiment index and the Baker and Wurgler (2006) sentiment index. High sentiment is identified as the periods above the medium of sentiment index and low sentiment is identified as the periods below the medium of sentiment index. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, and $f_{CMA,t}$ is the month-t value of the Fama–French investment factor. The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks. The testing period is 7/1977–6/2014 (444 months). Numbers in parentheses are t-statistics.

	Low-GOB	D2	D3	D4	D5	D6	D7	D8	D9	High-GOB	L−H
Panel A: University of Michigan sentiment index											
High sentiment: equal-weighted decile portfolios											
Raw (%)	1.896	1.801	1.621	1.528	1.415	1.430	1.320	1.052	1.026	1.130	0.765
	(4.70)	(5.10)	(4.83)	(4.44)	(4.31)	(4.00)	(3.85)	(3.13)	(2.90)	(2.74)	(5.07)
$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	1.016	0.914	0.694	0.653	0.540	0.579	0.493	0.150	0.107	0.274	0.741
	(6.57)	(8.26)	(6.27)	(6.24)	(4.64)	(5.22)	(4.28)	(1.20)	(0.81)	(1.47)	(4.57)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	1.046	0.970	0.771	0.685	0.650	0.579	0.544	0.239	0.175	0.371	0.675
	(6.62)	(8.67)	(6.98)	(6.43)	(5.74)	(5.10)	(4.66)	(1.91)	(1.30)	(1.96)	(4.11)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	1.130	0.904	0.654	0.632	0.523	0.557	0.451	0.127	0.120	0.399	0.731
	(7.34)	(7.94)	(6.06)	(6.18)	(4.52)	(5.11)	(4.12)	(1.05)	(0.92)	(2.12)	(4.38)
Low sentiment: equal-weighted decile portfolios											
Raw (%)	1.487	1.397	1.324	1.374	1.302	1.247	1.195	1.335	1.358	1.239	0.248
	(3.34)	(3.32)	(3.27)	(3.49)	(3.28)	(3.21)	(2.99)	(3.27)	(3.25)	(2.65)	(1.48)
$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.527	0.475	0.449	0.521	0.449	0.427	0.353	0.475	0.466	0.264	0.263
	(3.53)	(4.28)	(4.35)	(6.39)	(5.76)	(5.08)	(4.22)	(5.37)	(4.34)	(1.38)	(1.54)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.502	0.421	0.452	0.507	0.432	0.432	0.351	0.494	0.487	0.337	0.165
	(3.33)	(3.86)	(4.33)	(6.17)	(5.50)	(5.07)	(4.16)	(5.56)	(4.51)	(1.77)	(1.00)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.506	0.451	0.504	0.531	0.448	0.479	0.364	0.501	0.529	0.438	0.069
	(3.26)	(3.95)	(4.75)	(6.27)	(5.51)	(5.52)	(4.34)	(5.59)	(4.83)	(2.30)	(0.40)
High sentiment: value-weighted decile portfolios											
Raw (%)	1.855	1.515	1.369	1.347	1.418	1.134	1.223	1.057	1.004	0.801	1.054
	(4.21)	(4.58)	(4.21)	(4.12)	(4.33)	(3.71)	(3.97)	(3.48)	(3.30)	(2.13)	(3.34)
$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	2.401	1.909	1.873	1.785	1.901	1.540	1.611	1.300	1.279	1.161	1.240
	(7.05)	(6.33)	(6.79)	(6.12)	(6.67)	(5.55)	(5.81)	(4.37)	(4.44)	(3.36)	(4.16)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	2.389	1.863	1.938	1.781	2.061	1.614	1.736	1.413	1.380	1.412	0.977
	(6.85)	(6.04)	(6.88)	(5.97)	(7.20)	(5.71)	(6.18)	(4.68)	(4.72)	(4.12)	(3.35)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	1.378	0.730	0.720	0.507	0.749	0.300	0.463	-0.065	0.096	-0.142	1.521
	(6.41)	(4.00)	(5.19)	(3.68)	(4.71)	(2.04)	(3.14)	(-0.41)	(0.60)	(-0.64)	(4.93)
Low sentiment: value-weighted decile portfolios											
Raw (%)	1.258	0.954	1.114	1.138	1.020	0.897	1.062	0.941	0.945	1.005	0.253
	(3.11)	(2.61)	(3.29)	(3.33)	(3.19)	(2.72)	(3.10)	(2.49)	(2.33)	(2.29)	(0.88)
$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.894	0.651	0.828	0.940	0.801	0.679	0.802	0.645	0.570	0.514	0.380
	(2.49)	(1.95)	(2.66)	(2.96)	(2.69)	(2.19)	(2.57)	(1.88)	(1.56)	(1.39)	(1.33)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.952	0.717	0.940	1.021	0.844	0.779	0.898	0.781	0.718	0.664	0.288
	(2.64)	(2.14)	(3.06)	(3.22)	(2.81)	(2.53)	(2.90)	(2.31)	(2.00)	(1.83)	(1.02)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.570	0.288	0.494	0.650	0.369	0.351	0.482	0.292	0.223	0.187	0.383
	(2.68)	(1.75)	(3.93)	(4.47)	(3.49)	(3.22)	(4.06)	(2.20)	(1.59)	(1.06)	(1.28)

(continued)

	Low-GOB	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*High-GOB*	*L−H*
Panel B: Baker and Wurgler (2006) sentiment index											
High sentiment: equal-weighted decile portfolios											
Raw (%)	1.198	1.054	1.072	0.927	0.921	0.860	0.725	0.582	0.496	0.419	0.779
	(2.93)	(2.88)	(3.05)	(2.61)	(2.66)	(2.31)	(1.99)	(1.66)	(1.36)	(1.00)	(5.29)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.871	0.676	0.679	0.628	0.577	0.600	0.418	0.257	0.161	0.106	0.764
	(5.56)	(6.27)	(5.91)	(6.29)	(5.35)	(5.98)	(3.94)	(2.21)	(1.23)	(0.57)	(4.90)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.864	0.703	0.732	0.629	0.641	0.593	0.410	0.285	0.190	0.159	0.705
	(5.44)	(6.47)	(6.41)	(6.21)	(6.06)	(5.83)	(3.81)	(2.42)	(1.44)	(0.84)	(4.51)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	1.033	0.692	0.670	0.639	0.575	0.605	0.395	0.233	0.171	0.248	0.786
	(6.54)	(6.34)	(5.93)	(6.44)	(5.41)	(6.28)	(3.92)	(2.09)	(1.35)	(1.32)	(4.92)
Low sentiment: equal-weighted decile portfolios											
Raw (%)	2.234	2.161	1.896	2.002	1.819	1.833	1.823	1.821	1.917	1.970	0.264
	(5.15)	(5.33)	(4.91)	(5.30)	(4.84)	(4.96)	(4.89)	(4.69)	(4.81)	(4.37)	(1.56)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.628	0.620	0.438	0.563	0.391	0.422	0.384	0.345	0.411	0.352	0.276
	(4.24)	(5.31)	(4.33)	(6.39)	(4.26)	(4.41)	(3.93)	(3.36)	(3.69)	(1.85)	(1.56)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.624	0.579	0.451	0.563	0.391	0.432	0.425	0.398	0.449	0.443	0.181
	(4.17)	(4.98)	(4.41)	(6.32)	(4.21)	(4.46)	(4.40)	(3.96)	(4.05)	(2.37)	(1.05)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.617	0.623	0.446	0.531	0.347	0.423	0.337	0.315	0.438	0.486	0.131
	(4.07)	(5.16)	(4.38)	(6.08)	(3.77)	(4.38)	(3.55)	(3.09)	(3.91)	(2.61)	(0.73)
High sentiment: value-weighted decile portfolios											
Raw (%)	1.227	0.861	0.932	0.752	0.901	0.665	0.636	0.551	0.429	0.224	1.003
	(2.75)	(2.54)	(2.84)	(2.11)	(2.69)	(2.05)	(1.93)	(1.64)	(1.26)	(0.56)	(3.29)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	1.959	1.403	1.554	1.382	1.561	1.187	1.219	0.972	0.900	0.814	1.145
	(5.35)	(4.42)	(5.29)	(4.25)	(5.28)	(3.91)	(4.08)	(2.96)	(2.77)	(2.22)	(3.82)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	1.964	1.337	1.607	1.398	1.660	1.247	1.297	1.053	0.945	0.975	0.989
	(5.29)	(4.17)	(5.41)	(4.24)	(5.59)	(4.06)	(4.31)	(3.18)	(2.88)	(2.67)	(3.34)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	1.350	0.551	0.749	0.488	0.786	0.329	0.409	-0.107	-0.073	-0.111	1.461
	(6.35)	(3.03)	(5.63)	(3.33)	(5.35)	(2.32)	(3.01)	(-0.68)	(-0.45)	(-0.54)	(4.89)
Low sentiment: value-weighted decile portfolios											
Raw (%)	1.880	1.587	1.539	1.681	1.503	1.307	1.622	1.431	1.501	1.550	0.330
	(4.74)	(4.48)	(4.63)	(5.51)	(4.83)	(4.22)	(5.14)	(4.18)	(4.09)	(3.77)	(1.11)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	1.252	1.095	1.134	1.367	1.148	0.967	1.240	1.020	1.045	0.886	0.366
	(3.46)	(3.29)	(3.54)	(4.57)	(3.80)	(3.20)	(4.08)	(3.09)	(3.04)	(2.44)	(1.26)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	1.293	1.157	1.221	1.412	1.179	1.048	1.320	1.131	1.173	1.018	0.275
	(3.56)	(3.47)	(3.84)	(4.71)	(3.88)	(3.49)	(4.37)	(3.49)	(3.49)	(2.86)	(0.96)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.592	0.456	0.478	0.604	0.334	0.221	0.460	0.223	0.350	0.083	0.509
	(2.76)	(2.85)	(3.60)	(4.55)	(2.88)	(2.02)	(3.57)	(1.61)	(2.55)	(0.44)	(1.68)

Table 12

limits-to-arbitrage and growth opportunity bias

Using NYSE breakpoints, we divide the sample of NYSE/AMEX/NASDAQ non-financial and non-regulated stocks into five limits-to-arbitrage measure and then five GOB-based sub-samples within each limits-to-arbitrage group at the end of June each year starting from 1977. We hold the portfolios for the subsequent 12 months. Stocks below the bottom 20% of limits-to-arbitrage measure of NYSE stocks are defined as "Low-LA". Stocks above the above top 20% of limits-to-arbitrage measure of NYSE stocks are defined as "High-LA". The row labelled Raw shows the raw mean returns measured on a monthly basis. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, and $f_{CMA,t}$ is the month-t value of the Fama–French investment factor. We use three limits-to-arbitrage (LA) proxies measured at the end of June of year t: the negative dollar volume (DTV, \$000), price impact (RV, 10^6), and bid-ask spread (CS). The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks. 7/1977–6/2014 (444 months). Numbers in parentheses are t-statistics.

	Equal-weighted portfolios				Value-weighted portfolios			
	Panel A: DTV as a measure of limits-to-arbitrage							
	Low-GOB	$D3$	High-GOB	$L-H$	Low-GOB	$D3$	High-GOB	$L-H$
Low-LA(Raw (%))	1.273	1.140	0.990	0.283	1.090	1.059	0.869	0.220
	(4.27)	(4.71)	(3.63)	(1.65)	(4.44)	(4.99)	(3.52)	(1.29)
High-LA(Raw (%))	1.817	1.620	1.274	0.543	1.666	1.413	1.090	0.577
	(6.04)	(5.76)	(4.00)	(4.09)	(5.78)	(5.62)	(3.72)	(4.59)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}$							
Low-$LA(\alpha_{i,t})$	0.132	0.109	-0.218	0.350	0.118	0.138	-0.244	0.362
	(1.04)	(1.38)	(-1.95)	(2.12)	(0.99)	(1.71)	(-2.40)	(2.11)
High-$LA(\alpha_{i,t})$	0.425	0.327	-0.064	0.489	0.259	0.132	-0.307	0.566
	(3.29)	(2.91)	(-0.40)	(3.68)	(2.52)	(1.45)	(-2.52)	(4.23)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$							
Low-$LA(\alpha_{i,t})$	0.180	0.141	-0.121	0.301	0.064	0.166	-0.193	0.257
	(1.41)	(1.74)	(-1.11)	(1.81)	(0.52)	(1.95)	(-1.87)	(1.46)
High-$LA(\alpha_{i,t})$	0.395	0.320	-0.003	0.398	0.209	0.110	-0.247	0.456
	(2.94)	(2.69)	(-0.02)	(2.95)	(1.98)	(1.19)	(-1.96)	(3.36)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$							
Low-$LA(\alpha_{i,t})$	0.274	0.052	-0.289	0.564	0.124	0.034	-0.292	0.416
	(2.03)	(0.63)	(-2.53)	(3.15)	(0.98)	(0.38)	(-2.71)	(2.24)
High-$LA(\alpha_{i,t})$	0.439	0.384	0.107	0.332	0.188	0.054	-0.292	0.480
	(3.48)	(3.27)	(0.65)	(2.30)	(1.86)	(0.61)	(-2.33)	(3.38)

(continued)

	Equal-weighted portfolios				Value-weighted portfolios			
Panel B: *RV* as a measure of limits-to-arbitrage								
	Low-GOB	$D3$	High-GOB	$L-H$	Low-GOB	$D3$	High-GOB	$L-H$
Low-LA(Raw (%))	1.306	1.153	1.012	0.294	1.072	1.052	0.854	0.218
	(4.77)	(5.10)	(4.07)	(1.87)	(4.48)	(5.04)	(3.60)	(1.34)
High-LA(Raw (%))	1.780	1.558	1.296	0.484	1.625	1.383	1.143	0.482
	(5.81)	(5.45)	(3.99)	(3.69)	(5.23)	(5.10)	(3.69)	(3.60)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}$							
Low-$LA(\alpha_{i,t})$	0.205	0.154	-0.120	0.325	0.132	0.161	-0.221	0.353
	(1.83)	(1.93)	(-1.17)	(2.18)	(1.20)	(1.92)	(-2.27)	(2.18)
High-$LA(\alpha_{i,t})$	0.391	0.263	-0.064	0.455	0.190	0.073	-0.296	0.486
	(3.09)	(2.43)	(-0.40)	(3.47)	(1.75)	(0.82)	(-2.49)	(3.44)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$							
Low-$LA(\alpha_{i,t})$	0.241	0.183	-0.049	0.291	0.090	0.179	-0.175	0.264
	(2.11)	(2.23)	(-0.49)	(1.91)	(0.80)	(1.85)	(-1.79)	(1.62)
High-$LA(\alpha_{i,t})$	0.367	0.274	0.004	0.363	0.120	0.061	-0.257	0.377
	(2.73)	(2.34)	(0.02)	(2.74)	(1.08)	(0.66)	(-2.08)	(2.67)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$							
Low-$LA(\alpha_{i,t})$	0.299	0.009	-0.245	0.544	0.146	0.061	-0.283	0.429
	(2.54)	(0.11)	(-2.35)	(3.38)	(1.26)	(0.66)	(-2.71)	(2.44)
High-$LA(\alpha_{i,t})$	0.455	0.343	0.124	0.331	0.213	0.047	-0.231	0.444
	(3.54)	(2.96)	(0.75)	(2.34)	(1.65)	(0.53)	(-1.93)	(2.80)
Panel C: *CS* as a measure of limits-to-arbitrage								
	Low-GOB	$D3$	High-GOB	$L-H$	Low-GOB	$D3$	High-GOB	$L-H$
Low-LA(Raw (%))	1.359	1.246	1.055	0.305	1.250	1.137	0.896	0.353
	(6.14)	(5.96)	(4.78)	(3.03)	(5.76)	(5.43)	(3.85)	(1.95)
High-LA(Raw (%))	1.698	1.439	1.255	0.443	1.443	1.296	0.781	0.662
	(5.35)	(4.76)	(3.78)	(3.37)	(3.79)	(3.71)	(2.24)	(2.90)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}$							
Low-$LA(\alpha_{i,t})$	0.247	0.217	-0.056	0.302	0.272	0.213	-0.116	0.388
	(2.01)	(2.09)	(-0.49)	(2.82)	(2.00)	(1.71)	(-0.83)	(2.06)
High-$LA(\alpha_{i,t})$	0.296	0.084	-0.127	0.422	0.146	-0.028	-0.654	0.800
	(2.32)	(0.84)	(-0.79)	(3.28)	(0.70)	(-0.18)	(-3.79)	(3.36)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$							
Low-$LA(\alpha_{i,t})$	0.242	0.206	-0.048	0.289	0.180	0.168	-0.095	0.275
	(1.98)	(1.91)	(-0.42)	(2.76)	(1.33)	(1.28)	(-0.60)	(1.37)
High-$LA(\alpha_{i,t})$	0.291	0.151	-0.011	0.302	0.148	0.119	-0.469	0.617
	(2.13)	(1.46)	(-0.06)	(2.28)	(0.70)	(0.76)	(-2.76)	(2.56)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$							
Low-$LA(\alpha_{i,t})$	-0.033	-0.043	-0.318	0.285	0.004	-0.096	-0.185	0.189
	(-0.28)	(-0.43)	(-2.90)	(2.57)	(0.03)	(-0.78)	(-1.24)	(0.95)
High-$LA(\alpha_{i,t})$	0.429	0.207	0.107	0.322	0.496	0.238	-0.441	0.937
	(3.27)	(2.03)	(0.65)	(2.25)	(2.24)	(1.48)	(-2.64)	(3.60)