The Bias of Growth Opportunity

Cynthia M. Gong[a], Xindan Li[b], Di Luo[c], and Huainan Zhao[d]

[a] School of Business and Economics, Loughborough University, Loughborough, LE11 3TU, UK.
[b] School of Management and Engineering, Nanjing University, Nanjing, Jiangsu 210093, China.
[c] Business School, University of Southampton, Highfield Campus, Southampton, SO17 1BJ, UK.
[d] School of Business and Economics, Loughborough University, Loughborough, LE11 3TU, UK.

March 2021

Abstract

The bias of growth opportunity (*BGO*), 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, downward-biased *BGO* firms earn higher returns than upward-biased *BGO* firms, which is unexplained by the common asset pricing models. Cross-sectional regression results also confirm *BGO*'s power in predicting stock returns. To explain the anomaly, we show that the *BGO* premium is more pronounced when investor sentiment is high or when limits-to-arbitrage is severe, which suggests that the *BGO* is more likely to capture behavioral biases than systematic risk.

JEL classification: G12; G14; G30

Keywords: Bias of growth opportunity; Behavioral Finance; Asset Pricing; Anomaly

*We are grateful to Pu Gong, Hong Liu, Hersh Shefrin, Avanidhar (Subra) Subrahmanyam, Wei Zhang, and seminar and conference participants at Tianjin University, University of Aberdeen, the Behavioral Finance Working Group (BFWG) 2019 Conference at Queen Mary University of London, and Southern Finance Association (SFA) 2019 meeting for helpful comments and suggestions. We are grateful for financial support from the National Natural Science Foundation of China (Grant No.71991473 and No.71671076). All remaining errors are our own.

Emails: m.c.gong@lboro.ac.uk, xdli@nju.edu.cn, d.luo@soton.ac.uk, and h.zhao6@lboro.ac.uk

"The behavioral perspective allows for the possibility that market prices do not coincide with fundamental values. ...It is nonetheless important to estimate the gap between market price and fundamental value, because the speed with which the difference converges to zero in the future depends on their difference in the present."

—— Hersh Shefrin (2014, p.15)

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 correctly 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 misjudged by investors. If investors act irrationally to a firm's growth opportunity (i.e., overly optimistic or pessimistic) and if the misjudgment becomes large and persistent, it can have a lasting impact on the firm's valuation and returns.[2]

Prior studies have reported evidence that the difference between firms' market and fundamental valuations predict stock returns (Lee et al., 1999; Doukas et al., 2010; Bartram and Grinblatt, 2018). The difference between a firm's market and fundamental valuations is, however, likely to be mainly driven by the divergence on growth opportunities (i.e., present value of growth opportunity (PVGO)), as it is unobservable, hard to estimate, and normally constitutes the largest proportion of a firm's value. In recognizing the significance of growth opportunities (GO)

[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 et al., 2008; Kogan and Papanikolaou, 2014).

[2]On the other hand, illustrated in a "beauty contest", Keynes (1936) argues that investors do not necessarily base their investment decisions on fundamental valuations, instead they base their decisions on the choices they predict others are likely to make. Thus, misvaluations caused in the marketplace can also be intentional.

in valuation and returns, Trigeorgis and Lambertides (2014) study the role of growth option in explaining the cross-sectional stock returns. They find that growth options (GO) is negatively related to future returns.

However, as stated above, we know that the difference between firms' market and fundamental valuations predicts stock returns, but we do not know how the difference between firms' market growth opportunity (MGO) and fundamental growth opportunity (FGO) affects stock returns. Following Trigeorgis and Lambertides (2014), we measure MGO as the proportion of a firm's market value arising from its future growth opportunities (PVGO), and measure FGO by using the same "eight empirically observable growth option related variables" of Trigeorgis and Lambertides (2014), which determine a firm's fundamental value of growth opportunity. Trigeorgis and Lambertides (2014) argue that, in contrast to previous studies using indirect proxies for growth opportunities (e.g., book-to-market (B/M) ratio, earnings-to-price (E/P) ratio, or Tobin's q), they use "more direct theoretically based measures of the firm's growth options." Specifically, the yet-unexercised growth option's value is obtained from a time series cross-sectional regression of eight empirically observable and option-motivated variables for each firm. In their study, they provide the theoretical rationale for each of the variables employed, which makes it the best method available to capture the FGO.

Next, we define the difference between MGO and FGO as the *bias of growth opportunity* (BGO). A large BGO means the market valuation of a firm's grow opportunity is much higher than its fundamental valuation of growth opportunity. Thus, the BGO picks up the *difference* or *disagreement* between market and fundamental valuations of growth opportunity.[3] We know

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

from the behavioral finance literature that when the market goes ahead of its fundamentals, it will typically adjust, and its future returns will be lower. Based on this, we predict a *negative* relation between a firm's BGO and its future returns, i.e., the further ahead of the MGO relative to the FGO, the lower the future returns. In this study, we focus on testing this hypothesis.

Examining U.S. common stocks from 1977 to 2017,[4] we find a significant *negative* relation between BGO and stock returns. Firms in the most downward-biased BGO decile (i.e., growth potentials are most underestimated) significantly outperform that of the most upward-biased BGO decile (i.e., growth potentials are most overestimated) by 0.537% ($t = 4.97$) per month. The BGO 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 difference (alphas) between the most downward-biased and upward-biased BGO portfolios is 0.543% ($t = 4.68$) per month.

Building on the portfolio sorts, we also perform the Fama–MacBeth (1973) regression analysis to simultaneously control for BGO and key firm characteristics. We show that BGO is significantly related to stock returns after adjusting for size, book-to-market, momentum, return-on-assets, and asset growth. Brennan et al. (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 BGO consistently predicts future stock returns.

[4]Our sample 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).

We submit our results to a battery of robustness tests including using a gross-return weighting method of Asparouhova et al. (2010, 2013) to control for the potential bias caused in the rebalance method; the characteristics-adjusted returns of Daniel et al. (1997) and Wermers (2004) to control for size, book-to-market, and momentum; the double-sorted portfolios on both BGO and market capitalization following Fama and French (2008). Given high MGO indicates high expected growth by the market, and growth company measured by relative pricing ratios, such as price-to-cash flow or price-to-earnings ratio, also has low future returns; we double-sort portfolios based on both BGO and one of the relative pricing ratios. We also employ 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 et al. (2015) q-factor model (HXZqFM), the Stambaugh and Yuan (2017) mispricing factor model (SYmFM), and the most recent Hou et al. (2021) augmented q-factor model with expected investment growth (HMXZq5FM). The BGO premium stands firm to all these tests.

Intuitively, the most upward-biased (downward-biased) BGO stocks are the ones that their market values of growth opportunities are much larger (smaller) than the estimates of their fundamental values. It is possible that investors overreact (underreact) to the growth opportunities of these stocks, which results in lower (higher) subsequent returns,[5] and, hence, driving the BGO premium. Berk et al. (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 BGO premium, we investigate whether the results are driven by behavioral biases such as investor sentiment or limits-to-arbitrage. We find that the BGO premium survives only when investor sentiment is high or when limits-to-arbitrage is severe, which suggests

[5]Cooper et al. (2008) find evidence that investors tend to overreact to firms' past growth rates.

that the BGO is more likely to capture mispricing (i.e., the non-fundamental component of stock prices) than systematic risk.

The closest paper to our study is Trigeorgis and Lambertides (2014), which is the first study to extend the Fama–French (1992) model by incorporating growth option variables in explaining the cross section of stock returns. In their study, they find that growth option variables are negatively related to stock returns. The main contribution of our study is, however, to go beyond the growth opportunity itself and document the *bias* of growth opportunity (BGO) and its predictive power to the cross-sectional stock returns.[6] We find that BGO is significantly and negatively related to future returns. Most importantly, we show that BGO produces the strongest results than either MGO or FGO. Our study, hence, highlights new evidence that the bias of growth opportunity (BGO) is more important than the growth opportunity (MGO or FGO) itself in predicting future returns.

We expect the BGO to be widely used both in academic and in practice. Apart from forming trading strategies (such as long downward-biased BGO and short upward-biased BGO stocks) to exploit the anomaly, BGO can be used as proxies of investor behavioral biases (e.g., upward-biased BGO could indicate over-reaction) or measures of limits-to-arbitrage (e.g., large BGO could suggest severe limits-to-arbitrage). BGO also has the potential to be broadly used in corporate decision-making. For example, managers often consider acquiring other firms with high growth potential to maintain their growth momentum (Levine, 2017).[7] BGO can be used as a tool to evaluate their target companies, since a large BGO may well suggest investors

[6] Bali et al. (2020) show that growth options affect stock returns through the channel of expected idiosyncratic skewness, which plays an important role in explaining the profitability, distress, lotteryness, and volatility anomalies. Cai et al. (2019) show that investors' overreaction to growth opportunities can lead to expectation errors and cause the asset growth anomaly. Hirst et al. (2008) examine how growth opportunities affect stock returns in the UK.

[7] Ang et al. (2019) find that the long-term gain of acquirers is due to growth opportunity.

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 BGO is large, its cost of equity is low. BGO can, thus, be used as a timing tool for firms to tap the capital markets.[8]

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

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 2017, which covers NYSE/AMEX/NASDAQ ordinary common stocks.[9] We exclude regulated and financial firms, which have four-digit standard industrial classification (SIC) code between 4900–4999 and 6000–6999. We collect data on monthly stock returns, daily returns, daily trading volumes, daily prices per share from CRSP.[10] 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 et al. (2000) to calculate a firm's book value of equity. We also calculate the return-on-assets (ROA) following Lewellen (2015) and Bessembinder et al. (2019) and the total asset growth rate (AG) following Cooper et al. (2008).

[8]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 et al. (2003) and Polk and Sapienza (2008).

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

[10]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.

The key variable of our study is the bias of growth opportunity (BGO), which is the *difference* between a firm's market value of growth opportunity (MGO) and fundamental value of growth opportunity (FGO). We estimate the 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

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

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).[11] 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 (4%) below the corresponding cost of equity.[12]

Trigeorgis and Lambertides (2014) identify eight growth option related variables that determine the fundamental growth opportunity (FGO). We follow their approach in our estimation of FGO.

[11] Similar to Trigeorgis and Lambertides (2014), for periods 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). Missing observations are set to 0. Funds from operations are available from COMPUSTAT since 1971 (Xie, 2001).

[12] Cao et al. (2008) show that the estimation of $PVGO$ is not sensitive to alternative approximations of the discount rate.

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

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 (e.g., Bali and Cakici, 2008).[13] 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, the sum of long-term debt and current liabilities) 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.[14] $R\&D$ 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.[15] 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

[13] Arisoy (2010), Kraft et al. (2018), and Lambrinoudakis et al. (2019) also suggest that volatility is related to growth opportunity.

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

[15] Sales growth is used to proxy for growth opportunity in Pour and Lasfer (2013).

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.[16] We estimate Equation (2) over the previous 3-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 the fundamental value of growth opportunity.

Table 1 provides descriptive statistics for the main variables used in our study. The *MGO* and *FGO* are, on average, at 0.686 and 0.262, which suggest that, on average, 68.6% or 26.2% of firms' value come from the unexercised market or fundamental values of growth opportunity, resulting in an average *BGO* of 42.5%.

[Table 1 about here]

Table 2 studies the firm characteristics of *BGO* decile portfolios. We examine the averages of the book-to-market ratio (*B/M*)), asset growth (*AG*), capital investment growth (*CI*), and the past month maximum daily return for each *BGO* decile to gain a better understanding of the property of *BGO*. Following Titman et al. (2004), we measure *CI* as $\frac{CE_t}{(CE_{t-1}+CE_{t-2}+CE_{t-3})/3} - 1$, where *CE* is the ratio of capital expenditure to sales. Since investors tend to overreact to lottery-like stocks (i.e., stocks with a small chance to earn high returns), it is, therefore, helpful to look at the average of past month maximum daily return for each *BGO* decile. Following Bali et al. (2011), we measure the past month maximum daily return as the average of the five highest

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

daily returns during a month. We find that stocks in the most downward-biased BGO decile ($D1$) have higher $B/M_{i,t}$ and CI, but lower AG and maximum daily return than stocks in the most upward-biased BGO decile ($D10$). Interestingly, the most upward-biased stocks exhibit the highest asset growth and lotteryness properties. This indicates that investors are more likely to overreact to these stocks.

[Table 2 about here]

3 Empirical results

3.1 Results on portfolio sorts

To perform the portfolio analysis, we form portfolios 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):[17]

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

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).

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

[17] 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. Our results are, however, qualitatively similar using conventional (rebalancing) method.

(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.[18]

Table 3 reports the portfolio results.[19] For raw returns, we observe an economically and statistically significant *BGO* premium. Stocks in the most downward-biased *BGO* decile ($D1$) earn an average return of 1.623% per month, while stocks in the most upward-biased *BGO* decile ($D10$) earn an average return of 1.095% per month, generating a spread of 0.537% ($t = 4.97$) per month. Commonly used asset pricing models such as the FF3FM, the momentum-extended FF3FM, and the FF5FM are unable to explain the *BGO* premium.[20] After adjusting for the FF5FM, for example, the *BGO* premium is 0.543% ($t = 4.68$) per month. Importantly, all *BGO*

[18]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/.

[19]We use both equal- and value-weighted methods in our portfolio analysis. Since the results are highly consistent between these two methods, we report only the equal-weighted results to preserve space.

[20]We also take a longer horizon in measuring the portfolio performance. Specifically, we test the performance of *BGO* decile portfolios over the subsequent three and five years. We find that the *BGO* premiums remain mostly significant for up to five years.

premiums, both before and after risk adjustment, have t-statistics above 3, the t-cutoff point recommended by Harvey et al. (2016).[21]

[Table 3 about here]

Since the *FGO* entering the *BGO* variable with a negative sign, given Trigeorgis and Lambertides (2014) finding, it will make the *BGO* variable more positively correlate with the future return. Table 3, however, points to a negative relation between *BGO* and future return, which implies that the *MGO* is having a stronger effect than that of the *FGO*. To test this, we sort stocks into decile portfolios based on either the *MGO* or *FGO* to compare the individual effect of *GO*. Table 4 reports the results. It shows that the *MGO* is, indeed, having a stronger effect in predicting future returns than that of the *FGO*. However, comparing to our main results in Table 3, we can see that *BGO* produces the strongest results than the individual sort by either *MGO* or *FGO*. This suggests that the bias of growth opportunity (*BGO*) is more important than the growth opportunity (*MGO* or *FGO*) itself in predicting future returns.

[Table 4 about here]

3.2 Robustness on portfolio sorts

We next conduct various robustness tests to check our portfolio results. First, following Asparouhova et al. (2010) and Asparouhova et al. (2013), we use the gross-return-weighted

[21] Harvey et al. (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 et al. (2020) 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%.

returns to control for some potential biases caused by microstructure noise,[22] 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 5 reports the gross-return-weighed stock returns for the decile portfolios. It shows a similar pattern to the results in Table 3. The raw return difference between the gross-return-weighed downward-biased *BGO* decile ($D1$) and the upward-biased *BGO* decile ($D10$) is 0.518% ($t = 4.66$) per month. Using the benchmark models of the FF3FM, the momentum-extended FF3FM, and the FF5FM, the *BGO* premiums are 0.587%, 0.508%, and 0.547% per month, respectively. All of them are highly significant with t-statistics above 3.

[Table 5 about here]

Second, instead of using asset pricing models as our benchmarks, we use the characteristics-adjusted returns to test the *BGO* premium. Following Daniel et al. (DGTW, 1997) and Wermers (2004), the characteristics-adjusted returns are the difference between individual firm's returns and the DGTW benchmark portfolio returns.[23] Results in Table 6 show that, after adjusting for the DGTW characteristics, the *BGO* premium remains significant at 0.438% ($t = 4.18$) per month.

[Table 6 about here]

[22]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.

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

Third, we test the BGO 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, we first sort stocks into three size groups and then ten BGO 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 7 reports the returns of the BGO portfolios across each size group. As we can see, the BGO premium remains highly significant across all three size subsamples. Before any risk adjustment, the BGO premium of the micro-size subsample is 0.613% ($t = 3.71$) per month, and the corresponding figure is 0.443% ($t = 2.85$) for the small-size subsample, and 0.370% ($t = 2.83$) for the large-size subsample. The BGO premiums of different size subsamples are also robust to the FF3FM, the momentum-extended FF3FM, and the FF5FM.

[Table 7 about here]

Fourth, since high MGO indicates high expected growth by the market and growth company measured by relative pricing ratios, such as price-to-cash flow or price-to-earnings ratio, has low future returns; we, thus, double-sort portfolios based on both BGO and one of the relative pricing ratios to see whether the BGO premium can be explained by them.

Following Basu (1983), we measure earnings-to-price (E/P) as the ratio of income before extraordinary items (COMPUSTAT item 18) to market value of equity; and following Lakonishok et al. (1994), we measure cash flow-to-price (C/P) as the ratio of income before extraordinary items plus depreciation (item 14) to market value of equity.

We control for E/P or C/P by first forming quintile portfolios sorted by E/P or C/P. For each E/P or C/P quintile, we then sort stocks into decile portfolios based on BGO. In the spirit of Bali et al. (2011), for each BGO group, returns are averaged across E/P or C/P portfolios. This procedure creates BGO portfolios with similar levels of E/P or C/P, and, thus, controls for differences in E/P or C/P.

Table 8 reports the results. It shows that the BGO premiums remain highly significant after controlling for the relative pricing ratios such as E/P and C/P. Hence, BGO is a significant and independent factor to the relative pricing ratios.

[Table 8 about here]

Fifth, we control for the FGO to test whether the BGO premium can be explained by the fundamentals of growth opportunity. Specifically, in the spirit of Bali et al. (2011), we control for FGO by first forming quintile portfolios sorted by FGO; for each FGO quintile, we sort stocks into decile portfolios based on BGO; for each BGO group, returns are averaged across five FGO portfolios. This procedure creates BGO portfolios with similar levels of FGO, and, thus, controls for differences in FGO. Table 9 shows that the BGO premiums remain highly significant after controlling for the fundamental value of growth opportunity.

[Table 9 about here]

Finally, we measure portfolio performance based on some 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 et al. (2015) q-factor model (HXZqFM), the Stambaugh and Yuan (2017) mispricing factor model (SYmFM), and the most recent Hou et al. (2021) augmented q-factor model with expected investment growth (HMXZq5FM). Specifically, we run the following time-series regressions:

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

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

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

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

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,r} f_{ROA,t} + \beta_{i,c} f_{I/A,t} + \beta_{i,e} f_{EG,t} + \varepsilon_{i,t}, \quad (12)$$

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 et al. (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,[24] $f_{SMBSY,t}$ 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, $f_{PERF,t}$ is the month-t value of the SY performance factor,[25] and $f_{EG,t}$ is the month-t value of the Hou et al. (2021) (HMXZ) expected investment growth factor.[26]

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

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

[26]We obtain Hou et al. (2021) expected investment growth factor from global-q.org http://global-q.org/index.html.

Table 10 reports the results. As can be seen, the *BGO* premiums are, again, unexplained by these additional models. For instance, under the HXZ q-factor model (HXZqFM), the *BGO* premium is 0.550% ($t = 4.66$) per month; Under the HMXZ q5-factor model (HMXZq5FM), the *BGO* premium is 0.478% ($t = 3.67$) per month, despite the model's added power by incorporating the expected investment growth factor.

[Table 10 about here]

3.3 Fama–MacBeth regression results

To further test the return predictability of the *BGO*, we, in this subsection, run Fama–MacBeth (1973) regressions as follows:

$$R_{i,t+m} - R_{f,t+m} = \gamma_0 + \gamma_1 BGO_{i,t} + \epsilon_{i,t+1}, \quad (13)$$

$$R_{i,t+m} - R_{f,t+m} = \gamma_0 + \gamma_1 BGO_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} + \gamma_4 MOM_{i,t} + \epsilon_{i,t+1}, \quad (14)$$

$$\begin{aligned} R_{i,t+m} - R_{f,t+m} &= \gamma_0 + \gamma_1 BGO_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} \\ &+ \gamma_4 MOM_{i,t} + \gamma_5 ROA_{i,t} + \gamma_6 AG_{i,t} + \epsilon_{i,t+1}, \end{aligned} \quad (15)$$

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 $t+m$, $BGO_{i,t}$ is firm i's bias of growth opportunity, $ln(MV)_{i,t}$ 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. $BGO_{i,t}$, $ln(MV)_{i,t}$, $ln(B/M)_{i,t}$, $ROA_{i,t}$, and $AG_{i,t}$ are measured at the end of June of year t.

Table 11 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 BGO. After controlling for key firm characteristics such as size, book-to-market, momentum, return-on-assets, and asset growth, the predictive power of BGO 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.[27]

Brennan et al. (1998) argue that the standard Fama–MacBeth (1973) procedure as in Eqs. (13), (14), and (15) 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 et al., 2009):

$$R^*_{i,t} = R_{i,t} - R_{f,t} - \beta_{i,m} f_{MKT,t} - \beta_{i,s} f_{SMB,t} - \beta_{i,h} f_{HML,t}, \tag{16}$$

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.[28] We run the Fama-MacBeth regressions using Eqs. (13) to (15) but with the

[27]See, for example, Fama and French (1993), Jegadeesh and Titman (1993), Cooper et al. (2008), and Lewellen (2015).
[28]The results (untabulated) are qualitatively similar based on the Fama and French (2015) five-factor model risk-adjusted returns.

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 11 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 overall market capitalization, can affect portfolio returns. Hou et al. (2020) argue that ordinary least squares can be dominated by microcaps because of their high proportion in the 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 stocks (Novy-Marx and Velikov, 2016).

To control for the microcap effect, we define stocks with a market capitalization below the 20% of NYSE stocks as microcaps (Fama and French, 2008), and exclude the microcaps in our Fama–MacBeth regressions, as in Green et al. (2017). Table 12 reports the results. It shows that the relationship between BGO and future stock returns remains intact.[29]

[Table 12 about here]

Recently, Lewellen (2015) and Bessembinder et al. (2019) 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.

[29] We also form portfolios with all-but-micro breakpoints (Hou et al., 2020) 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.

(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 the changes in noncash current assets minus the changes in current liabilities less short-term debt and taxes payable. In particular, $OA = (dCA - dCASH) - (dCL - dSTD - dTP) - DP$, where dCA is 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 year's 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.[30]

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

[30]Chou et al. (2013) find a turnover premium for up to 5 years.

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

In addition to the above variables, we also control for the firm's age (*Age*) since the growth potential of firms typically falls as they grow older. Further, we control for the maximum daily return as a successful exercise of uncertain growth option can lead to a high lottery payoff (Bali et al., 2020). Table 13 reports the results. It shows that *BGO* continues to predict cross-sectional stock returns after controlling for all these additional variables.

[Table 13 about here]

3.4 Behavioral explanations on *BGO* premium

Our analysis, so far, shows that firms with downward-biased *BGO* earn higher future returns than those with upward-biased *BGO*, and the *BGO* premium is unexplained by the risk-based methods. Could the *BGO* 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 (De Long et al., 1990). Irrational investors are more likely to overact to firms' growth opportunities, which results in the bias of growth opportunity, 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, 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 *BGO* premium.

3.4.1 Investor sentiment and *BGO* 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 et al., 2012; Hribar and McInnis, 2012; Seybert and Yang, 2012; Stambaugh et al., 2012, 2014; Firth et al., 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. Shefrin (2019) argue that the wedge between market price and fundamental value not only persists but also grows due to sentiment risk. As a consequence, anomalies should be more pronounced during high-sentiment periods.

We conjecture that if *BGO* captures behavioral biases, then the *BGO* premium should be more pronounced in high-sentiment periods. Given that PVGO is positively correlated with aggregate idiosyncratic volatility (Cao et al, 2008), and stocks with high volatility are usually those with a strong speculative appeal (Baker and Wurgler, 2007), it is reasonable to expect that the *BGO* premium is more pronounced in periods of high investor sentiment when the "propensity to speculate" is high, since speculative stocks 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 et al., 2015).

We, thus, examine the performance of *BGO* portfolios during high and low sentiment periods. We use the University of Michigan consumer sentiment index in our main analysis.[31] Table

[31] The University of Michigan consumer sentiment index is obtained from the University of Michigan Surveys of Consumers website: http://www.sca.isr.umich.edu/. We also find similar results by using the Baker and Wurgler (2006) sentiment index. Results are, however, not reported to preserve space.

14 reports the *BGO* premiums for high- and low-sentiment periods. As can be seen, the *BGO* premiums are significant only in high-sentiment periods. Using the FF5FM, for example, the *BGO* premium in high-sentiment periods is 0.836% (t = 5.92) per month. However, the corresponding *BGO* premium in low-sentiment period is 0.188% (t = 1.08) per month. Further, the *BGO* premiums exhibit significant differences between high and low sentiment periods. This adds further evidence that investor sentiment plays an important role in explaining the *BGO* premiums.

[Table 14 about here]

3.4.2 Limits-to-arbitrage and *BGO* premium

We now turn to examine whether the *BGO* 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 et al., 2010; Brav et al., 2010). Given arbitrage is risky, costly, and limited,[32] the *BGO* premium should be more pronounced for stocks with high limits-to-arbitrage.

We postulate that if the relation between *BGO* and stock returns is related to limits-to-arbitrage, it should be more pronounced when arbitrage costs are high than when the arbitrage

[32] A large body of literature has examined the limits-to-arbitrage explanation for various asset pricing anomalies. For example, Ali et al. (2003) find that the book-to-market effect is concentrated in firms with high transaction costs and large idiosyncratic volatility. Mashruwala et al. (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 et al. (2011) highlight the limits-to-arbitrage explanation for the asset growth anomaly. McLean (2010) finds that 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 limits-to-arbitrage.

costs are low. To test this, we first sort stocks into ten arbitrage-costs groups; For each group, we then sort stocks into five BGO portfolios. We use two arbitrage-costs measures in our study:

(i) The dollar volume measure of Brennan et al. (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.

Table 15 reports the results. As can be seen, the BGO premiums are more pronounced when the limits-to-arbitrage (LA) is high. For example, using the dollar volume (DTV) measure (Panel A), the BGO premium for high-LA stocks is 0.624% (t = 4.27) per month under the FF3FM. However, the corresponding BGO premium for low-LA stocks is 0.116% (t = 0.67) per month. Further, the BGO premiums exhibit significant differences between high and low limits-to-arbitrage stocks. Overall, our results in Tables 14 and 15 show that investor sentiment and limits-to-arbitrage provide reasonable explanations for the BGO premium.

[Table 15 about here]

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 leading to a bias of growth opportunity (BGO): the divergence between market and fundamental valuations of growth opportunity. We conjecture that the BGO has an ability to predict future stock returns as it is likely to reflect the behavioral biases of investors.

Examining U.S. common stocks from 1977 to 2017, we find a significant negative relation between BGO and future stock returns. In the portfolio sort, firms with downward-biased BGO earn higher future returns than firms with upward-biased BGO. The BGO premium is not explained by the standard asset pricing models. Further, cross-sectional regression results also confirm BGO's ability in predicting future returns after controlling for the 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 BGO premium, we turn to behavioral aspects to seek a better understanding of the anomaly. We find that the BGO premium is more pronounced when investor sentiment is high and when limits-to-arbitrage is severe, which suggests that the BGO is more likely to capture behavioral biases than systematic risk.

We expect the BGO to be widely used both in academic and in practice. Apart from forming trading strategies to exploit the anomaly, BGO can be used as proxies of investor behavioral biases or measures of limits-to-arbitrage. It can also be broadly used in corporate decision-making. For example, managers often consider acquiring other firms with high growth potential to maintain their growth momentum. BGO can be used as a tool to evaluate their target companies, since a high BGO 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 BGO is high, its cost of equity is low. BGO can, thus, be used as a timing tool for firms to tap the capital markets. The relation between BGO and corporate financing and investment decision-making is, however, another avenue for future research.

References

Ali, A., Hwang, L.-S., and Trombley, M. A. (2003). Arbitrage risk and the book-to-market anomaly. *Journal of Financial Economics*, 69(2):355–373.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56.

Ang, J. S., Daher, M. M., and Ismail, A. K. (2019). How do firms value debt capacity? Evidence from mergers and acquisitions. *Journal of Banking and Finance*, 98:95–107.

Antoniou, C., Doukas, J. A., and Subrahmanyam, A. (2015). Investor sentiment, beta, and the cost of equity capital. *Management Science*, 62(2):347–367.

Arisoy, Y. E. (2010). Volatility risk and the value premium: Evidence from the French stock market. *Journal of Banking and Finance*, 34(5):975–983.

Asparouhova, E., Bessembinder, H., and Kalcheva, I. (2010). Liquidity biases in asset pricing tests. *Journal of Financial Economics*, 96(2):215–237.

Asparouhova, E., Bessembinder, H., and Kalcheva, I. (2013). Noisy prices and inference regarding returns. *Journal of Finance*, 68(2):665–714.

Baker, M., Stein, J. C., and Wurgler, J. (2003). When does the market matter? Stock prices and the investment of equity-dependent firms. *Quarterly Journal of Economics*, 118(3):969–1005.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, 61(4):1645–1680.

Baker, M. and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2):129–152.

Baker, M., Wurgler, J., and Yuan, Y. (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics*, 104(2):272–287.

Bali, T. G. and Cakici, N. (2008). Idiosyncratic volatility and the cross section of expected returns. *Journal of Financial and Quantitative Analysis*, 43(1):29–58.

Bali, T. G., Cakici, N., and Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99(2):427–446.

Bali, T. G., Del Viva, L., Lambertides, N., and Trigeorgis, L. (2020). Growth options and related stock market anomalies: Profitability, distress, lotteryness, and volatility. *Journal of Financial and Quantitative Analysis*, 55(7):2150–2180.

Banerjee, S. (2011). Learning from prices and the dispersion in beliefs. *Review of Financial Studies*, 24(9):3025–3068.

Banerjee, S. and Kremer, I. (2010). Disagreement and learning: Dynamic patterns of trade. *Journal of Finance*, 65(4):1269–1302.

Barberis, N. and Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance*, 1:1053–1128.

Bartram, S. M. and Grinblatt, M. (2018). Agnostic fundamental analysis works. *Journal of Financial Economics*, 128(1):125–147.

Berk, J. B., Green, R. C., and Naik, V. (1999). Optimal investment, growth options, and security returns. *Journal of Finance*, 54(5):1553–1607.

Bessembinder, H., Cooper, M. J., and Zhang, F. (2019). Characteristic-based benchmark returns and corporate events. *Review of Financial Studies*, 32(1):75–125.

Brav, A. and Heaton, J. B. (2002). Competing theories of financial anomalies. *Review of Financial Studies*, 15(2):575–606.

Brav, A., Heaton, J. B., and Li, S. (2009). The limits of the limits of arbitrage. *Review of Finance*, 14(1):157–187.

Brennan, M. J., Chordia, T., and Subrahmanyam, A. (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns1. *Journal of Financial Economics*, 49(3):345 – 373.

Cai, C. X., Li, P., and Zhang, Q. (2019). Overreaction to growth opportunities: An explanation of the asset growth anomaly. *European Financial Management*, 25(4):747–776.

Cao, C., Simin, T. T., and Zhao, J. (2008). Can growth options explain the trend in idiosyncratic risk. *Review of Financial Studies*, 21(6):2599–2633.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52(1):57–82.

Chordia, T., Huh, S.-W., and Subrahmanyam, A. (2009). Theory-based illiquidity and asset pricing. *Review of Financial Studies*, 22(9):3629–3668.

Chou, P.-H., Huang, T.-Y., and Yang, H.-J. (2013). Arbitrage risk and the turnover anomaly. *Journal of Banking and Finance*, 37(11):4172–4182.

Cooper, M. J., Gulen, H., and Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *Journal of Finance*, 63(4):1609–1651.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance*, 52(3):1035–1058.

Davis, J. L., Fama, E. F., and French, K. R. (2000). Characteristics, covariances, and average returns: 1929 to 1997. *Journal of Finance*, 55(1):389–406.

De Long, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, 98(4):703–738.

Doukas, J. A., Kim, C. F., and Pantzalis, C. (2010). Arbitrage risk and stock mispricing. *Journal of Financial and Quantitative Analysis*, 45(4):907–934.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3 – 56.

Fama, E. F. and French, K. R. (2008). Dissecting anomalies. *Journal of Finance*, 63(4):1653–1678.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(4):607–636.

Firth, M., Wang, K., and Wong, S. M. (2014). Corporate transparency and the impact of investor sentiment on stock prices. *Management Science*, 61(7):1630–1647.

Green, J., Hand, J. R., and Zhang, X. F. (2017). The characteristics that provide independent information about average us monthly stock returns. *Review of Financial Studies*, 30(12):4389–4436.

Harvey, C. R., Liu, Y., and Zhu, H. (2016). ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *Journal of Finance*, 56(4):1533–1597.

Hirst, I. R., Danbolt, J., and Jones, E. (2008). Required rates of return for corporate investment appraisal in the presence of growth opportunities. *European Financial Management*, 14(5):989–1006.

Hou, K., Mo, H., Xue, C., and Zhang, L. (2021). An augmented q-factor model with expected growth. *Review of Finance*, 25(1):1–41.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, 28(3):650–705.

Hou, K., Xue, C., and Zhang, L. (2020). Replicating anomalies. *Review of Financial Studies*, 33(5):2019–2133.

Hribar, P. and McInnis, J. (2012). Investor sentiment and analysts' earnings forecast errors. *Management Science*, 58(2):293–307.

Jacobs, H. (2015). What explains the dynamics of 100 anomalies? *Journal of Banking and Finance*, 57:65–85.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48(1):65–91.

Keynes, J. M. (1936). *The general theory of employment, interest, and money*. London, Macmillan.

Kogan, L. and Papanikolaou, D. (2014). Growth opportunities, technology shocks, and asset prices. *Journal of Finance*, 69(2):675–718.

Kraft, H., Schwartz, E., and Weiss, F. (2018). Growth options and firm valuation. *European Financial Management*, 24(2):209–238.

Lambrinoudakis, C., Skiadopoulos, G., and Gkionis, K. (2019). Capital structure and financial flexibility: Expectations of future shocks. *Journal of Banking and Finance*, 104:1–18.

Lee, C., Myers, J., and Swaminathan, B. (1999). What is the intrinsic value of the Dow? *Journal of Finance*, 54(5):1693–1741.

Lemmon, M. and Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies*, 19(4):1499–1529.

Levine, O. (2017). Acquiring growth. *Journal of Financial Economics*, 126(2):300–319.

Lewellen, J. (2015). The cross-section of expected stock returns. *Critical Finance Review*, 4(1):1–44.

Li, D. and Zhang, L. (2010). Does q-theory with investment frictions explain anomalies in the cross section of returns? *Journal of Financial Economics*, 98(2):297–314.

Li, X. and Luo, D. (2016). Investor sentiment, limited arbitrage, and the cash holding effect. *Review of Finance*, 21(6):2141–2168.

Lipson, M. L., Mortal, S., and Schill, M. J. (2012). On the scope and drivers of the asset growth effect. *Journal of Financial and Quantitative Analysis*, 46(06):1651–1682.

Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, 82(3):631–671.

Liu, W. and Strong, N. (2008). Biases in decomposing holding-period portfolio returns. *Review of Financial Studies*, 21(5):2243–2274.

Mashruwala, C., Rajgopal, S., and Shevlin, T. (2006). Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs. *Journal of Accounting and Economics*, 42(1):3–33.

McLean, R. D. (2010). Idiosyncratic risk, long-term reversal, and momentum. *Journal of Financial and Quantitative Analysis*, 45(4):883–906.

Mclean, R. D. and Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, 71(1):5–32.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1):1–28.

Novy-Marx, R. and Velikov, M. (2015). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Pastor, L. and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3):642–685.

Polk, C. and Sapienza, P. (2008). The stock market and corporate investment: A test of catering theory. *Review of Financial Studies*, 22(1):187–217.

Pour, E. K. and Lasfer, M. (2013). Why do companies delist voluntarily from the stock market? *Journal of Banking and Finance*, 37(12):4850–4860.

Seybert, N. and Yang, H. I. (2012). The party's over: The role of earnings guidance in resolving sentiment-driven overvaluation. *Management Science*, 58(2):308–319.

Shefrin, H. (2014). Free cash flow, valuation and growth opportunities bias. *Journal of Investment Management*, 12(4):4–26.

Shefrin, H. (2019). Valuation bias and limits to nudges. *Journal of Portfolio Management*, 45(5):112–124.

Shen, J., Yu, J., and Zhao, S. (2017). Investor sentiment and economic forces. *Journal of Monetary Economics*, 86:1–21.

Shleifer, A. and Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, 52(1):35–55.

Shumway, T. (1997). The delisting bias in CRSP data. *Journal of Finance*, 52(1):327–340.

Shumway, T. and Warther, V. A. (1999). The delisting bias in CRSP's Nasdaq data and its implications for the size effect. *Journal of Finance*, 54(6):2361–2379.

Sloan, R. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 71(3):289–315.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104(2):288–302.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2014). The long of it: Odds that investor sentiment spuriously predicts anomaly returns. *Journal of Financial Economics*, 114(3):613–619.

Stambaugh, R. F. and Yuan, Y. (2016). Mispricing factors. *Review of Financial Studies*, 30(4):1270–1315.

Titman, S., Wei, K. J., and Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, 39(4):677–700.

Trigeorgis, L. and Lambertides, N. (2014). The role of growth options in explaining stock returns. *Journal of Financial and Quantitative Analysis*, 49(3):749–771.

Wermers, R. (2004). Is money really "smart"? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence. Working Paper.

Xie, H. (2001). The mispricing of abnormal accruals. *The Accounting Review*, 76(3):357–373.

Yu, J. and Yuan, Y. (2011). Investor sentiment and the mean–variance relation. *Journal of Financial Economics*, 100(2):367–381.

Table 1
Descriptive statistics

This table reports descriptive statistics for the following variables. The 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). The fundamental value of growth opportunity (FGO) is the corresponding estimated value from the model of equation (2) as in Trigeorgis and Lambertides (2014). The bias of growth opportunity (BGO) 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 the book value of equity to the 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. 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 2017. The mean, standard deviation, Q1 (bottom 25%), median, and Q3 (top 25%) are reported in the table.

	BGO	MGO	FGO	$MV(\$m)$	B/M	ROA	AG
Mean	0.425	0.686	0.262	2327.303	0.873	0.007	0.138
Stdev	7.613	7.305	2.639	13566.059	1.606	0.196	0.588
Q1	-1.278	-0.476	0.318	25.282	0.341	-0.007	-0.031
Medium	-0.087	0.446	0.596	122.987	0.609	0.041	0.063
Q3	0.618	1.005	1.133	736.919	1.045	0.081	0.181
N	91600						

Table 2

Characteristics of the BGO decile portfolios

Using NYSE breakpoints, we form decile portfolios at the end of June each year. This table reports the characteristics of these portfolios. The notation B/M is the book-to-market ratio, AG is the total asset growth rate, CI is the capital investment growth, and MAX is the past month maximum daily return. The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks from 1977 to 2017. The numbers in parentheses are t-statistics.

	$D1$ (Downward)	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$ (Upward)	$D1-D10$
B/M	1.143	0.903	0.811	0.770	0.741	0.712	0.717	0.738	0.781	1.086	0.057
	(21.15)	(21.20)	(21.20)	(21.88)	(23.11)	(20.93)	(22.93)	(23.81)	(20.06)	(19.65)	(0.99)
AG	0.078	0.111	0.125	0.137	0.158	0.144	0.153	0.167	0.167	0.132	-0.054
	(6.29)	(11.28)	(11.68)	(9.80)	(15.45)	(15.39)	(13.43)	(17.34)	(14.29)	(10.76)	(-3.67)
CI	0.997	0.112	0.109	0.176	0.095	0.112	1.086	0.147	0.209	0.416	0.581
	(1.83)	(3.66)	(2.87)	(3.81)	(4.34)	(4.75)	(1.53)	(5.38)	(5.73)	(2.46)	(1.01)
MAX	0.044	0.038	0.035	0.034	0.034	0.033	0.034	0.035	0.038	0.049	-0.004
	(22.38)	(23.02)	(25.16)	(25.35)	(25.59)	(28.18)	(24.76)	(24.39)	(21.86)	(17.31)	(-2.50)

Table 3
Performance of the *BGO* decile portfolios

Using NYSE breakpoints, we form equal-weighted decile portfolios at the end of June each year and hold them for the subsequent 12 months. The row labeled 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 7/1977–6/2017 (480 months). The numbers in parentheses are t-statistics.

	$D1$ (Downward)	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$ (Upward)	$D1-D10$
Raw (%)	1.632	1.469	1.474	1.391	1.220	1.288	1.170	1.108	1.081	1.095	0.537
	(5.92)	(5.92)	(6.02)	(5.61)	(4.91)	(5.31)	(4.73)	(4.20)	(4.14)	(3.67)	(4.97)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.381	0.270	0.267	0.181	-0.008	0.080	-0.026	-0.136	-0.174	-0.212	0.593
	(4.19)	(3.68)	(4.00)	(2.62)	(-0.11)	(1.11)	(-0.41)	(-1.68)	(-2.14)	(-1.75)	(5.39)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,wml}f_{wml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.385	0.290	0.288	0.183	0.048	0.133	0.010	-0.054	-0.127	-0.144	0.529
	(3.95)	(3.80)	(4.09)	(2.60)	(0.68)	(1.82)	(0.16)	(-0.67)	(-1.52)	(-1.13)	(4.68)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,rmw}f_{rmw,t}+\beta_{i,cma}f_{cma,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.455	0.274	0.240	0.158	-0.054	0.010	-0.036	-0.113	-0.195	-0.088	0.543
	(4.84)	(3.49)	(3.57)	(2.26)	(-0.77)	(0.14)	(-0.57)	(-1.45)	(-2.47)	(-0.71)	(4.68)

Table 4

Performance of the *MGO* and *FGO* decile portfolios

We form equal-weighted decile portfolios at the end of June each year and hold them for the subsequent 12 months. The row labeled *R*aw 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 7/1977–6/2017 (480 months). The numbers in parentheses are t-statistics.

	$D1$	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$	$D1-D10$
Panel A: market growth opportunity (MGO)											
Raw (%)	1.689	1.530	1.501	1.464	1.335	1.256	1.198	0.980	0.915	0.968	0.720
	(6.16)	(6.11)	(6.34)	(6.21)	(5.55)	(5.22)	(4.44)	(3.33)	(2.90)	(2.65)	(3.59)
$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.357	0.256	0.283	0.262	0.133	0.088	-0.003	-0.239	-0.359	-0.330	0.687
	(3.38)	(3.11)	(3.65)	(3.85)	(2.19)	(1.43)	(-0.04)	(-2.69)	(-3.12)	(-1.84)	(4.01)
$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,wml}f_{wml,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.390	0.285	0.322	0.274	0.151	0.123	0.058	-0.153	-0.286	-0.218	0.609
	(3.64)	(3.24)	(4.00)	(4.04)	(2.48)	(2.02)	(0.80)	(-1.69)	(-2.40)	(-1.11)	(3.26)
$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,rmw}f_{rmw,t}+\beta_{i,cma}f_{cma,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.279	0.149	0.160	0.134	0.058	0.032	0.069	-0.108	-0.147	0.052	0.227
	(2.65)	(1.85)	(2.18)	(2.06)	(0.95)	(0.55)	(0.97)	(-1.20)	(-1.27)	(0.27)	(1.35)
Panel B: fundamental growth opportunity (FGO)											
Raw (%)	1.518	1.360	1.398	1.415	1.438	1.469	1.387	1.380	1.318	0.936	0.582
	(6.31)	(5.81)	(5.95)	(6.16)	(5.97)	(5.81)	(5.20)	(4.99)	(4.12)	(2.50)	(2.00)
$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.171	-0.002	0.062	0.118	0.144	0.165	0.101	0.088	0.038	-0.343	0.514
	(1.48)	(-0.02)	(0.76)	(1.48)	(2.00)	(2.08)	(1.22)	(0.94)	(0.32)	(-1.99)	(2.22)
$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,wml}f_{wml,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.220	0.038	0.090	0.162	0.161	0.220	0.125	0.161	0.129	-0.214	0.434
	(1.79)	(0.41)	(1.07)	(2.01)	(2.14)	(2.60)	(1.37)	(1.60)	(0.90)	(-1.14)	(1.73)
$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,rmw}f_{rmw,t}+\beta_{i,cma}f_{cma,t}+\varepsilon_{i,t}$											
$\alpha_{i,t}$	0.031	-0.164	-0.105	0.004	0.090	0.138	0.155	0.149	0.307	0.074	-0.042
	(0.26)	(-1.82)	(-1.41)	(0.05)	(1.33)	(1.73)	(1.68)	(1.43)	(2.34)	(0.44)	(-0.19)

Table 5

Robustness test on BGO using 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 labeled 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 7/1977–6/2017 (480 months). The numbers in parentheses are t-statistics.

	$D1$ (Downward)	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$ (Upward)	$D1-D10$
Raw (%)	1.572	1.436	1.431	1.350	1.221	1.237	1.141	1.072	1.061	1.054	0.518
	(5.68)	(5.70)	(5.71)	(5.45)	(4.71)	(4.98)	(4.59)	(4.00)	(4.02)	(3.49)	(4.66)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.317	0.223	0.197	0.115	-0.046	0.009	-0.085	-0.208	-0.205	-0.270	0.587
	(3.12)	(2.57)	(2.62)	(1.53)	(-0.58)	(0.11)	(-1.12)	(-2.28)	(-2.10)	(-1.94)	(5.14)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \beta_{i,wml} f_{wml,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.429	0.344	0.315	0.210	0.143	0.152	0.063	-0.013	-0.038	-0.079	0.508
	(3.74)	(3.66)	(3.83)	(2.69)	(1.47)	(1.81)	(0.84)	(-0.15)	(-0.39)	(-0.54)	(4.14)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \beta_{i,rmw} f_{rmw,t} + \beta_{i,cma} f_{cma,t} + \varepsilon_{i,t}$										
$\alpha_{i,t}$	0.424	0.262	0.213	0.087	-0.067	-0.040	-0.104	-0.184	-0.206	-0.123	0.547
	(3.60)	(2.58)	(2.46)	(1.12)	(-0.77)	(-0.41)	(-1.31)	(-1.83)	(-1.97)	(-0.81)	(4.51)

Table 6

Robustness test on BGO using characteristics-adjusted returns

Using NYSE breakpoints, we form equal-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 et al. (DGTW, 1997) and Wermers (2004), the characteristics-adjusted returns are the difference between an 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 (432 months). The numbers in parentheses are t-statistics.

$D1$ (Downward)	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$ (Upward)	$D1-D10$
0.349	0.247	0.285	0.216	0.071	0.124	-0.008	-0.048	-0.104	-0.089	0.438
(5.02)	(3.86)	(4.79)	(3.53)	(1.07)	(2.16)	(-0.13)	(-0.71)	(-1.71)	(-0.94)	(4.18)

Table 7
Robustness test on BGO 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 BGO-based sub-samples within each MV group at the end of June each year starting from 1977. We hold the equal-weighted portfolios for the subsequent 12 months. Stocks below the 20% of the market capitalization of NYSE stocks are defined as "Micro." Stocks above the 20% but below 50% of the market capitalization of NYSE stocks are defined as "Small." Stocks above the 50% of the market capitalization of NYSE stocks are defined as "Large." The row labeled 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 7/1977–6/2017 (480 months). The numbers in parentheses are t-statistics.

	$D1$ (Downward)	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$ (Upward)	$D1-D10$
Micro(Raw (%))	1.692	1.697	1.622	1.375	1.502	1.300	1.456	1.264	1.226	1.079	0.613
	(5.64)	(5.96)	(5.74)	(4.93)	(5.42)	(4.29)	(4.87)	(4.24)	(3.92)	(3.26)	(3.71)
Small(Raw (%))	1.391	1.582	1.461	1.384	1.273	1.207	1.160	1.100	1.006	0.948	0.443
	(4.63)	(5.85)	(5.28)	(5.15)	(4.80)	(4.52)	(4.15)	(3.83)	(3.53)	(3.05)	(2.85)
Big(Raw (%))	1.329	1.369	1.301	1.159	1.097	1.078	1.041	1.137	0.985	0.959	0.370
	(5.11)	(5.80)	(5.51)	(4.91)	(4.89)	(4.78)	(4.62)	(4.84)	(4.24)	(3.85)	(2.83)
$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}$											
Micro($\alpha_{i,t}$)	0.436	0.461	0.360	0.107	0.267	0.042	0.174	-0.059	-0.106	-0.203	0.639
	(3.10)	(3.62)	(2.75)	(0.89)	(2.35)	(0.31)	(1.33)	(-0.45)	(-0.67)	(-1.12)	(3.83)
Small($\alpha_{i,t}$)	0.046	0.304	0.158	0.111	-0.003	-0.059	-0.161	-0.233	-0.336	-0.471	0.518
	(0.43)	(3.23)	(1.84)	(1.16)	(-0.04)	(-0.62)	(-1.73)	(-2.16)	(-3.06)	(-3.48)	(3.14)
Big($\alpha_{i,t}$)	0.166	0.226	0.152	0.003	0.004	0.001	-0.066	0.030	-0.118	-0.204	0.370
	(1.63)	(2.78)	(1.95)	(0.04)	(0.05)	(0.01)	(-0.87)	(0.34)	(-1.31)	(-1.91)	(2.86)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$											
Micro($\alpha_{i,t}$)	0.465	0.484	0.438	0.154	0.278	0.102	0.200	0.025	-0.026	-0.109	0.574
	(3.09)	(3.68)	(3.19)	(1.23)	(2.28)	(0.67)	(1.48)	(0.18)	(-0.16)	(-0.57)	(3.30)
Small($\alpha_{i,t}$)	0.022	0.336	0.162	0.127	0.022	0.013	-0.136	-0.135	-0.242	-0.395	0.416
	(0.20)	(3.53)	(1.83)	(1.33)	(0.22)	(0.13)	(-1.41)	(-1.21)	(-2.13)	(-2.96)	(2.53)
Big($\alpha_{i,t}$)	0.146	0.216	0.169	0.067	0.045	0.043	-0.029	0.120	-0.054	-0.129	0.275
	(1.43)	(2.56)	(2.18)	(0.86)	(0.59)	(0.55)	(-0.39)	(1.40)	(-0.59)	(-1.22)	(2.23)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$											
Micro($\alpha_{i,t}$)	0.593	0.567	0.412	0.147	0.322	0.155	0.319	0.019	-0.083	0.080	0.513
	(4.17)	(3.94)	(3.00)	(1.21)	(2.62)	(1.00)	(2.33)	(0.14)	(-0.50)	(0.44)	(3.03)
Small($\alpha_{i,t}$)	0.007	0.212	0.055	-0.028	-0.133	-0.191	-0.238	-0.362	-0.427	-0.545	0.552
	(0.07)	(2.34)	(0.67)	(-0.30)	(-1.58)	(-2.17)	(-2.68)	(-3.30)	(-3.95)	(-4.00)	(3.25)
Big($\alpha_{i,t}$)	0.163	0.163	0.074	-0.065	-0.155	-0.161	-0.190	-0.119	-0.266	-0.322	0.485
	(1.49)	(1.96)	(0.92)	(-0.84)	(-2.07)	(-2.02)	(-2.45)	(-1.38)	(-2.94)	(-2.94)	(3.25)

Table 8

Robustness test on BGO controlling for earnings-to-price (E/P) and cash flow-to-price (C/P)

Using NYSE breakpoints, we form equal-weighted quintile portfolios at the end of June each year and hold them for the subsequent 12 months based on the earnings-to-price (E/P) or cash flow-to-price (C/P). Then, we form equal-weighted decile portfolios at the end of June each year and hold them for the subsequent 12 months based on the BGO within each E/P or C/P quintile portfolios. This table reports the average performance of decile BGO portfolios across the five control E/P or C/P quintiles. The row labeled 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 7/1977–6/2017 (480 months). The numbers in parentheses are t-statistics.

	$D1$ (Downward)	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$ (Upward)	$D1-D10$
Panel A: controlling for earnings-to-price (E/P)											
Raw (%)	1.613	1.509	1.434	1.350	1.246	1.185	1.181	1.203	1.085	1.134	0.478
	(5.97)	(5.90)	(5.59)	(5.33)	(5.00)	(4.71)	(4.76)	(4.51)	(4.16)	(3.97)	(5.12)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.381	0.278	0.203	0.119	0.025	-0.043	-0.050	-0.043	-0.175	-0.145	0.527
	(4.38)	(3.84)	(2.75)	(1.69)	(0.35)	(-0.55)	(-0.71)	(-0.57)	(-1.94)	(-1.35)	(5.56)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,wml}f_{wml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.384	0.273	0.238	0.148	0.049	0.029	-0.007	-0.003	-0.098	-0.078	0.462
	(4.12)	(3.67)	(2.98)	(2.06)	(0.70)	(0.37)	(-0.10)	(-0.04)	(-1.07)	(-0.69)	(4.79)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,rmw}f_{rmw,t}+\beta_{i,cma}f_{cma,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.450	0.259	0.202	0.109	0.010	-0.075	-0.086	0.017	-0.207	-0.052	0.502
	(4.98)	(3.52)	(2.57)	(1.56)	(0.15)	(-0.93)	(-1.22)	(0.22)	(-2.32)	(-0.48)	(5.17)
Panel B: controlling for cash flow-to-price (C/P)											
Raw (%)	1.558	1.514	1.370	1.375	1.206	1.209	1.309	1.144	1.123	1.116	0.441
	(5.58)	(5.86)	(5.33)	(5.51)	(4.98)	(4.98)	(5.12)	(4.57)	(4.33)	(3.84)	(4.51)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.323	0.278	0.128	0.155	-0.004	0.010	0.083	-0.084	-0.143	-0.183	0.506
	(3.80)	(3.87)	(1.79)	(2.30)	(-0.05)	(0.14)	(1.16)	(-1.12)	(-1.57)	(-1.62)	(5.07)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,wml}f_{wml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.323	0.285	0.156	0.179	0.070	0.054	0.130	-0.058	-0.074	-0.108	0.431
	(3.60)	(3.62)	(2.21)	(2.42)	(0.94)	(0.74)	(1.77)	(-0.77)	(-0.81)	(-0.91)	(4.22)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,rmw}f_{rmw,t}+\beta_{i,cma}f_{cma,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.435	0.271	0.107	0.136	-0.070	-0.037	0.061	-0.096	-0.173	-0.075	0.510
	(4.83)	(3.57)	(1.54)	(2.00)	(-0.88)	(-0.50)	(0.86)	(-1.23)	(-1.93)	(-0.65)	(4.82)

Table 9

Robustness test on BGO controlling for the fundamental growth opportunity

Using NYSE breakpoints, we form equal-weighted quintile portfolios at the end of June each year and hold them for the subsequent 12 months based on the fundamental growth opportunity (FGO). Then, we form equal-weighted decile portfolios at the end of June each year and hold them for the subsequent 12 months based on the growth opportunity bias BGO within each FGO quintile portfolios. This table reports the average performance of decile BGO portfolios across the five control FGO quintiles. The row labeled 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 7/1977–12/2016 (480 months). The numbers in parentheses are t-statistics.

	$D1$ (Downward)	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$ (Upward)	$D1-D10$
Raw (%)	1.528	1.613	1.433	1.443	1.248	1.275	1.220	1.168	1.115	1.013	0.516
	(5.69)	(6.36)	(5.82)	(5.83)	(5.16)	(5.13)	(4.87)	(4.57)	(4.02)	(3.44)	(4.95)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.257	0.377	0.202	0.189	0.025	0.049	-0.007	-0.048	-0.119	-0.246	0.503
	(2.85)	(5.22)	(2.98)	(2.56)	(0.34)	(0.76)	(-0.11)	(-0.64)	(-1.39)	(-2.15)	(4.88)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,wml}f_{wml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.273	0.377	0.209	0.237	0.075	0.095	0.036	0.037	-0.098	-0.172	0.445
	(2.92)	(4.82)	(2.93)	(3.19)	(1.01)	(1.42)	(0.52)	(0.50)	(-1.16)	(-1.40)	(4.13)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\beta_{i,rmw}f_{rmw,t}+\beta_{i,cma}f_{cma,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.287	0.388	0.163	0.109	-0.047	0.025	-0.026	-0.015	-0.086	-0.094	0.381
	(3.14)	(4.91)	(2.39)	(1.48)	(-0.63)	(0.39)	(-0.38)	(-0.20)	(-1.05)	(-0.79)	(3.60)

Table 10
Performance of the *BGO* 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 et al. (2015) q-factor model (HXZqFM), the Stambaugh and Yuan (2017) mispricing factor model (SYmFM), and the Hou et al. (2021) q5-factor model (HMXZq5FM), 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 et al., 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, and $f_{EG,t}$ is the month-t value of the Hou et al. (2021) (HMXZ) expected investment growth 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 7/1977–6/2017 (480 months). However, when using the SY factors, the testing period is 7/1977–12/2016 (474 months). The numbers in parentheses are t-statistics.

	$D1$ (Downward)	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$ (Upward)	$D1-D10$
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,p}f_{PSF,t}+\varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.357	0.268	0.244	0.172	-0.016	0.072	-0.028	-0.137	-0.168	-0.217	0.574
	(3.94)	(3.60)	(3.65)	(2.50)	(-0.23)	(1.02)	(-0.45)	(-1.63)	(-2.05)	(-1.77)	(5.10)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,l}f_{LF,t}+\varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.328	0.284	0.301	0.224	0.096	0.162	0.099	-0.016	-0.090	-0.327	0.655
	(1.81)	(1.93)	(2.19)	(1.63)	(0.70)	(1.19)	(0.72)	(-0.10)	(-0.57)	(-1.56)	(5.62)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{ME,t}+\beta_{i,r}f_{ROA,t}+\beta_{i,c}f_{I/A,t}+\varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.581	0.386	0.332	0.221	0.059	0.088	0.048	-0.020	-0.099	0.031	0.550
	(5.37)	(4.35)	(4.00)	(3.03)	(0.73)	(0.95)	(0.76)	(-0.25)	(-1.20)	(0.23)	(4.66)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,ssy}f_{SMBSY,t}+\beta_{i,mgmt}f_{MGMT,t}+\beta_{i,perf}f_{PERF,t}+\varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.363	0.261	0.193	0.143	-0.013	0.069	-0.049	-0.086	-0.160	-0.048	0.410
	(3.11)	(2.85)	(2.16)	(1.70)	(-0.15)	(0.76)	(-0.65)	(-0.87)	(-1.55)	(-0.29)	(3.14)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{ME,t}+\beta_{i,r}f_{ROA,t}+\beta_{i,c}f_{I/A,t}+\beta_{i,e}f_{EG,t}+\varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.502	0.342	0.265	0.201	0.047	0.129	0.033	0.014	-0.056	0.023	0.478
	(4.30)	(3.61)	(2.92)	(2.51)	(0.54)	(1.37)	(0.50)	(0.15)	(-0.60)	(0.16)	(3.67)

Table 11
Testing BGO on Fama–MacBeth (1973) regressions

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

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

where $R^*_{i,t+m}$ is stock i's return in month $t+m$ in excess of the risk-free rate in month $t+m$ $(m = 1, 2, ..., 12)$, or stock i's risk-adjusted returns based on rolling regression. $BGO_{i,t}$ is firm i's bias of growth opportunity, $ln(MV)_{i,t}$ 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. $BGO_{i,t}$, $ln(MV)_{i,t}$, $ln(B/M)_{i,t}$, $ROA_{i,t}$, 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. The testing period is 7/1977–6/2017 (480 months). The numbers in parentheses are t-statistics.

Constant	BGO	$ln(MV)$	$ln(B/M)$	MOM	ROA	AG
			Panel A: raw returns			
0.939	-0.081					
(3.68)	(-3.26)					
1.415	-0.078	-0.083	0.228	0.311		
(4.07)	(-3.43)	(-2.05)	(3.29)	(2.70)		
1.446	-0.072	-0.082	0.205	0.279	0.001	-0.449
(4.19)	(-3.22)	(-2.04)	(3.01)	(2.45)	(2.68)	(-7.65)
			Panel B: risk-adjusted returns			
0.038	-0.078					
(0.54)	(-3.69)					
0.417	-0.075	-0.069	0.042	0.151		
(2.14)	(-3.77)	(-2.37)	(0.90)	(1.17)		
0.448	-0.071	-0.071	0.019	0.127	0.001	-0.326
(2.31)	(-3.59)	(-2.47)	(0.42)	(0.99)	(2.83)	(-6.41)

Table 12

Testing BGO on 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:

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

where $R^*_{i,t+m}$ is stock i's return in month $t+m$ in excess of the risk-free rate in month $t+m$ ($m = 1, 2, ..., 12$), or stock i's risk-adjusted returns based on rolling regressions. $BGO_{i,t}$ is firm i's bias of growth opportunity, $ln(MV)_{i,t}$ 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. $BGO_{i,t}$, $ln(MV)_{i,t}$, $ln(B/M)_{i,t}$, $ROA_{i,t}$, 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. The testing period is 7/1977–6/2017 (480 months). The numbers in parentheses are t-statistics.

Constant	BGO	$ln(MV)$	$ln(B/M)$	MOM	ROA	AG
Panel A: raw returns						
0.745	-0.196					
(3.02)	(-3.27)					
1.044	-0.188	-0.038	0.103	0.408		
(2.33)	(-4.43)	(-0.95)	(1.43)	(2.28)		
1.083	-0.165	-0.049	0.105	0.418	0.004	-0.318
(2.45)	(-4.18)	(-1.25)	(1.41)	(2.34)	(4.51)	(-3.83)
Panel B: risk-adjusted returns						
-0.060	-0.149					
(-1.12)	(-3.97)					
-0.285	-0.138	0.017	-0.127	0.239		
(-2.20)	(-4.24)	(1.19)	(-2.88)	(1.39)		
-0.253	-0.115	0.006	-0.119	0.251	0.003	-0.161
(-1.94)	(-3.71)	(0.43)	(-2.54)	(1.47)	(4.33)	(-2.36)

Table 13

Testing BGO on 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 $(t+12)$:

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

where $R^*_{i,t+m}$ is stock i's return in month $t+m$ in excess of the risk-free rate in month $t+m$ $(m = 1, 2, ..., 12)$, or stock i's risk-adjusted returns based on rolling regressions. $BGO_{i,t}$ is firm i's bias of growth opportunity, $ln(MV)_{i,t}$ 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. $BGO_{i,t}$, $ln(MV)_{i,t}$, $ln(B/M)_{i,t}$, $ROA_{i,t}$, 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*, *Sales*, *Age*, and MAX. 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. The testing period is 7/1977–6/2017 (480 months). The numbers in parentheses are t-statistics.

Constant	BGO	$ln(MV)$	$ln(B/M)$	MOM	ROA	AG	*Beta*	*Accruals*	*Dividend*	*Log return*	$IVOL$	*Illiquidity*	*Turnover*	*Leverage*	*Sales*	*Age*	*Max*
Panel A: raw returns																	
1.984	-0.076	-0.105	0.108	0.305	0.001	-0.339	0.198	-0.754	0.504	-0.082	-20.923	0.018	-0.519	-0.088	0.007	-0.004	0.038
(8.02)	(-3.60)	(-3.44)	(2.20)	(2.70)	(1.52)	(-5.61)	(1.27)	(-2.46)	(0.55)	(-1.20)	(-4.47)	(5.07)	(-3.89)	(-3.61)	(0.75)	(-2.50)	(1.51)
Panel B: risk-adjusted returns																	
1.319	-0.065	-0.088	0.029	0.225	0.001	-0.293	-0.136	-0.559	1.202	0.283	-23.072	0.018	-0.427	-0.091	0.006	-0.003	0.023
(8.25)	(-3.30)	(-4.25)	(0.67)	(1.71)	(1.70)	(-5.05)	(-1.56)	(-1.95)	(1.59)	(3.74)	(-5.74)	(5.60)	(-3.52)	(-3.95)	(0.74)	(-2.61)	(0.95)

Table 14
***BGO* and Investor sentiment**

Using NYSE breakpoints, we form equal-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. The high sentiment is identified as the periods above the medium of sentiment index and the low sentiment is identified as the periods below the medium of sentiment index. The row labeled *R*aw 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 examine whether the *BGO* premiums exhibit significant differences between high and low sentiment periods following Stambaugh et al. (2012) and Shen et al. (2017). The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks. The testing period is 7/1977–6/2017 (480 months). The numbers in parentheses are t-statistics.

	$D1$ (Downward)	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$ (Upward)	$D1-D10$
					High sentiment						
Raw (%)	1.807	1.543	1.504	1.412	1.219	1.220	1.080	0.999	0.981	0.963	0.844
	(4.83)	(4.68)	(4.76)	(4.32)	(3.90)	(4.01)	(3.35)	(2.88)	(2.95)	(2.51)	(6.50)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.992	0.709	0.687	0.586	0.397	0.403	0.320	0.169	0.134	0.149	0.843
	(6.92)	(6.34)	(6.49)	(5.53)	(3.72)	(3.59)	(3.27)	(1.39)	(1.10)	(0.95)	(6.16)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	1.032	0.782	0.729	0.603	0.483	0.507	0.370	0.257	0.198	0.224	0.808
	(7.05)	(6.96)	(6.77)	(5.56)	(4.57)	(4.59)	(3.74)	(2.12)	(1.61)	(1.41)	(5.78)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	1.136	0.733	0.650	0.565	0.364	0.348	0.298	0.184	0.110	0.300	0.836
	(7.96)	(6.45)	(6.21)	(5.39)	(3.44)	(3.23)	(3.14)	(1.53)	(0.92)	(1.90)	(5.92)
					Low sentiment						
Raw (%)	1.449	1.391	1.443	1.369	1.221	1.359	1.265	1.221	1.186	1.232	0.217
	(3.56)	(3.73)	(3.83)	(3.64)	(3.14)	(3.56)	(3.34)	(3.05)	(2.93)	(2.67)	(1.26)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.528	0.544	0.583	0.509	0.332	0.486	0.396	0.315	0.269	0.229	0.299
	(4.46)	(5.33)	(5.97)	(5.58)	(3.58)	(5.82)	(5.11)	(3.04)	(2.37)	(1.24)	(1.74)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.504	0.525	0.580	0.497	0.351	0.491	0.407	0.371	0.288	0.266	0.238
	(4.23)	(5.11)	(5.86)	(5.39)	(3.76)	(5.81)	(5.20)	(3.67)	(2.51)	(1.42)	(1.39)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.513	0.559	0.599	0.508	0.315	0.464	0.417	0.371	0.285	0.325	0.188
	(4.22)	(5.28)	(6.07)	(5.40)	(3.39)	(5.57)	(5.21)	(3.58)	(2.51)	(1.76)	(1.08)
					High-Low sentiment						
Raw (%)	0.358	0.151	0.061	0.043	-0.002	-0.140	-0.186	-0.222	-0.204	-0.270	0.627
	(0.65)	(0.30)	(0.12)	(0.09)	(-0.00)	(-0.29)	(-0.37)	(-0.42)	(-0.39)	(-0.45)	(2.93)
	$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,mkt}f_{mkt,t}+\beta_{i,smb}f_{smb,t}+\beta_{i,hml}f_{hml,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.464	0.165	0.104	0.077	0.065	-0.082	-0.076	-0.146	-0.135	-0.080	0.544
	(2.50)	(1.09)	(0.72)	(0.55)	(0.46)	(-0.59)	(-0.61)	(-0.91)	(-0.81)	(-0.33)	(2.49)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.527	0.257	0.150	0.106	0.132	0.016	-0.037	-0.114	-0.090	-0.042	0.570
	(2.80)	(1.69)	(1.03)	(0.74)	(0.94)	(0.11)	(-0.29)	(-0.72)	(-0.54)	(-0.17)	(2.58)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$										
$\alpha_{i,t}$	0.623	0.174	0.051	0.057	0.050	-0.117	-0.119	-0.186	-0.175	-0.025	0.648
	(3.32)	(1.12)	(0.35)	(0.40)	(0.35)	(-0.86)	(-0.95)	(-1.18)	(-1.06)	(-0.10)	(2.90)

Table 15

***BGO* and Limits-to-arbitrage**

Using NYSE breakpoints, we divide the sample of NYSE/AMEX/NASDAQ non-financial and non-regulated stocks into ten limits-to-arbitrage and then five *BGO*-based sub-samples within each limits-to-arbitrage group at the end of June each year. We hold the portfolios for the subsequent 12 months. Stocks below the bottom 20% of the limits-to-arbitrage measure of NYSE stocks are defined as "Low-*LA*." Stocks above the above top 20% of the limits-to-arbitrage measure of NYSE stocks are defined as "*H*igh-*LA*." The row labeled *R*aw 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 two limits-to-arbitrage (*LA*) proxies measured at the end of June of year t: the negative dollar volume (*DTV* and price impact (*RV*). The sample includes NYSE/AMEX/NASDAQ non-financial and non-regulated stocks. The testing period is 7/1977–6/2017 (480 months). The numbers in parentheses are t-statistics.

	Panel A: *DTV* as a *LA*				Panel B: *RV* as a *LA*			
	*D*1 (Downward)	*D*3	*D*5 (Upward)	*D*1−*D*5	*D*1 (Downward)	*D*3	*D*5 (Upward)	*D*1−*D*5
Low-*LA*(*R*aw (%))	0.709	0.672	0.557	0.151	0.807	0.646	0.565	0.242
	(2.44)	(2.89)	(2.23)	(0.83)	(3.27)	(3.04)	(2.53)	(1.42)
*H*igh-*LA*(*R*aw (%))	1.411	1.238	0.829	0.581	1.331	1.118	0.678	0.652
	(5.12)	(4.38)	(2.65)	(3.83)	(4.63)	(3.98)	(2.14)	(4.55)
*H*igh−Low-*LA*(*R*aw (%))	0.702	0.566	0.272	0.430	0.523	0.472	0.113	0.410
	(3.08)	(2.33)	(1.01)	(1.71)	(2.45)	(2.06)	(0.41)	(1.78)
	$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{mkt,t} + \beta_{i,smb} f_{smb,t} + \beta_{i,hml} f_{hml,t} + \varepsilon_{i,t}$							
Low-*LA*($\alpha_{i,t}$)	-0.018	0.075	-0.134	0.116	0.163	0.092	-0.036	0.200
	(-0.13)	(0.78)	(-1.08)	(0.67)	(1.56)	(1.11)	(-0.30)	(1.21)
*H*igh-*LA*($\alpha_{i,t}$)	0.572	0.411	-0.052	0.624	0.482	0.269	-0.201	0.684
	(4.17)	(2.82)	(-0.30)	(4.27)	(3.48)	(2.05)	(-1.20)	(4.88)
*H*igh−Low-*LA*($\alpha_{i,t}$)	0.590	0.336	0.082	0.508	0.319	0.177	-0.165	0.484
	(3.07)	(1.88)	(0.38)	(2.17)	(1.98)	(1.16)	(-0.80)	(2.24)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$							
Low-*LA*($\alpha_{i,t}$)	0.046	0.160	-0.020	0.066	0.196	0.147	0.037	0.159
	(0.33)	(1.66)	(-0.17)	(0.38)	(1.88)	(1.67)	(0.31)	(0.96)
*H*igh-*LA*($\alpha_{i,t}$)	0.579	0.410	-0.026	0.604	0.489	0.282	-0.149	0.638
	(4.02)	(2.65)	(-0.14)	(3.96)	(3.39)	(1.98)	(-0.84)	(4.35)
*H*igh−Low-*LA*($\alpha_{i,t}$)	0.533	0.250	-0.006	0.539	0.292	0.135	-0.186	0.479
	(2.69)	(1.33)	(-0.03)	(2.28)	(1.76)	(0.85)	(-0.85)	(2.14)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$							
Low-*LA*($\alpha_{i,t}$)	0.191	0.007	-0.188	0.379	0.297	-0.003	-0.166	0.463
	(1.34)	(0.07)	(-1.43)	(2.02)	(2.73)	(-0.04)	(-1.35)	(2.70)
*H*igh-*LA*($\alpha_{i,t}$)	0.620	0.477	0.099	0.521	0.593	0.326	-0.013	0.606
	(4.54)	(3.16)	(0.55)	(3.39)	(4.18)	(2.33)	(-0.07)	(4.10)
*H*igh−Low-*LA*($\alpha_{i,t}$)	0.429	0.469	0.287	0.141	0.296	0.329	0.154	0.142
	(2.26)	(2.62)	(1.27)	(0.57)	(1.83)	(2.09)	(0.72)	(0.65)