Is There A Growth Premium? Evidence from A Decomposition of Book-to-Market Ratio*

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Abstract

This paper proposes a time–series decomposition of book–to–market ratio into a trend component and a mean–reverting component (I_{BM}). Under the framework of stock valuation with growth options, we demonstrate that I_{BM} is negatively related to the growth option intensity and therefore negatively related to the expected stock return. We document significant empirical evidence consistent with a growth premium as low I_{BM} stocks earn significantly higher future returns. The return predictability of I_{BM} is robust to the adjustment of various risk factors and to controlling for other predictors. High (low) I_{BM} firms tend to lose (gain) more growth opportunities in the future and have a higher (lower) propensity to experience innovation declines.

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Abstract

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JEL Classification: G12

Keywords: Book-to-Market Ratio, Growth Option, Growth Premium, Stock Return

1 Introduction

The conventional wisdom suggests that the growth stocks, characterized by the low book–to–market ratio (BM), should earn higher expected returns than the value (high BM) stocks because growth options are riskier than existing assets. However, the empirical evidence overwhelmingly points to the opposite: value stocks earn higher average returns than growth stocks (e.g., Fama and French (1992, 1998)). Numerous explanations for the value premium have been proposed.[1] Among these studies, several of them have questioned the adequacy of using BM to measure growth or value. The critique can be even dated back to Lakonishok, Shleifer, and Vishny (1994) who assert that "BM is not a 'clean' variable uniquely associated with economically interpretable characteristics of the firms" to gauge firms' growth options.

A consequential research question is whether one can extract a "clean" component from BM to solely measure the amount of firms' growth options. Originated from the framework of stock valuation with growth options, this study provides a novel decomposition of BM into a time–varying persistent trend component and a mean–reverting transitory component named as I_{BM}. The model's main implications are: (i). I_{BM} is closely associated with a firm's growth options; (ii). I_{BM} has a negative relationship with future stock returns. Different from recent BM decompositions such as Daniel and Titman (2006), Gerakos and Linnainmaa (2017), and Golubov and Konstantinidi (2019) which concentrate on understanding the driving forces of BM's return predictability, our decomposition focuses on isolating a firms' growth options component from BM as an economically interpretable characteristic.

Our approach of extracting growth options information directly from BM and consequently testing the existence of a growth premium is rooted in the framework of stock valuation with growth options.[2] According to this framework, the market value of equity

[1] A short list of previous studies includes Lakonishok, Shleifer, and Vishny (1994), Fama and French (1995, 1996), Berk, Green, and Naik (1999), Petkova and Zhang (2005), Zhang (2005), Lettau and Wachter (2007), Guo, Savickas, Wang, and Yang (2009), Garlappi and Yan (2011), Kogan and Papanikolaou (2014), Guo, Wu, and Yu (2017), and Golubov and Konstantinidi (2019).

[2] Important studies in this literature include Cochrane (1991, 1996), Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarimo (2004), Bernardo, Chowdhry, and Goyal (2007),

consists of two parts: one is determined by the existing assets, and the other is driven by the future growth options. A potential negative relationship between our proxy of growth option intensity, I_{BM}, and future stock returns implies a growth premium.

In our empirical tests, we use the time–series moving average of BM as the proxy of the time–varying trend component of BM, while employing the deviation of current BM from its time–varying trend as the measure of the growth option intensity (I_{BM}). We document significant evidence consistent with the postulated growth premium. When stocks are sorted on I_{BM} into deciles, the average next–quarter portfolio return decreases from decile 1 to decile 10. The raw value–weighted high–minus–low (H–L) spread between deciles 10 and 1 is -2.05% per quarter (-8.21% per year) and statistically significant at the 1% confidence level ($t = -3.82$). Further confirming that the results are not driven by small stocks, we find similar H–L spreads for the sub sample without microcap stocks. Adjusting portfolio returns by the standard risk factors does not change the spreads in any significant way. Double portfolio sorts and Fama–MacBeth regressions further demonstrate that the negative relationship between I_{BM} and future stock return can not be explained by a number of return predictors including momentum, profitability, investment, share issuance, earnings surprise, idiosyncratic volatility, and liquidity. As the horizon increases, the return predictability of I_{BM} declines but remains significant up to at least four quarters.

We then investigate whether the negative relation between I_{BM} and future stock returns is consistent with a rational story or a mispricing effect. To examine whether the return differentials delivered by I_{BM} is a risk premium, we investigate whether high I_{BM} firms tend to be the ones with lower future growth options. We consider four up–to–date growth option measures including the sensitivity to idiosyncratic volatility (Ai and Kiku (2016)), the growth option conversion (Purnanandam and Rajan (2018)), the financial leverage (Purnanandam and Rajan (2018)), and the investment–specific technology shocks (Kogan and Papanikolaou (2014)).

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and Hillier, Grinblatt, and Titman (2011).

These four growth options related measures represent different types of information of a firm's growth opportunities. We find that firms with higher I_{BM} derive less of their values from growth options in the future, regardless which one of the growth option measures is considered. That is, firms with high I_{BM} have significantly lower future sensitivity to idiosyncratic volatility, lower growth option conversion, lower financial leverage, and lower investment–specific technology shocks. These findings are consistent with our decomposition results and vote for a rational story of the return predictability.

A natural question is: what are the plausible causes for high I_{BM} firms to encounter decreasing future growth opportunities? Our further diagnostic test reveals that those firms are the ones with a higher probability to experience innovation declines, which can be quantitatively measured by low patent citations and low economic value of patents (Atanassov (2013); Hall, Jaffe, and Trajtenberg (2005); Kogan, Papanikolaou, Seru, and Stoffman (2017)). Endogenous growth models imply that innovations determine growth (Grossman and Helpman (1991); Klette and Kortum (2004); Romer (1990)). Firms that fail to innovate experience lower growth (Kogan, Papanikolaou, Seru, and Stoffman (2017)). High I_{BM} positively relates to the degree of innovation declines and therefore gauges the corresponding firm's lower future growth options.

One may concern that mispricing–based explanations for our empirical findings can exist. To explore this possibility, we empirically check whether the limit–to–arbitrage (LTA hereafter) effect can influence the return predictability of I_{BM}. Using idiosyncratic volatility and institutional ownership as measures of LTA (Golubov and Konstantinidi (2019)), we find no supporting evidence for LTA to affect the predictive power of I_{BM} on future stock returns. Specifically, when we perform independent portfolio sorts, the results indicate that the long–short return spread generated by I_{BM} is not concentrated in stocks with either high or low degree of LTA but is relatively evenly distributed across stocks with different degree of LTA. That is, the I_{BM} carries a risk premium rather than votes for mispricing explanations.

Our paper significantly contributes to two strands of literature. First, the proposed time–series decomposition of BM adds a new dimension to the literature on detecting the information contents for different parts of BM and extracting information from various BM decompositions (e.g., Daniel and Titman (2006); Fama and French (2008a); Rhodes-Kropf, Robinson, and Viswanathan (2005); Golubov and Konstantinidi (2019)). For instance, Daniel and Titman (2006) and Fama and French (2008a) decompose log of BM into stock returns and a proxy for tangible information based on accounting performance. Rhodes-Kropf, Robinson, and Viswanathan (2005) and Golubov and Konstantinidi (2019) decompose the BM into firm–specific error, sector error, and the value–to–book components. They find the return predictability of BM is mainly from market–to–value components but not from the value–to–book component. Furthermore, Gerakos and Linnainmaa (2017) decompose the value factor (HML) into two components, one correlates to the change of firm size and the other orthogonal to the size effect. They find that the value premium comes from the component related to the change of firm size. Our decomposition differs from the prior approaches by incorporating firm's growth options into stock valuation but only requiring the time–series data of BM.

Second, our research can also be positioned in the literature of discussing various measures of firm growth options and their asset pricing implications. Among these studies, Ai and Kiku (2016) argue that the sensitivity to idiosyncratic volatility gauges firm's growth opportunity, while Kogan and Papanikolaou (2014) document that the exposure to the investment–specific technology shocks is an additional measure. Beyond that, cash flow duration (Lettau and Wachter (2007)), book leverage, and operating leverage (Novy-Marx (2011)) can all capture certain aspects of the firms' growth opportunities. Our study differs from this strand of literature by extracting a measure of growth option directly from BM.

The paper proceeds as follows. Section 2 presents the theoretical motivation of the BM decomposition. We first review the related decomposition method and then propose a new time–series decomposition of BM. Section 3 reports the empirical results. We testify the relation between I_{BM} and expected stock returns, and the relation between I_{BM} and growth options. Section 4 concludes. All supporting materials are reported in the Appendix.

2 Growth Options and Book-to-Market Decomposition

This section first reviews some previous BM decompositions that attempt to infer growth options. We then propose a new decomposition of BM which explicitly incorporates growth options in stock valuation and construct an innovative time–series measure of growth option intensity.

2.1 Previous Decompositions

Rhodes-Kropf, Robinson, and Viswanathan (2005) decompose the log market-to-book ratio of firm i in the following way:

$$m_{it} - b_{it} = \underbrace{m_{it} - v(\theta_{it}; \alpha_{jt})}_{\text{FSE}} + \underbrace{v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)}_{\text{TSSE}} + \underbrace{v(\theta_{it}; \alpha_j) - b_{it}}_{\text{LRVTB}}, \tag{1}$$

where $v(\theta_{it}; \alpha_{jt})$ is the firm's fundamental value based on firm characteristics (θ_{it}) and their long run multiples (α_j). The first difference on the right–hand side is the firm–specific error (FSE), the second difference is the time–series sector error ($TSSE$), and the third difference is the long–run value–to–book ratio ($LRVTB$). They argue that the sum of FSE and $TSSE$ ($FSE + TSSE$) measures a firm's mispricing and LRVTB measures the firm's growth options. Rhodes-Kropf, Robinson, and Viswanathan (2005) use within–industry cross-sectional regression to estimate $v(\theta_{it}; \alpha_{jt})$ and $v(\theta_{it}; \alpha_j)$ and consequently obtain the mispricing and growth options components, respectively.[3]

[3] Jaffe, Jindra, Pedersen, and Voetmann (2020) adopt the modification suggested by Hertzel and Li (2010) so that no forward-looking information is used in estimating the fundamental values. For each year and each of the 12 Fama–French industries, estimate the following regression:

$$m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt} \ln(NI)^+_{it} + \alpha_{3jt} I_{(<0)} \ln(NI)^+_{it} + \alpha_{4jt} LEV_{it} + \varepsilon_{it},$$

Some recent studies apply the above decomposition to reexamine the value premium. Golubov and Konstantinidi (2019) and Jaffe, Jindra, Pedersen, and Voetmann (2020) find that the value premium is entirely attributed to the mispricing component, not the growth options component. Both studies focus on the value premium and neither finds the existence of a growth premium.

It is important to note that $v(\theta_{it}; \alpha_j)$, the fundamental value in defining the growth options component (LRVTB), is mostly driven by the current firm fundamentals based on firm characteristics (θ_{it}) rather than the market value. Moreover, the multiples α_j are supposed to be constant within the industry and vary slowly since they are historical averages. Therefore, the interpretation of LRVTB as growth options may be inappropriate if the growth options are manifested in the market value, time-varying, and non-homogenous within the industry.

Daniel and Titman (2006) consider a time–series decomposition of log book-to-market ratio (BM) that allows for time–varying, firm–specific, non–fundamental related growth options:

$$\begin{aligned} BM_t = \log(B_t/P_t) &= BM_{t-\tau} + \log(B_t/B_{t-\tau}) - \log(P_t/P_{t-\tau}) \\ &= BM_{t-\tau} + r^B(t-\tau, t) - r(t-\tau, t), \end{aligned} \quad (2)$$

where, following their notation, B is the book value, P is the market value, and τ is a positive number. The log book–to–market ratio is equal to the τ–period–ago log book–to–market ratio ($BM_{t-\tau}$), plus the log book return (r^B), minus the log market return (r).

As Daniel and Titman point out, if the poor earnings convey sufficiently bad information about the firm's future earnings, then the market return (r) to the earnings surprises fall proportionally more, i.e. $|r| > |r^B|$, and there is an overall increase of BM. As a result,

where NI^+ is the absolute value of net income, $I_{(<0)}$ is an indicator function for negative net income observations, and LEV is the leverage ratio. Long–run multiples (α_j) are calculated by industry as the average annual multiple from the beginning period to the current year.

poor (good) earnings cause higher decrease (increase) in market return, leading to an increase (decrease) in BM. This implies that low BM stocks have higher realized earnings than high BM stocks, and therefore should earn higher future stock returns. This finding is consistent with the interpretation of the value premium in Lakonishok, Shleifer, and Vishny (1994) and Fama and French (1995).

However, Daniel and Titman (2006) argue that this interpretation ignores the possibility that prices can move for reasons that are orthogonal to current performance information. In particular, if a firm receives good (bad) news about future growth options, this information will increase (decrease) its market value without influencing the book value, thereby decreasing (increasing) the firms' BM. They further show that high book–to–market stocks are "distressed", which is against the above interpretation of the value premium. In particular, they find that the firm's past book return (r^B) doesn't predict future stock return, but the past market return negatively predicts future stock return. While Daniel and Titman (2006) focus on showing evidence refuting the distressed explanation of the value premium, they don't further pursue the growth options interpretation. The decomposition in equation (2) indicates that the growth options need to be part of the stock price and be modelled at the firm level.

2.2 Modeling Growth Options

In a seminal work, Berk, Green, and Naik (1999) build a novel model of growth options that aims to explain various return predictive relations including the value premium. The key premise is that the market value of the firm consists of two parts: existing assets and growth options. Their elaborate model assumptions generate analytical solutions for the growth options that are useful for numerical simulations. We follow the less technical, but same in spirit, approach of Bernardo, Chowdhry, and Goyal (2007) to incorporate growth options into the market value of stock. Specifically, we write the market value of stock, i.e. the stock price, as the sum of two parts:

$$M_t = V_t + C_t, \tag{3}$$

where V_t is the present value of existing assets, i.e. future cash flows generated by the book equity B_t, and C_t is the present value of the growth options. The growth options are basically call options written on V_t as well as other state variables such as the interest rate.[4] Hence, the expected next–period return of the stock is the weighted sum of the expected returns of V_t and C_t:

$$E(r_{t+1}) = w_t^V E(r_{t+1}^V) + w_t^C E(r_{t+1}^C) \tag{4}$$

where $w_t^V = V_t/(V_t + C_t) = 1/(1 + C_t/V_t)$ and $w_t^C = C_t/(V_t + C_t) = 1 - w_t^V$ are weights, and $r_{t+1}^V = V_{t+1}/V_t - 1$ and $r_{t+1}^C = C_{t+1}/C_t - 1$ are the returns of V_t and C_t, respectively. A well-known fact from the option pricing theory is that the return of a call option is greater than that of the underlying (e.g., Cox and Rubinstein (1985)), that is, $E(r_{t+1}^C) > E(r_{t+1}^V)$.[5] Hence, the higher the growth options value, the higher the expected return of the stock.

The BM can be expressed as

$$\frac{B_t}{M_t} = \frac{B_t}{V_t + C_t} = \frac{1}{1 + \frac{C_t}{V_t}} \frac{B_t}{V_t} = w_t^V \frac{B_t}{V_t} = (1 - w_t^C)\frac{B_t}{V_t}. \tag{5}$$

In other words, the stock's book-to-market ratio is equal to the BM of the existing asset (B_t/V_t) scaled by the weight of it. Equation (5) implies that, everything else fixed, a higher value of B_t/M_t can be caused by: (i) lower w_t^C; (ii) higher B_t/V_t; or (iii)the both. In (i), if w_t^C gets lower, C_t decreases together with the increase of BM value. Then, based on equation (4), a lower expected stock return can be obtained. It reveals that the higher the value of BM, the lower the expected return of the stock. This result vote for growth premium but conflicts with the arguments of Lakonishok, Shleifer, and Vishny (1994) and Fama and

[4]In Berk, Green, and Naik (1999), the interest rate is the only underlying state variable.

[5]In Bernardo, Chowdhry, and Goyal (2007), they show, within the CAPM framework, that the beta of the growth options is higher than that of the existing assets.

French (1995) in which there is a positive relation between BM and expected return. In (ii), if B_t/V_t gets higher, V_t tends to be relatively lower together with the increase of BM value. Then, based on equation (4), a higher expected stock return can be obtained. It implies that the higher the value of BM, the higher the expected return of the stock. This result is consistent with the empirical findings in the previous literature of value premium. Hence, "BM is not a 'clean' variable uniquely associated with economically interpretable characteristics of the firms" (Lakonishok, Shleifer, and Vishny (1994)). The aggregate impact of the increase of BM on the expected stock returns mainly depends on the source of the fluctuation of BM.

The lack of empirical evidence for a growth premium is mainly due to the fact that C_t is not observable. We then exploit the time-series variations of BM to extract information about C_t or C_t/V_t.

2.3 A Time Series Decomposition and Implications

Motivated by the insight of Daniel and Titman (2006), we propose a model-free decomposition.

Intuitively, B_t/V_t should be persistent because V_t is fully determined by the existing assets. Hence, the time-series variations of BM are mostly driven by the variations of C_t/V_t. Consider the special case, in which B and V are constant but C deviates slightly from its sample mean $\overline{C}$. The first–order Taylor expansion shows that the B/M can be approximated by:

$$\frac{B}{M} = \frac{B}{V+C} \approx \frac{B}{V+\overline{C}} + \left[-\frac{B(C-\overline{C})}{(V+\overline{C})^2}\right]. \tag{6}$$

That is, BM nearly equals to the sum of its sample mean, $\frac{B}{V+\overline{C}}$, and the negative value of the fluctuation of C from the mean of it [6], $\left[-\frac{B(C-\overline{C})}{(V+\overline{C})^2}\right]$. In a general framework, the current

[6]The intuition becomes more obvious if we examine the market-to-book ratio, M/B, instead. In this setting, $M_t/B_t = V_t/B_t + C_t/B_t$. If V_t/B_t is persistent, which is very likely, the variations of M_t/B_t is mostly from the variations of C_t/B_t, or C_t/V_t since V_t is closely related to B_t.

value is of BM_t can be decomposed into two components. The first component stands for the time-varying mean of the series, and the second term is treated as the mean-reverting adjustment of the BM_t, which is obviously negative related to the market value of growth options, C_t.

To exploit the intuition, we propose the following econometric decomposition of BM:

$$\frac{B_t}{M_t} = \mu_t + \varepsilon_t, \tag{7}$$

where μ_t is the persistent time–varying conditional mean of BM, and ε_t is the temporary mean-reverting component. Following the earlier discussion, ε_t should be driven largely by the variation in C_t relative to V_t.

Empirically, we use the rolling–window mean to approximate μ_t and the difference between the current B_t/M_t and μ_t to approximate ε_t. Specifically,

$$\frac{B_t}{M_t} = BM_{ave,t} + I_{BM,t}, \quad \text{where} \tag{8}$$

$$BM_{ave,t} = \frac{1}{s}\sum_{i=1}^{s}\frac{B_{t-i}}{M_{t-i}}, \tag{9}$$

$$I_{BM,t} = \frac{B_t}{M_t} - BM_{ave,t}, \tag{10}$$

where s is the size of the rolling window. $BM_{ave,t}$, the s–period moving average of BM, is the trend component and should be highly persistent. I_{BM}, on the other hand, measures the deviation from the trend which is the mean-reverting temporary component in B_t/M_t. Combining the results of equation (6) and equation (10), $I_{BM,t}$ captures the information of C_t/V_t and should be negatively related to growth option intensity.

Alternatively, we can decompose $\log(B/M)$ in a similar way. We will mainly use the decomposition (10) in the paper, but conduct robustness checks using the log version in the appendix. Since we work with quarterly frequency in the empirical analysis, the moving average approach is appropriate to mitigate seasonality in the data. If we consider the annual frequency, it is possible to model BM as a unit root process. That is, μ_t is just the lagged BM and ε_t is the difference between the current BM and lagged BM. We consider this construction for robustness in the appendix.

How are the components of the B/M decomposition (8) related to the expected stock returns? Moving average smooths out the impact of temporary component caused by variation of growth options. Hence, $BM_{ave,t}$ should be highly correlated with B_t/V_t. Then the classical discounted dividend model argument of Fama and French (1995) implies a positive relation between $BM_{ave,t}$ and the expected stock return. The empirical approaches of Lakonishok, Shleifer, and Vishny (1994) and Fama and French (1995) also generate the same relation. Meanwhile, it is important to note that $I_{BM,t}$ is negatively correlated with the intensity of growth options as we mentioned above. Therefore, due to the positive relation between growth option intensity and the expected returns, $I_{BM,t}$ is negatively related to the expected stock return.

In sum, we postulate a positive relationship between $BM_{ave,t}$ and expected stock return but a negative relation between $I_{BM,t}$ and expected stock return. In light of the existing empirical evidence, it is not surprising if we find $BM_{ave,t}$ positively predicts future stock returns. New to the literature, we will show that $I_{BM,t}$ negatively predicts cross–sectional stock returns, supporting the existence of a growth premium. Consistent with the inference from the previous section, the aggregate impact of the increase of BM on the expected stock returns is determined by the variations of $BM_{ave,t}$ and $I_{BM,t}$.

2.4 Comparison of I_{BM} and Intangible Return

Last by not the least, it is critical to understand the differences between I_{BM} and the intangible return defined by Daniel and Titman (2006). Each year, they estimate the following cross–sectional regression with lagged 5–year log BM ratio:

$$r_i(t-5,t) = \gamma_0 + \gamma_{BM} \cdot bm_{i,t-5} + \gamma_B \cdot r_i^B(t-5,5) + u_{i,t},$$

where r and r^B are past 5–year log stock return and log book return. The intangible return ($r^{I(B)}$) is the regression residual, which measures the portion of stock return not explained by the fundamental performance.[7] Ignoring the difference in the length of the lagged window, the intangible return can be expressed as

$$r_i^{I(B)} = r_i - \hat{\gamma}_0 - \hat{\gamma}_{BM} \cdot bm_{i,t-5} - \hat{\gamma}_B \cdot r_i^B.$$

If $\hat{\gamma}_0 = 0$ and $\hat{\gamma}_{BM} = \hat{\gamma}_B = 1$, then

$$r_i^{I(B)} = r_i - r_i^B - bm_{i,t-5} = -bm_{i,t}.$$

In this special case, the intangible return is equal to the negative log BM. This is consistent with the negative relation between $r_i^{I(B)}$ and future return documented in Daniel and Titman (2006) and the value premium. If we use the log version of I_{BM} with unit root process, then

$$I_{BM} = bm_{i,t} - bm_{i,t-5} = r_i - r_i^B.$$

Comparing the above two expressions, the innovation in BM is clearly different from the intangible return. In general, the estimated regression coefficients in constructing $r_i^{I(B)}$ are different from those in the special case so that the difference between the two becomes even more obvious. It is notable that the regression coefficients are fixed for all stocks in each year, imposing some cross–sectional restrictions on the relation between stock returns and fundamentals. When constructing I_{BM}, we only use the firm's own historical BM data. Most importantly, as we will show later, the relation between I_{BM} and future stock return is negative, opposite to that in the value premium. Not only I_{BM} is constructed in a unique way, its empirical implications are also different from those of the intangible return.

[7] Daniel and Titman (2006) also consider other measures of fundamental performance and find similar results.

3 Empirical Evidence

3.1 Data Descriptions

We use the stock return and accounting data of all $NYSE$, $AMEX$, and $NASDAQ$ firms from the $CRSP$ and $COMPUSTAT$ during 1971–2018, excluding the financial stocks (four–digit SIC codes between 6000 and 6999) and stocks with end–of–quarter share price less than \$1. The book–to–market ratio, B/M, is the ratio of quarterly book equity to quarter-end market capitalization. Quarterly book equity is constructed by following Hou, Xue, and Zhang (2015). To ensure no forward–looking information is used in predicting returns, the book value (and all other accounting variables) is the one that has been *reported* by the end of the current quarter.[8] We require a firm to have at least 16 quarters of B/M to be included in the sample. For the base case presented in the paper, we use 8-quarter rolling-windows to construct $BM_{ave,t}$ and $I_{BM,t}$.

One problem with the basic quarterly $COMPUSTAT$ data is restatements, which can potentially cause forward looking information being used in portfolio formation (e.g., Livnat and López-Espinosa (2008)). We will conduct the empirical analysis mostly on the "point–in–time" version of quarterly $COMPUSTAT$, which provides historically accurate fundamentals. However, the choice of data leads to a shorter sample from 1987, since the un–restated data are only available from 1987.[9]

As an alternative, we use the annual fundamentals and define I_{BM} as the change of the annual BM. Specifically, we follow the approach of Asness and Frazzini (2013) to construct BM at the end of June in each year by dividing the book value of the previous fiscal year by the stock price at the end of June. Note that this is similar to how we construct quarterly BM. Asness and Frazzini (2013) show that "using a more–current price is superior to the

[8]Since a firm files the financial reports after a fiscal quarter, the accounting variables used are actually those for the previous fiscal quarter.

[9]We thank the referee for pointing out this not well understood fact and suggesting to use un–restated data instead of the basic quarterly COMPUSTAT data.

standard method of using prices at fiscal year–end." We replicate our analysis with the annual data in the appendix and don't find any significant changes to our main findings. One main advantage of using the quarterly data is the larger number of sample observations. Another advantage is more efficient trading by incorporating new information quickly.

We incorporate a number of control variables which are listed in Table 1. Size (ME) is the end–of–quarter market capitalization. Lagged one–month return (REV) is the return of month t. REV is included to control for the short–term reversal effect. Momentum (MOM) at the end of month t is the cumulative return between month $t-11$ and month $t-1$. We follow the convention in the literature by skipping month t when predicting the return of month $t+1$. Gross profitability (GP) is defined as in Novy-Marx (2013), which is equal to quarterly revenue minus quarterly cost of goods sold scaled by quarterly total asset. Idiosyncratic volatility ($IVOL$) is defined strictly following Ang, Hodrick, Xing, and Zhang (2006). The earnings surprise (SUE) is defined as the quarter t–end price–scaled difference between the earnings reported in quarter t and earnings reported in quarter $t-1$.[10] $ILLIQ$ is the illiquidity measure of Amihud (2002). Daniel and Titman (2006) argue that share issuances can capture the intangible return in their BM decomposition. Following their approach, the composite share issuance (CSI) is the logarithm of the current/lagged 2–year market capitalization minus the cumulative 2–year stock returns. The investment (INV) is the quarterly capital expenditure divided by the lagged quarterly total assets.[11]

Table 2 reports the summary statistics and the correlation matrix for I_{BM}, BM_{ave}, B/M, and the control variables. The mean and median of I_{BM} are close to zero as expected, but the standard deviation is high, indicating large variations across stocks and over time. The 5th and 95th percentiles are about -0.5 and 0.5, respectively. The correlation between I_{BM}

[10] The advantage of this version of SUE is that it is defined for most stocks. We have considered alternative definitions of earnings surprises and found similar results. For example, SUE can be constructed as the quarter t–end price–scaled difference between the earnings reported in quarter t and the median of analysts' forecasts.

[11] In addition to the listed variables, we have examined a number of other predictors and found similar results, which are available upon request.

and BM_{ave} is close to zero. The correlation between I_{BM} and B/M is 0.33, much lower than that between BM_{ave} and B/M, 0.915. These numbers indicate that BM_{ave} captures the overall level of B/M while I_{BM} contains information nearly orthogonal with that in BM_{ave}. The correlations between I_{BM} and past returns (REV and MOM) are relatively high (-0.130 and -0.198, respectively) compared to the correlations with other control variables. This is not surprising because a large change in B/M may come from the large change of market capitalization as we discuss in Section 2.2. The only other control variable with a high correlation with I_{BM} is CSI at -0.135. Despite the low correlations, we will incorporate the control variables in our analysis.

3.2 I_{BM} and Stock Returns

To test the negative return predictability of I_{BM}, we use two standard methods: portfolio sorts and cross–sectional regressions of Fama and Macbeth (1973). For single portfolio sorts, we rank stocks by I_{BM} into decile portfolios, and then report future value–weighted portfolio returns.[12] The negative return predictability suggests a decreasing pattern of portfolio returns from decile 1 to decile 10. To check if the return predictability of I_{BM} is not explained by other predictors, we conduct sequential double portfolios sorts. That is, we first sort stocks into quintiles on a control variable such as ME and then further rank stocks within each portfolio into quintiles by I_{BM}. If the control variable explains the return predictability of I_{BM}, we expect the decreasing pattern of returns in I_{BM} to be much less pronounced within each control variable quintile. Not shown in the paper for brevity, we have also conducted independent double sorts and obtained similar results. To compute the t–statistics of average portfolio returns, we use the Newey and West (1987) adjusted standard errors with six lags although increasing the number of lags does not change the results. For Fama–MacBeth regressions, the dependent variable is the future stock return while the independent variables include I_{BM} and the controls. We expect the average estimated coefficient of I_{BM}

[12]The results for equal–weighted returns are even stronger and available upon requests.

to be significantly negative. The cross–sectional regressions allow us to examine the marginal explanatory power of I_{BM} in the presence of multiple predictors.

3.2.1 Single Portfolio Sorts

Panel A of Table 3 reports the average value–weighted returns and equally–weighted characteristics of the decile portfolios formed by sorting stocks on I_{BM} for the full sample. The equal–weighted returns are even more significant and not shown for brevity. The raw average quarterly return decreases from 3.97% for decile 1 to 1.92% for decile 10. The high–minus–low (H–L) spread between deciles 10 and 1 is −2.05% per quarter (or −8.21% per year) and significant at the 1% level ($t = -3.82$). To check whether the significant H–L spread can be explained by the existing risk factors, we estimate the factor–adjusted returns using the five–factor model of Fama and French (2016) and the four-factor model of Carhart (1997). The 5-factor- and 4-factor-adjusted H–L spreads are −2.02% ($t = -3.54$) and −1.74% ($t = -2.97$), respectively.

Looking at the characteristics of decile portfolios, ME and GP are hump-shaped but B/M, $IVOL$, and $ILLIQ$ are U-shaped. MOM, REV, SUE, and CSI are all decreasing, suggesting that stocks with bad past performance tend to have higher values of I_{BM}. Only INV increases with I_{BM}. Although we have shown that the H–L spread is not explained by the factors including momentum and profitability, we will conduct more tests with double portfolio sorts and Fama–MacBeth regressions.

Fama and French (2008b) emphasize that many asset pricing anomalies are concentrated in microcap stocks, which account for 60% of all listings but only a small fraction of market capitalization. Value–weighting returns already mitigates this problem to a large extent. We further address this concern by excluding microcap stocks, which are below the 20th percentile of NYSE market cap. Panel B shows the results for this sub-sample. The portfolios returns show the same decreasing pattern as in the full sample. The H–L spreads, raw or factor-adjusted, are slightly lower than those in the full sample, but remain economically and statistically significant.[13]

3.2.2 Double Portfolio Sorts

We now apply double portfolio sorts to examine whether the cross–sectional return predictability of I_{BM} can be explained by the control variables. Table 4 reports, for the full sample, the average value–weighted H–L spreads within the quintile portfolios of the control variables. The results for the sub-sample without microcaps are similar.

Panel A shows the raw H–L spreads. It is not surprising that BM_{ave} can not explain the negative relation between I_{BM} and future stock return. The H–L spreads of all five quintiles are negative and their magnitudes are consistent with the results of single portfolio sorts. The average raw H–L spread of five BM_{ave} quintiles is -1.31%, highly significant at the 1% level.

The return predictability of I_{BM} is even stronger if stocks are first screened by ME as the average H–L spread across the ME quintiles is larger than that of single portfolio sorts. Interestingly, the negative relation between I_{BM} and future return is more pronounced in REV quintiles 1, 3 and 5 but in MOM quintiles 3 and 4. The results for the other control variables are similar. The only exception is $ILLIQ$. The H–L spread is negative and significant for the first four quintiles but positive and significant for the highest quintile. Finally, we consider another measure of profitability, ROE, which has been shown to be a strong return predictor (e.g., Hou, Xue, and Zhang (2015)). In each ROE quintile, the H–L spread is negative. The magnitude is particularly large and statistically significant for the first four quintiles.

Panel B reports the 5–factor adjusted H–L spreads. The results are even more significant than those for raw returns. Not shown in the paper, we have found similar patterns for the 4–factor adjusted H–L spreads. In sum, the evidence from the double portfolio sorts

[13]Not shown in the paper, we have repeated the portfolio sorts using NYSE breakpoints, which is another way to mitigate the effect of small stocks. The results for the NYSE breakpoints are similar and available upon requests.

indicates that the control variables are not able to explain the return predictability of I_{BM}.

3.2.3 Fama–MacBeth Regressions

Table 5 reports the estimation results of Fama–MacBeth regressions for four regression specifications. The univariate model (1) contains I_{BM} as the only explanatory variable. Model (2) extends model (1) by controlling for BM_{ave}. Model (3) contains all variables but I_{BM} and BM_{ave}. Models (4) is most general and includes everything. We have found similar results for a number of alternative specifications but don't report due to the limit length of the paper.

Panel A shows the OLS regression estimates. In the univariate model (1), the average coefficient of I_{BM} is -1.71, significant at the 1% level ($t = -4.88$). Adding BM_{ave} actually leads to a more significant coefficient. In the most general model (4), the average coefficient of I_{BM} is still -1.11, and significant at the 1% level ($t = -3.41$). BM_{ave} positively predicts stock returns, consistent with the value premium. The estimated coefficients of the other control variables have the same signs as those documented in the literature.

A concern of the OLS regressions is that all stocks are treated equally so that the estimated coefficients are driven by small stocks. This is similar to over–weighting small stocks in equally–weighted portfolios. We address this concern in two ways. First, we estimate the regression for the sub-sample of all but microcaps. The results are similar to those for the full sample. Second, we estimate the value–weighted least square regressions recommended by Green, Hand, and Zhang (2017). The estimation results are shown in Panel B. Not surprisingly, the magnitude and statistical significance of the coefficient on I_{BM} become slightly lower due to the value–weight scheme. Nonetheless, the average coefficient of I_{BM} remains negative and significant at least at the 5% level in every model specification. The reduced statistical significance should not be surprising because the value weighting causes the predictability of many predictors to become much weaker or even insignificant.

3.2.4 Long–Run Predictability

One interesting question is whether the return predictability of I_{BM} holds beyond one quarter. Intuitively, if there is certain persistence in firm's growth opportunities, then the effect of I_{BM} on stock returns should also persist. To verify this, we estimate Fama–MacBeth regressions for stock returns in quarters $t+2$, $t+3$, and $t+4$, and report the results in Table 6. We only present the OLS results for two regression specifications. We have also considered other regression specifications and the value–weighted OLS estimation, and have found similar results. The evidence indicates that I_{BM} negatively predicts future returns up to quarter $t+4$. For the univariate model (1), the coefficient of I_{BM} for $t+2$ is even larger than that for $t+1$ in Table 5. The magnitude of the coefficient and t-statistic decline with the horizon, but remains significant up to $t+4$. In the general model (2), the magnitude of the coefficient unsurprisingly decreases while the t-statistic decreases with the horizon but remains significant at least at the 5% level.

3.3 I_{BM} and Growth Options

As we show in Section 2.3, I_{BM} extracts information of firm's growth options from BM and presents negative relation with growth options. Hence, high I_{BM} firms tend to be the ones with lower growth option intensity and lower expected returns. This statement is consistent with a rational explanation of the postulated growth premium.

In this section, we empirically investigate whether high I_{BM} firms tend to be the ones with lower growth option intensity. We test this relation by examining the effect of I_{BM} on four growth option measures: exposure to idiosyncratic volatility, growth option conversion, financial leverage, and exposure to investment–specific technology (IST) shocks. Furthermore, we design empirical tests to illustrate the economic intuition behind the low growth options of high I_{BM} firms.

3.3.1 Relationship with Growth Options

We select four different growth option measures to investigate the relation between I_{BM} and growth options. A high value of I_{BM} indicates a significant reduction to a firm's growth opportunities. Exposure to idiosyncratic volatility by Ai and Kiku (2016) has been proposed to be the direct measure of firm's growth opportunities. We then expect there is a significantly negative relation between I_{BM} and this measure. Meanwhile, the reduction of growth opportunities can be caused by the conversion of growth options. If so, I_{BM} is expected to be negatively related with the measure of growth option conversion (Purnanandam and Rajan (2018)). However, if the reduction is not caused by growth option conversion, decrease of growth opportunities still implies a low financial leverage (Purnanandam and Rajan (2018)) and there is negative relation between I_{BM} and firm's financial leverage. Finally, when a firm's growth opportunities decrease, this firm would have low exposure to the investment–specific technology shock, which also implies a negative relation between I_{BM} and the measure of this exposure. In sum, we use these four measures to verify the negative relation between I_{BM} and growth options. All these measures have been constructed by using lagged information. To be consistent with the results in Section 2, we empirical test the relation between I_{BM} and the future values of these measures.

Ai and Kiku (2016) propose to measure growth opportunities by β^{ID}, the firms' exposure to idiosyncratic volatility news. They show empirically that β^{ID} is positively associated with firms' future investment and growth. We strictly follow their to construct β^{ID}. First, we estimate the monthly firm–level volatility by realized return variance and the aggregate market volatility by summing up squared daily returns. We then obtain the innovations in idiosyncratic volatility as the regression residuals of log firm–level volatility on its own lag and the log market volatility. β^{ID} is estimated by regressing the log stock returns on innovations in its idiosyncratic volatility using monthly data of rolling 3–year window. Because I_{BM} is negatively related to a firm's growth option intensity, it should negatively predict future β^{ID}. We test this claim by estimating Fama-MacBeth regressions, where the dependent variable is the future β^{ID} in quarters $t+1$, $t+2$, $t+3$, or $t+4$. The estimation results shown in Panel A of Table 7 strongly support this claim as the average estimated coefficient of I_{BM} is significantly negative in all cases.

A high value of I_{BM} indicates significant reduction to a firm's growth opportunities. As a result, the firm will convert lower amount of growth options in the future. To test this claim, we adopt the measure of growth option conversion (GOC) by Purnanandam and Rajan (2018), which is the change of quarterly capital expenditure scaled by corresponding lagged quarterly total assets. We estimate Fama–MacBeth regressions of future GOC on I_{BM}, and expect the coefficient to be negative. Panel B of Table 7 reports the estimation results, where GOC in quarters $t+1$, $t+2$, $t+3$, or $t+4$ is regressed on I_{BM} with and without the control variables. Consistent with our prediction, the average coefficient of I_{BM} is negative in both univariate and multivariate regressions up to quarter $t+4$, and significant at the 1% level up to quarter $t+3$ and at the 5% level for quarter $t+4$. The declining pattern as the horizon increases is consistent with the similar declining pattern of return predictability. The evidence, therefore, supports the notion that as a firm experiences a decrease in growth options – a high value of I_{BM}, it will convert fewer growth options in the future.

Purnanandam and Rajan (2018) argue that growth option conversion reduces information asymmetry about the firm, which in turn leads to lower leverage as a result of the lower cost of issuing information–sensitive securities such as equity. In our setting, a high value of I_{BM} implies a reduction in growth options, which may or may not be caused by conversion of growth options. Nonetheless, the argument of Purnanandam and Rajan (2018) still implies lower financial leverage. We define LEV as the ratio of total debt in a quarter scaled to the lagged total assets. Alternative versions of leverage do not change the results in any significant ways. We test this prediction in the same way as for growth option conversion. Panel C of Table 7 reports the estimation results of the Fama–MacBeth regressions, where LEV in quarters $t+1$, $t+2$, $t+3$, or $t+4$ is the dependent variable. The average coefficient of I_{BM} is negative and significant at the 1% up to quarter $t+4$. As a firm experiences a decrease in growth options – a high value of I_{BM}, it has lower information asymmetry and therefore faces lower costs of issuing equity relative to debt.

Kogan and Papanikolaou (2014) explain the value premium by arguing that low BM firms are more exposed to IST shocks which carry a negative risk premium. They measure IST shocks by the returns of a long–short portfolio by long investment goods producers and short consumer goods producers (IMC). The exposure to IST shocks is then captured by β^{IMC}, the covariance between stock returns and the long–short portfolio returns. We follow Kogan and Papanikolaou (2014) to build the IMC portfolio by first classifying industries as producing either investment or consumption goods according to the NIPA Input–Output tables, and then matching firms to industries according to their NAICS codes. β^{IMC} is the estimated coefficient of a 24–month rolling window regression of stock returns on the IMC portfolio returns. Again, we expect I_{BM} to be negatively related to β^{IMC} because a firm with fewer growth opportunities is less exposed to IST shocks. Panel D of Table 7 shows the results of Fama-MacBeth regressions with β^{IMC} in quarters $t+1$, $t+2$, $t+3$, or $t+4$ as the dependent variable. The coefficient of I_{BM} is negative in all cases and remains significant at the 10% level up to quarter t+4. Nonetheless, the evidence is consistent with our argument that high I_{BM} stocks have lower growth options.

3.3.2 The Economic Intuition

A natural question on the relationship between I_{BM} and growth options is how can we visualize the stocks with high I_{BM} and subsequently lower growth options?[14] We answer this question by revisiting the Schumpeterian endogenous growth models, which argue that technological innovation is the key driver for firm and economic growth (Grossman and Helpman (1991); Klette and Kortum (2004); Romer (1990)). Does the negative association between I_{BM} and growth option intensity hinge on the firms' innovation? In this section, we examine whether the firms with higher current I_{BM} are the ones with lower market value

[14]We thank the referee for raising this point.

of innovation and lower future patent citations (Kogan, Papanikolaou, Seru, and Stoffman (2017)).

We use a portfolio sort approach to detect the relationship between I_{BM} and innovation. In each time period, we sort the universe of the stocks into deciles based on I_{BM} and report the equal–weighted average innovation measures. Following Kogan, Papanikolaou, Seru, and Stoffman (2017) and Hall, Jaffe, and Trajtenberg (2005), the measures include raw market value of patents (ξ), time–adjusted market value of patents (ξ_{Adj}), raw patent citations ($nCites$), and adjusted patent citations ($CiteAdj$). Table 8 presents the portfolio sorting results. The results indicate that across all innovation measures, the degree of innovation of high I_{BM} stocks is significantly lower than that of low I_{BM} ones. In other words, the high I_{BM} ones tend to have lower market value of patents and lower future citations, experiencing innovation declines.

3.4 I_{BM} and Limits to Arbitrage

One may argue that the return predictive power of I_{BM} can potentially come from the limits to arbitrage for investors. For instance, the higher future stock returns earned by low I_{BM} stocks can be attributed to short–sale constraints which limit arbitrageurs' ability to profit from security overvaluation. Prior studies (Asquith, Pathak, and Ritter (2005) and Nagel (2005)) document that the short–sale constraints can be gauged by institutional ownership because higher institutional ownership increases the supply of lendable shares. We examine whether I_{BM} derives its return predictive power through the LTA channel by performing a sequential double portfolio sort based on the level of institutional ownership and I_{BM}. If the long–short return spread of I_{BM} concentrates in the stocks with low institutional ownership, the return predictability of I_{BM} likely comes from the channel of short sale constraints. The results presented in Panel A of Table 9 vote against the short sale constraints as a channel for the return predictability of I_{BM} since the I_{BM} long–short return spreads are similar across high and low quintile portfolios of institutional ownership.

Beyond the short–sale constraints, we also examine the other dimension of LTA. Prior literature such as Ali, Hwang, and Trombley (2003) measures the arbitrage risk by idiosyncratic volatility ($IVOL$). The stocks with higher $IVOL$ tend to be the ones with short–run prices deviated further from the fundamental values. The large price deviation of high $IVOL$ stocks can make arbitrageurs hard to differentiate noise from actual mistakes, therefore potentially scaling back the shares they plan to short.

To examine the potential impact of the arbitrage risk on the return predictability of I_{BM}, we perform the independent two–way portfolio sorts on the $IVOL$ and I_{BM}. The corresponding results are reported in Panel B of Table 9. Even though the I_{BM} long–short portfolio return spreads are different across different $IVOL$ quintiles, the return spreads are obviously not increasing (or decreasing) monotonically but yield a weak hump–shaped pattern with the largest spread appearing in Quintile 4. In other words, the arbitrage risk cannot explain the return predictability of I_{BM}. Overall, our above findings rule out the channel of LTA and point to a risk–based explanation for the return predictive power of I_{BM}.

4 Conclusions

The existing empirical evidence overwhelmingly supports the existence of a value premium. This is, high BM (value) stocks earn higher returns than low BM (growth) stocks. The evidence contradicts the conventional wisdom that growth stocks are riskier and should earn higher returns. Although a number of researchers have argued that the book–to–market ratio is not a clean measure of value or growth, no prior studies have explicitly tested the existence of a growth premium. We fill the gap in the literature by proposing a decomposition of BM into the sum of the persistent time–varying trend and a temporary mean-reverting innovation component. We argue that, under reasonable assumptions, the mean-reverting component, I_{BM}, captures the intensity of firm's growth options and is consequently negatively related to the expected stock return.

We document significant evidence consistent with a growth premium in addition to the existing value premium. Consistent with the growth option argument, we find that I_{BM} is negatively related to existing measures of growth options. We also provide a visualized economic interpretation such that the firms with higher current I_{BM} and hence lower future growth options are the ones experiencing innovation declines in the future. We do not find solid evidence supporting the mispricing based explanation by examining the relation between I_{BM} and measures of limit to arbitrage. Our findings are robust to alternative methods and econometric techniques, and can't be explained by existing return predictors.

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Table 1: Variable Definitions

This table shows the detailed definitions of the main variables in the empirical analysis.

B/M	The ratio of the quarterly book equity to the quarter-end market capitalization. The quarterly book equity is constructed following the footnote 9 of Hou, Xue, and Zhang (2015), which is a quarterly version of the annual book equity in Davis, Fama, and French (2000). To mitigate the forward-looking bias, all accounting variables are those reported during the current quarter.
BM_{ave}	The 8–quarter rolling–window average B/M.
I_{BM}	The innovation of book–to–market ratio is equal to the current B/M minus BM_{ave}.
ME	The quarter-end market capitalization is the product of shares outstanding and quarter-end stock price.
REV	The stock return of the current month.
MOM	The cumulative stock return of the lagged 11 months, skipping the current month.
GP	Following Novy-Marx (2013),the gross profitability is the quarterly sales minus quarterly cost of goods sold scaled by the contemporaneous quarterly total assets.
$IVOL$	The idiosyncratic volatility is the volatility of the Fama–French 3–factor regression residuals for the current quarter, a quarterly version of Ang, Hodrick, Xing, and Zhang (2006)'s monthly measure.
SUE	The earnings surprise is defined as the price–scaled difference of the two most recent consecutive quarterly earnings.
$ILLIQ$	The illiquidity measure of Amihud (2002) is constructed as the rolling annual average of the ratio of daily absolute stock return and dollar volume.
CSI	Following Daniel and Titman (2006), the composite share issuance is defined as the logarithm of the current/lagged 2–year market capitalization minus the cumulative 2–year stock returns. The 2–year horizon is chosen to be consistent with the 8–quarter rolling window for constructing I_{BM}.
INV	The investment is the quarterly capital expenditure scaled by the lagged quarterly total assets.
GOC	Following Purnanandam and Rajan (2018), the growth option conversion is the difference between the two consecutive quarterly capital expenditures scaled by the lagged quarterly total assets.
LEV	The leverage is the ratio of the total book debt scaled by the lagged total assets.
β^{ID}	The exposure to idiosyncratic volatility is defined by strictly following Ai and Kiku (2016). We first construct the firm–level volatility and the aggregate market volatility. We then obtain the innovations in idiosyncratic volatility as the regression residuals of log firm–level volatility on its own lag and the log market volatility. β^{ID} is estimated by regressing the log stock returns on innovations in its idiosyncratic volatility using monthly data of rolling 3–year window.

Table 1 – Continued

This table shows the detailed definitions of the main variables in the empirical analysis.

β^{IMC}	Following Kogan and Papanikolaou (2014), IMC is the stock return spread between the investment and consumption good producers (IMC portfolio). To construct the IMC portfolio, we first classify industries as producing either investment or consumption goods according to the NIPA Input–Output tables. We then match firms to industries according to their NAICS codes. β^{IMC} is the estimated coefficient of a 24–month rolling window regression of stock returns on the IMC portfolio returns.
ξ	Following Kogan, Papanikolaou, Seru, and Stoffman (2017), ξ is the raw market value of patents. We download the data from Professor Noah Stoffman's website.
ξ_{Adj}	Following Kogan, Papanikolaou, Seru, and Stoffman (2017), xi_{Adj} is the time–adjusted market value of patents. We download the data from Professor Noah Stoffman's website.
$nCites$	Following Kogan, Papanikolaou, Seru, and Stoffman (2017) and Hall, Jaffe, and Trajtenberg (2005), $nCites$ is the number of future patent citations. We download the data from Professor Noah Stoffman's website.
$CiteAdj$	Following Kogan, Papanikolaou, Seru, and Stoffman (2017) and Hall, Jaffe, and Trajtenberg (2005), $CiteAdj$ is the adjusted number of future patent citations. We download the data from Professor Noah Stoffman's website.

Table 2: Data Descriptions

This table reports the summary statistics and correlations for quarterly I_{BM}, BM_{ave}, B/M, and the control variables for the sample period of 1971–2018. The variables are defined in Table 1. In Panel A, we report the summary statistics including mean, standard deviation, skewness, 5th, 10th, 25th, 50th(Median), 75th, 90th, and 95th percentiles for the variables. Panel B reports the pairwise Pearson correlations of the variables.

Panel A: Summary Statistics

	Mean	Stdev.	Skew.	5th	10th	25th	Median	75th	90th	95th
I_{BM}	0.018	0.824	7.327	-0.468	-0.275	-0.095	0.001	0.100	0.304	0.533
B/M	0.912	1.963	12.431	0.129	0.176	0.326	0.568	0.961	1.661	2.128
BM_{ave}	0.962	2.261	10.031	0.156	0.192	0.330	0.574	0.977	1.529	1.989

Panel B: Correlation Matrix

	B/M	BM_{ave}	ME	REV	MOM	GP	$IVOL$	SUE	$ILLIQ$	CSI	INV
I_{BM}	0.330	-0.079	-0.006	-0.130	-0.198	-0.024	0.057	-0.011	0.019	-0.135	0.040
B/M	1	0.915	-0.037	-0.056	-0.102	-0.063	0.010	-0.001	0.025	-0.153	0.027
BM_{ave}	0.915	1	-0.034	-0.003	-0.018	-0.056	-0.020	0.003	0.017	-0.034	0.015

Table 3: Unrestated Single Portfolio Sorts

This table reports, using the unrestated $COMPUSTAT$ data, the value–weighted average next–quarter returns and equal-weighted average firm characteristics of decile portfolios formed by sorting stocks on I_{BM}. R_{raw} is the raw return, R_{FF} is the 5-factor-adjusted return following Fama and French (2016), and R_C is the 4-factor-adjusted return following Carhart (1997). The row of H–L spreads reports the differences of average returns between decile 10 and decile 1, with the corresponding Newey–West t-statistics shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively. The returns, MOM, GP, REV, $IVOL$, SUE, CSI, and INV are reported in percentage. Panel A reports the results for the full sample, while Panel B reports the results for the sub sample by excluding the microcap stocks, whose market capitalizations fall below the 20th percentile of NYSE stocks.

Decile	R_{raw}	R_{FF}	R_C	I_{BM}	ME($Bil.)	B/M	MOM	GP	REV	$IVOL$	SUE	$ILLIQ$	CSI	INV
Panel A: Full Sample														
1	3.97	3.75	3.92	-0.79	0.66	1.56	44.75	0.07	6.32	19.91	0.98	0.46	0.31	3.44
2	3.76	3.32	3.37	-0.20	1.53	0.70	40.52	0.07	5.66	15.00	1.36	0.20	0.34	3.57
3	2.87	2.73	2.61	-0.10	2.53	0.61	32.40	0.08	4.42	12.90	0.54	0.13	0.32	3.59
4	2.89	2.99	2.90	-0.04	3.71	0.93	25.65	0.08	3.29	12.07	0.75	0.10	0.28	3.70
5	2.62	2.46	2.79	-0.01	3.97	0.98	18.73	0.09	2.22	12.13	2.28	0.11	0.21	3.79
6	2.28	2.84	3.05	0.02	3.45	1.01	12.21	0.09	1.08	12.38	3.57	0.12	0.15	3.87
7	2.14	2.58	3.00	0.06	3.00	0.78	5.24	0.09	-0.40	12.79	2.89	0.13	0.08	3.89
8	2.18	2.17	2.79	0.13	1.97	0.81	-3.49	0.08	-1.93	13.99	-0.18	0.18	0.01	3.95
9	2.04	2.05	2.40	0.25	1.08	1.08	-15.39	0.07	-3.69	16.15	2.65	0.29	-0.14	3.94
10	1.92	1.73	2.18	0.81	0.45	1.77	-32.33	0.06	-7.24	21.14	3.64	0.53	-0.40	3.95
H–L	-2.05***	-2.02***	-1.74***											
	(-3.82)	(-3.54)	(-2.97)											
Panel B: All But Microcap														
1	3.97	3.94	4.38	-1.85	1.08	2.11	51.98	0.07	7.30	14.83	1.40	0.09	0.42	3.59
2	3.58	3.41	3.51	-0.17	2.05	0.65	41.76	0.07	5.89	12.30	0.50	0.05	0.38	3.66
3	2.91	2.76	3.01	-0.08	3.08	0.56	33.84	0.08	4.68	11.09	0.67	0.04	0.34	3.61
4	2.86	2.75	3.06	-0.04	4.18	0.54	27.56	0.08	3.63	10.62	0.61	0.03	0.29	3.70
5	2.62	2.92	3.14	-0.01	4.78	0.56	21.09	0.09	2.62	10.74	1.48	0.03	0.23	3.83
6	2.25	2.27	2.78	0.02	4.22	0.57	15.43	0.10	1.52	10.83	1.76	0.03	0.17	3.91
7	2.32	2.31	2.94	0.05	3.67	0.61	8.82	0.09	0.38	11.11	4.76	0.04	0.12	3.92
8	1.98	1.98	2.83	0.10	2.72	0.69	1.32	0.08	-0.99	11.64	3.09	0.04	0.05	4.00
9	2.11	2.01	2.76	0.19	1.58	0.89	-8.45	0.07	-2.48	12.70	1.13	0.05	-0.04	4.10
10	1.40	1.29	2.54	1.07	0.84	3.40	-23.32	0.06	-5.11	15.07	5.80	0.07	-0.25	4.20
H–L	-2.57***	-2.65***	-1.84***											
	(-4.03)	(-4.21)	(-3.40)											

Table 4: Double Portfolio Sorts

This table reports, using the unrestated *COMPUSTAT* data, the value-weighted average next-quarter returns of portfolios formed by double sorting stocks on the I_{BM} and control variables. In addition to those control variables in Table 2, we include ROE as a measure of profitability. For each control variable, we first sort stocks into quintiles by the control variable, and then within each quintile, we further sort stocks into quintiles by I_{BM}. We then report the H–L spread in percentage between I_{BM} quintiles 5 and 1 within each control variable quintile. The corresponding Newey-West t-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, 1% confidence levels, respectively. Panel A shows the raw H–L spreads, while panel B shows the 5-factor adjusted H–L spreads.

Panel A: Raw Return Spread											
Quintile	BM_{ave}	log ME	REV	MOM	$IVOL$	GP	SUE	$ILLIQ$	CSI	INV	ROE
Q1	-1.93***	-1.63**	-1.87***	-0.42	-0.93**	-2.89***	-1.92***	-2.45***	-1.46*	-2.51***	-2.60***
	(-3.11)	(-2.35)	(-3.03)	(-0.29)	(-1.98)	(-3.30)	(-2.88)	(-2.99)	(-1.75)	(-3.62)	(-3.20)
Q2	-1.22*	-2.71***	-0.56	-0.15	-1.13**	-0.17	-1.75***	-1.92***	-1.88**	-1.41**	-2.93***
	(-1.85)	(-3.80)	(-0.73)	(-0.08)	(-2.07)	(-0.84)	(-2.74)	(-2.68)	(-2.40)	(-2.53)	(-4.14)
Q3	-0.59	-3.06***	-1.92***	-1.95***	-1.50**	-0.42	-2.21***	-2.89***	-2.18***	-0.93	-2.14***
	(-0.74)	(-4.22)	(-2.95)	(-2.77)	(-2.33)	(-1.09)	(-3.79)	(-4.05)	(-3.18)	(-1.49)	(-2.80)
Q4	-0.81	-2.11***	-1.03*	-1.90***	-1.80**	-0.33	-1.40**	-1.53***	-1.99***	-1.22**	-1.72**
	(-1.02)	(-2.69)	(-1.74)	(-3.01)	(-2.41)	(-0.40)	(-2.10)	(-3.33)	(-2.97)	(-2.09)	(-2.35)
Q5	-2.02***	-1.52**	-2.88***	-0.24	-2.25***	-2.21***	-1.83***	-0.05	-2.31***	-2.44***	-0.70
	(-3.49)	(-2.31)	(-4.04)	(-0.55)	(-3.37)	(-3.00)	(-2.59)	(-0.24)	(-3.62)	(-4.11)	(-0.73)

Panel B: FF 5–Factor Adjusted Return Spread											
Quintile	BM_{ave}	log ME	REV	MOM	$IVOL$	GP	SUE	$ILLIQ$	CSI	INV	ROE
Q1	-2.70***	-2.20***	-2.47***	-1.13*	-1.64***	-3.14***	-2.15***	-2.71***	-1.22*	-2.33***	-2.89***
	(-4.33)	(-2.88)	(-4.21)	(-1.75)	(-3.46)	(-3.82)	(-3.23)	(-3.17)	(-1.79)	(-3.09)	(-3.32)
Q2	-2.08***	-3.10***	-1.02	-0.52	-1.91***	-0.72	-2.00***	-2.02***	-2.13***	-1.02*	-3.05***
	(-3.91)	(-4.15)	(-0.97)	(-0.62)	(-3.70)	(-1.55)	(-2.98)	(-2.59)	(-2.64)	(-1.83)	(-3.76)
Q3	-1.73**	-4.40***	-2.55***	-2.67***	-2.05***	-1.18**	-2.42***	-3.04***	-2.46***	-1.08*	-1.95***
	(-2.44)	(-5.05)	(-3.90)	(-3.71)	(-3.29)	(-2.06)	(-4.11)	(-4.94)	(-3.20)	(-1.77)	(-2.66)
Q4	-1.80**	-2.53***	-1.67**	-2.89***	-3.01***	-0.99*	-1.71**	-1.71***	-1.72**	-0.82	-1.58*
	(-2.28)	(-3.43)	(-2.52)	(-4.09)	(-5.25)	(-1.78)	(-2.04)	(-3.01)	(-2.30)	(-1.65)	(-1.57)
Q5	-2.85***	-1.99***	-3.52***	-0.80	-3.43***	-3.35***	-2.21***	-0.18	-1.92***	-2.57***	-0.81
	(-4.60)	(-2.86)	(-4.95)	(-0.93)	(-4.64)	(-4.03)	(-3.57)	(-0.34)	(-2.71)	(-3.79)	(-1.16)

Table 5: Unrestated Fama–MacBeth Regressions

This table reports, using the unrestated COMPUSTAT data, the estimation results of Fama–MacBeth regressions in four model specifications. The dependent variable is the next-quarter stock return, and the explanatory variables include I_{BM} and the control variables. In addition to the average estimated coefficients and adjusted R^2, the Newey-West t-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, 1% confidence levels, respectively. In Panel A, the regressions are estimated by the OLS, while in Panel B, the regressions are estimated by the value–weighted OLS of Green, Hand, and Zhang (2017).

VARIABLE		*OLS*			VARIABLE		*WLS*		
NAME	(1)	(2)	(3)	(4)	NAME	(1)	(2)	(3)	(4)
I_{BM}	-1.71***	-1.78***		-1.11***	I_{BM}	-1.63***	-1.58***		-0.96**
	(-4.88)	(-5.28)		(-3.41)		(-2.76)	(-2.58)		(-2.18)
B/M_{ave}		0.62***		0.53**	B/M_{ave}		0.55**		0.49**
		(3.04)		(2.42)			(2.27)		(1.96)
$\log ME$			-0.50***	-0.66***	$\log ME$			-0.18	-0.24
			(-3.86)	(-3.30)				(-1.08)	(-0.85)
REV			-2.63***	-1.83**	REV			-0.23	-0.18
			(-3.05)	(-2.09)				(-1.44)	(-1.13)
MOM			1.38***	1.18**	MOM			3.35***	3.68***
			(2.63)	(2.23)				(3.51)	(3.15)
GP			5.94***	6.63***	GP			5.04***	5.85***
			(4.02)	(5.15)				(3.99)	(4.47)
$IVOL$			-0.06**	-0.07***	$IVOL$			-0.02	-0.03
			(-2.14)	(-2.67)				(-0.80)	(-1.17)
SUE			0.41	0.31	SUE			-0.66	0.52
			(0.92)	(1.21)				(-1.21)	(0.44)
$ILLIQ$			0.59***	0.28***	$ILLIQ$			0.14*	0.17*
			(3.50)	(2.65)				(1.74)	(1.88)
CSI			-0.20***	-0.14**	CSI			-0.22*	-0.15*
			(-2.88)	(-2.39)				(-1.86)	(-1.71)
INV			-2.61**	-1.89*	INV			-1.30	-1.49*
			(-2.24)	(-1.73)				(-1.25)	(-1.93)
Adj. R^2	0.009	0.014	0.073	0.088	Adj. R^2	0.012	0.031	0.165	0.171

Table 6: Long-Horizon Fama–MacBeth Regressions

This table reports the Fama–MacBeth regression results of stock returns of quarters $t+2$, $t+3$, and $t+4$ on I_{BM} and the control variables observed in quarter t. For each horizon, we show the OLS estimates of two model specifications. In addition to the average estimated coefficients and adjusted R^2, the corresponding Newey-West t-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, 1% confidence levels, respectively.

	MODEL	I_{BM}	BM_{ave}	$\log ME$	REV	MOM	GP	$IVOL$	SUE	$ILLIQ$	CSI	INV	Adj. R^2
RET_{t+2}	(1)	-2.65***											0.010
		(-3.22)											
	(2)	-2.96***	0.41***	-0.10**	0.21	0.06	6.25***	-0.09**	0.35	0.62***	-0.41*	-1.84*	0.079
		(-3.44)	(2.63)	(-2.51)	(0.32)	(0.49)	(2.87)	(-2.02)	(1.00)	(2.90)	[-1.77)	(-1.92)	
RET_{t+3}	(1)	-2.30***											0.009
		(-2.94)											
	(2)	-2.13***	0.56**	-0.09*	-0.33	0.14	5.80***	-0.08	0.19	0.84**	-0.57**	-1.52*	0.071
		(-2.79)	(2.47)	(-1.77)	(-1.29)	(0.91)	(2.70)	(-1.59)	(0.66)	(2.36)	(-2.09)	(-1.81)	
RET_{t+4}	(1)	-1.96***											0.009
		(-2.71)											
	(2)	-2.05**	0.61**	-0.05	-0.21	-0.17	5.10**	-0.07	0.62	0.75**	-0.23	-0.93	0.060
		(-2.50)	(2.23)	(-1.53)	(-0.88)	(-0.85)	(2.37)	(-1.44)	(1.02)	(2.22)	(-1.05)	(-0.60)	

Table 7: I_{BM} and Measures of Future Growth Options

This table reports the Fama–MacBeth regression results of a firm's four future growth option measures (β^{ID}, GOC, LEV, and β^{IMC}) in quarters $t+1$, $t+2$, $t+3$, and $t+4$ on I_{BM} and the control variables. For each horizon, we show the OLS estimates of two model specifications, one without controls and the other with all the control variables as in Table **??**. In addition to the adjusted R^2, we only show the average estimated coefficient on I_{BM} and the corresponding Newey–West t-statistic in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Variable	t+1		t+2		t+3		t+4	
Name	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: β^{ID}								
I_{BM}	-0.835***	-0.797***	-0.775***	-0.741***	-0.720***	-0.694***	-0.670***	-0.636***
	(-7.62)	(-7.29)	(-7.51)	(-7.08)	(-6.95)	(-6.63)	(-6.33)	(-5.92)
CONTROLS	NO	YES	NO	YES	NO	YES	NO	YES
Adj. R^2	0.014	0.052	0.012	0.048	0.012	0.045	0.009	0.041
Panel B: GOC								
I_{BM}	-0.009***	-0.007***	-0.008***	-0.007***	-0.006***	-0.006***	-0.005***	-0.004***
	(-6.20)	(-4.27)	(-5.93)	(-3.99)	(-4.83)	(-4.41)	(-4.05)	(-3.66)
CONTROLS	NO	YES	NO	YES	NO	YES	NO	YES
Adj. R^2	0.046	0.128	0.040	0.114	0.039	0.102	0.036	0.088
Panel C: Book LEV								
I_{BM}	-0.022***	-0.019***	-0.020***	-0.015***	-0.017***	-0.013***	-0.013***	-0.011***
	(-4.97)	(-4.35)	(-4.58)	(-4.04)	(-3.75)	(-3.41)	(-3.00)	(-2.81)
CONTROLS	NO	YES	NO	YES	NO	YES	NO	YES
Adj. R^2	0.018	0.094	0.015	0.088	0.012	0.082	0.010	0.066
Panel D: β^{IMC}								
I_{BM}	-0.147***	-0.122***	-0.116***	-0.098***	-0.091**	-0.084**	-0.086*	-0.070*
	(-3.28)	(-2.79)	(-2.72)	(-2.60)	(-2.31)	(-2.12)	(-1.91)	(-1.77)
CONTROLS	NO	YES	NO	YES	NO	YES	NO	YES
Adj. R^2	0.011	0.083	0.009	0.075	0.008	0.064	0.006	0.049

Table 8: I_{BM} and Innovations

This table reports, the value–weighted average innovation proxies of decile portfolios formed by sorting stocks on I_{BM}. Following Kogan, Papanikolaou, Seru, and Stoffman (2017) and Hall, Jaffe, and Trajtenberg (2005), ξ is the raw market value of patents. xi_{Adj} is the time–adjusted market value of patents. $nCites$ is the number of future patent citations. $CiteAdj$ is the adjusted number of future patent citations. We download the data from Professor Noah Stoffman's website.The row of H–L spreads reports the differences of average returns between decile 10 and decile 1, with the corresponding Newey–West t-statistics shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

I_{BM} Decile	(1) ξ	(2) ξ_{Adj}	(3) nCites	(4) CiteAdj
Low	420.06	26.17	156.72	17.56
2	386.05	28.88	204.75	22.19
3	234.25	20.52	177.43	18.16
4	161.86	14.76	137.99	13.33
5	115.71	11.02	140.96	12.47
6	100.56	9.21	125.49	12.44
7	92.78	7.64	134.42	13.18
8	83.49	7.77	114.85	11.50
9	105.53	10.78	122.17	12.85
High	78.81	7.62	127.14	11.93
H–L	-341.25***	-18.55***	-29.58**	-5.63**
t Stats.	(-8.75)	(-6.31)	(-2.44)	(-2.10)

Table 9: LTA and I_{BM}

This table reports the value-weighted average next-quarter returns of portfolios formed by double sorting stocks on the I_{BM} and proxies of LTA. For each LTA proxies, we first sort stocks into quintiles by the LTA proxy, and then within each quintile, we further sort stocks into quintiles by I_{BM}. We then report the H–L spread in percentage between I_{BM} quintiles 5 and 1 within each control variable quintile. The corresponding Newey-West t-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, 1% confidence levels, respectively. Panel A is corresponding to the sorts with $IVOL$ and I_{BM}, while Panel B is for the sorts using institutional ownership and I_{BM}.

Panel A: $IVOL$ Sorts

I_{BM}		$IVOL$ Quintiles			
Quintiles	LOW	Q_2	Q_3	Q_4	HIGH
LOW	3.56	3.96	4.30	4.08	2.46
Q_2	3.46	3.85	3.48	3.11	1.74
Q_3	2.91	3.49	2.92	2.83	1.36
Q_4	2.66	3.34	2.56	1.48	0.03
HIGH	3.15	2.65	2.36	1.19	0.80
HIGH - LOW	-0.409	-1.312*	-1.944***	-2.886***	-1.662**
t Stats.	(-0.54)	(-1.78)	(-2.70)	(-3.79)	(-2.05)
FF5–Adjusted	-0.603	-1.735**	-2.174**	-3.332***	-2.283***
t Stats.	(-0.74)	(-2.31)	(-3.04)	(-4.25)	(-2.86)

Panel B: Institutional Ownership Sorts

I_{BM}		IO Quintiles			
Quintiles	LOW	Q_2	Q_3	Q_4	HIGH
LOW	3.60	3.93	3.36	4.42	3.63
Q_2	3.52	2.91	3.72	3.87	4.34
Q_3	2.72	2.94	3.80	3.62	3.19
Q_4	2.41	2.85	3.11	3.11	3.73
HIGH	1.81	2.29	2.88	3.05	2.20
HIGH - LOW	-1.791***	-1.639***	-0.481	-1.373**	-1.432**
t Stats.	(-2.84)	(-2.78)	(-0.73)	(-2.29)	(-2.12)
FF5–Adjusted	-1.786***	-1.430**	0.165	-1.356**	-1.449**
t Stats.	(-2.88)	(-2.07)	(0.25)	(-1.99)	(-2.37)

Appendix

BM Migration

To understand the underpinning of the decomposition of BM into I_{BM} and BM_{ave}, we examine the migrations of BM. This can show how BM is driven by the two components.

We construct the transition matrix from quarter t to quarter $t+1$ or $t+8$ as follows. At the end of quarter t, we sort stocks into ascending BM decile portfolios. We then sort stocks into deciles based on quarter $t+1$ or $t+8$ value of BM. The transition matrix shows the fractions of stocks within a decile in quarter t move into another decile in quarter $t+s$, where $s=1$ or 8. If BM is not persistent, the entries of the transition matrix should be all close to 10%. The diagonal elements represent the percentage of stocks remain in the same decile in quarter $t+s$. If BM is persistent, we expect the diagonal elements are significantly larger than 10% while the off-diagonal elements are small and decline as they move further away from the diagonal. In the extreme case of no migration, the diagonal entries are all equal to 1, and the off–diagonal entries are all zero.

Panel A (B) in Table A.1 reports the transition matrix of BM from quarter t to quarter $t+1$ ($t+8$). Note that the sum of each column (row) is equal to 1. To gauge the degree of persistence, we consider the diagonal of the matrix. For the lowest (highest) BM decile in quarter t, 77.1% (81.4%) of the stocks remain in the same decile in quarter $t+1$. The persistence is confirmed by the transition matrix in Panel B for t–to–$t+8$. For the lowest (highest) BM decile in quarter t, 46.1% (55.7%) of the stocks remain in the same decile after 8 quarters. The persistence in BM declines but still prevails once we move away from the top and bottom deciles. For deciles 5 and 6 in Panel A, the diagonal elements for the t–to–$t+1$ matrix are 38.4% and 38.3%, respectively. The proportion of stocks that move up or down a decile from decile 5 or decile 6 is about 2/3 of that remaining in the same decile.

In spite of being persistent, the off-diagonal elements of the transition matrices indicate significant migrations across BM deciles. As shown in Panel B, in 8 quarters, about 54% of the stocks classified within the lowest BM decile migrate to other deciles. In fact, about 1% of these stocks move into the highest decile. The evidence confirms the conjecture of Gerakos and Linnainmaa (2017) that BM contains both permanent and temporary components. Kamara, Korajczyk, Lou, and Sadka (2016) argue that the value premium is priced for intermediate horizons such as 24 to 36 months. According to their observation, the persistent component in BM is best captured at the intermediate horizons, consistent with our choice of 8 quarters to decompose BM into I_{BM} and BM_{ave}.

To verify that I_{BM} and BM_{ave} are proxies of the temporary and permanent components of BM, we show their transition matrices in Tables A.2 and A.3, respectively. The results of Tables A.2 indicate that I_{BM} is not persistent. For example, as shown in Panel B, the stocks in decile 1 at t migrate almost evenly into other deciles after 8 quarters. More surprisingly, about 33% of the stocks in decile 10 at t migrate into decile 1 after 8 quarters. On the other hand, the results of Tables A.3 show that BM_{ave} is highly persistent. The fraction of stocks in decile 1 at time t that move into deciles 9 and 10 at time $t+8$ is below 1%. The evidence confirms BM_{ave} as a proxy of the permanent component while I_{BM} as a proxy of the temporary component.

Annual Data

We have also considered using annual data to define I_{BM}. Because annual fundamentals are basically cumulative sums of quarterly fundamentals, we adopt another alternative construction of I_{BM}. Assuming B_t/M_t to be the book–to–market ratio of year t, we define:

$$\hat{I}_{BM} = B_t/M_t - B_{t-1}/M_{t-1}.$$

That is, we treat BM as a unit root process so that the first difference is the innovation. we follow the approach of Asness and Frazzini (2013) to construct BM at the end of June in each year by dividing the book value of the previous fiscal year by the stock price at the end of June. This is a slight modification of the method in Fama and French (1992). Note that $\hat{I}_{BM}$ remains constant until June of next year. We repeat all the analysis with this alternative measure but only present two tables.

Tables A.4 and A.5 show the results of single portfolio sorts and Fama–MacBeth regressions for $\hat{I}_{BM}$. In addition to quarter $t+1$, we also report results for quarters $t+2$, $t+3$, and $t+4$. The evidence indicates that $\hat{I}_{BM}$ negatively predict returns of quarters $t+1$ and $t+2$. For quarters $t+3$ and $t+4$, the relation between $\hat{I}_{BM}$ and return is mostly negative but insignificant. This is not surprising as the predictability of quarterly BM innovation decays over time. Quarters $t+3$ and $t+4$ in the annual data are often more than one year after the book value being recorded. The results for the annual data are consistent with our findings for the quarterly data.

Table A.1: Transition Matrix of B/M

This table reports the transition matrix of B/M–sorted portfolios. At the end of quarter t, all stocks are sorted into ascending B/M deciles. For each decile, the table reports the time–series average of the fraction of stocks in the decile in quarter t fall into another decile in quarter $t+s$. Panel A shows the results for $s = 1$, while Panel B shows the results for $s = 8$.

Panel A: t to t+1

					t+1					
t	1	2	3	4	5	6	7	8	9	10
1	0.94	0.059	0.001	0	0	0	0	0	0	0
2	0.056	0.851	0.09	0.002	0	0	0	0	0	0
3	0.002	0.088	0.795	0.112	0.003	0	0	0	0	0
4	0.001	0.002	0.108	0.756	0.127	0.005	0.001	0	0	0
5	0	0.001	0.004	0.123	0.731	0.134	0.005	0.001	0	0
6	0	0	0.001	0.005	0.132	0.724	0.133	0.004	0.001	0
7	0	0	0	0.001	0.006	0.13	0.736	0.123	0.003	0
8	0	0	0	0	0.001	0.005	0.122	0.771	0.1	0.001
9	0	0	0	0	0	0.001	0.002	0.1	0.837	0.059
10	0	0	0	0	0	0	0	0.001	0.059	0.939
Total	1	1	1	1	1	1	1	1	1	1

Panel B: t to t+8

					t+8					
t	1	2	3	4	5	6	7	8	9	10
1	0.650	0.210	0.061	0.030	0.016	0.012	0.007	0.005	0.004	0.004
2	0.192	0.383	0.210	0.094	0.050	0.031	0.019	0.011	0.007	0.003
3	0.058	0.205	0.297	0.196	0.105	0.060	0.035	0.022	0.014	0.006
4	0.029	0.088	0.200	0.243	0.188	0.110	0.066	0.039	0.026	0.010
5	0.018	0.046	0.103	0.192	0.226	0.184	0.114	0.067	0.035	0.015
6	0.013	0.024	0.055	0.115	0.192	0.219	0.182	0.117	0.061	0.023
7	0.010	0.016	0.031	0.063	0.117	0.188	0.229	0.196	0.112	0.038
8	0.009	0.015	0.021	0.038	0.059	0.112	0.196	0.258	0.219	0.072
9	0.010	0.009	0.015	0.020	0.036	0.062	0.114	0.210	0.332	0.193
10	0.011	0.004	0.007	0.009	0.013	0.020	0.036	0.074	0.189	0.638
Total	1	1	1	1	1	1	1	1	1	1

Table A.2: Transition Matrix of I_{BM}

This table reports the transition matrix of I_{BM}–sorted portfolios. At the end of quarter t, all stocks are sorted into ascending I_{BM} deciles. For each decile, the table reports the time–series average of the fraction of stocks in the decile in quarter t fall into another decile in quarter $t+s$. Panel A shows the results for $s = 1$, while Panel B shows the results for $s = 8$.

Table A.1:Transition Matrix of B/M

Panel A: t to t+1

	t+1									
t	1	2	3	4	5	6	7	8	9	10
1	0.687	0.178	0.04	0.017	0.012	0.01	0.009	0.01	0.011	0.025
2	0.132	0.408	0.227	0.09	0.041	0.027	0.022	0.019	0.018	0.015
3	0.036	0.176	0.307	0.215	0.107	0.056	0.036	0.03	0.021	0.014
4	0.02	0.073	0.176	0.262	0.206	0.116	0.065	0.042	0.026	0.015
5	0.013	0.039	0.089	0.18	0.245	0.197	0.119	0.066	0.035	0.016
6	0.012	0.029	0.054	0.095	0.18	0.237	0.202	0.115	0.056	0.019
7	0.012	0.023	0.036	0.06	0.105	0.186	0.243	0.204	0.101	0.029
8	0.015	0.025	0.028	0.039	0.058	0.102	0.187	0.265	0.216	0.065
9	0.022	0.025	0.024	0.027	0.032	0.049	0.091	0.194	0.339	0.197
10	0.051	0.024	0.019	0.015	0.014	0.02	0.026	0.055	0.177	0.605
Total	1	1	1	1	1	1	1	1	1	1

Panel B: t to t+8

	t+8									
t	1	2	3	4	5	6	7	8	9	10
1	0.176	0.109	0.083	0.068	0.059	0.058	0.063	0.083	0.107	0.195
2	0.073	0.095	0.1	0.098	0.091	0.096	0.107	0.116	0.122	0.101
3	0.048	0.084	0.098	0.109	0.11	0.121	0.123	0.119	0.109	0.079
4	0.037	0.072	0.094	0.112	0.128	0.135	0.133	0.124	0.101	0.066
5	0.03	0.068	0.099	0.122	0.135	0.135	0.134	0.116	0.098	0.062
6	0.031	0.071	0.104	0.126	0.139	0.135	0.126	0.112	0.096	0.06
7	0.041	0.088	0.11	0.126	0.127	0.121	0.115	0.104	0.099	0.068
8	0.065	0.116	0.123	0.113	0.106	0.101	0.095	0.095	0.1	0.085
9	0.128	0.16	0.121	0.087	0.075	0.067	0.068	0.085	0.096	0.112
10	0.371	0.137	0.068	0.039	0.03	0.031	0.036	0.046	0.072	0.172
Total	1	1	1	1	1	1	1	1	1	1

Table A.3: Transition Matrix of BM_{ave}

This table reports the transition matrix of BM_{ave}–sorted portfolios. At the end of quarter t, all stocks are sorted into ascending BM_{ave} deciles. For each decile, the table reports the time–series average of the fraction of stocks in the decile in quarter t fall into another decile in quarter $t+s$. Panel A shows the results for $s = 1$, while Panel B shows the results for $s = 8$.

Panel A: t to $t+1$

	$t+1$									
t	1	2	3	4	5	6	7	8	9	10
1	0.915	0.080	0.004	0.001	0.000	0.000	0.000	0.000	0.000	0.000
2	0.082	0.799	0.111	0.006	0.001	0.000	0.000	0.000	0.000	0.000
3	0.002	0.115	0.742	0.130	0.009	0.002	0.001	0.000	0.000	0.000
4	0.001	0.004	0.137	0.706	0.141	0.009	0.002	0.001	0.000	0.000
5	0.000	0.001	0.006	0.148	0.688	0.146	0.009	0.002	0.001	0.000
6	0.000	0.000	0.001	0.007	0.153	0.690	0.141	0.007	0.001	0.000
7	0.000	0.000	0.000	0.001	0.006	0.147	0.712	0.128	0.004	0.000
8	0.000	0.000	0.000	0.000	0.001	0.005	0.132	0.752	0.108	0.001
9	0.000	0.000	0.000	0.000	0.000	0.001	0.003	0.109	0.824	0.062
10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.062	0.936
Total	1	1	1	1	1	1	1	1	1	1

Panel B: t to $t+8$

	$t+8$									
t	1	2	3	4	5	6	7	8	9	10
1	0.564	0.216	0.092	0.050	0.029	0.020	0.013	0.008	0.004	0.002
2	0.229	0.304	0.194	0.107	0.067	0.042	0.027	0.017	0.009	0.003
3	0.096	0.211	0.247	0.174	0.113	0.068	0.045	0.026	0.016	0.005
4	0.045	0.120	0.192	0.211	0.167	0.117	0.074	0.043	0.025	0.007
5	0.024	0.064	0.119	0.182	0.197	0.171	0.118	0.073	0.039	0.012
6	0.015	0.037	0.070	0.126	0.184	0.197	0.171	0.115	0.067	0.018
7	0.010	0.021	0.040	0.078	0.122	0.180	0.214	0.185	0.115	0.033
8	0.007	0.014	0.026	0.042	0.071	0.120	0.188	0.251	0.212	0.069
9	0.006	0.009	0.014	0.022	0.037	0.066	0.117	0.213	0.328	0.188
10	0.004	0.004	0.006	0.008	0.012	0.018	0.033	0.068	0.185	0.663
Total	1	1	1	1	1	1	1	1	1	1

Table A.4: Annual Single Portfolio Sorts

This table reports, using the annual COMPUSTAT data, the value–weighted average future returns in quarters $t+1$, $t+2$, $t+3$, and $t+4$ of decile portfolios formed by sorting stocks on $\hat{I}_{BM}$. R_{raw} is the raw return, R_{FF} is the 5-factor-adjusted return following Fama and French (2016), and R_C is the 4-factor-adjusted return following Carhart (1997). The row of H–L spreads reports the differences of average returns between decile 10 and decile 1, with the corresponding Newey-West t-statistics shown in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively. Panel A reports the results for the full sample, while Panel B reports the results for the sub sample by excluding the microcap stocks, whose market capitalizations fall below the 20th percentile of NYSE stocks.

	R_{raw}				R_{FF}				R_C			
Decile	$t+1$	$t+2$	$t+3$	$t+4$	$t+1$	$t+2$	$t+3$	$t+4$	$t+1$	$t+2$	$t+3$	$t+4$
Panel A: Full Sample												
1	3.84	4.12	3.06	2.74	2.20	4.86	3.05	3.21	1.93	4.83	3.03	3.27
2	3.49	4.14	2.17	3.49	1.35	5.14	3.00	2.87	1.26	5.11	2.92	2.90
3	2.78	4.34	1.37	2.47	1.27	4.50	3.50	3.51	1.69	4.49	3.25	3.53
4	1.58	5.40	0.74	3.90	1.05	5.09	2.78	3.19	1.04	5.09	2.64	3.22
5	2.94	5.81	1.96	2.55	0.32	4.68	2.31	2.96	0.30	4.67	1.97	3.00
6	1.92	5.76	1.42	3.04	0.23	3.99	2.76	3.33	0.22	3.98	2.73	3.37
7	1.65	4.40	3.00	3.61	0.89	4.06	2.42	3.13	0.89	4.05	1.98	3.16
8	1.78	3.24	0.91	3.28	-0.14	4.01	1.89	3.05	-0.15	4.00	1.84	3.08
9	0.55	3.08	1.31	1.87	0.31	3.52	2.67	3.44	0.29	3.48	2.63	3.48
10	0.98	1.36	2.44	1.05	-0.09	2.68	2.46	2.56	-0.10	2.65	2.42	2.60
H–L	-2.87***	-2.75***	-0.62	-1.69	-2.29***	-2.18***	-0.59	-0.65	-2.03**	-2.18***	-0.61	-0.67
	[-3.10]	[-2.99]	[-0.41]	[-1.49]	[-2.75]	[-2.68]	[-0.31]	[-0.69]	[-2.54]	[-2.78]	[-0.49]	[-0.55]
Panel B: All But Microcap												
1	3.65	4.41	2.17	3.09	2.40	4.92	2.97	2.80	2.29	4.90	3.10	2.84
2	3.06	4.58	2.53	4.13	2.17	4.92	2.96	3.14	2.16	4.59	3.08	3.53
3	2.87	3.84	1.20	2.74	1.35	4.67	2.61	3.24	1.33	4.67	2.66	3.06
4	2.89	5.39	0.63	4.18	1.36	4.74	2.10	3.16	1.36	4.60	2.14	3.11
5	1.60	5.48	1.94	2.88	1.03	4.77	2.09	3.12	1.02	4.25	2.14	3.06
6	1.67	5.36	0.86	2.60	0.42	4.46	2.06	3.02	0.41	4.45	2.11	3.15
7	2.23	4.30	3.24	3.28	0.14	3.90	2.21	3.08	0.13	3.89	2.26	3.19
8	1.54	4.05	0.92	3.47	0.63	3.83	2.20	3.03	0.62	3.81	2.27	3.26
9	2.09	4.12	1.84	1.78	0.23	3.59	2.47	3.49	0.21	3.58	2.53	3.17
10	0.42	1.66	1.46	1.87	-0.21	2.67	2.63	2.47	-0.17	2.82	2.38	2.67
H–L	-3.24***	-2.75**	-0.71	-1.22*	-2.61***	-2.25***	-0.34	-0.33	-2.46***	-2.08**	-0.72	-0.18
	[-3.24]	[-2.44]	[-0.65]	[-1.84]	[-2.83]	[-2.79]	[-0.88]	[-0.61]	[-2.92]	[-2.55]	[-1.13]	[-0.25]

Table A.5: Annual Fama–MacBeth Regressions

This table reports, using the annual COMPUSTAT data, the estimation results of Fama–MacBeth regressions in two model specifications. The dependent variable is the stock return of quarter $t+1$, $t+2$, $t+3$, or $t+4$, and the explanatory variables include I_{BM} and the control variables. In addition to the average estimated coefficients and adjusted R^2, the Newey-West t-statistics are shown in brackets. *, **, and *** indicate significance at the 10%, 5%, 1% confidence levels, respectively. The regressions are estimated by the OLS.

	$t+1$		$t+2$		$t+3$		$t+4$	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
I_{BM}	-0.390***	-0.337***	-0.251***	-0.185**	0.007	0.188	-0.138*	-0.070
	[-3.58]	[-3.03]	[-2.89]	[-2.08]	[0.14]	[1.01]	[-1.81]	[-1.02]
$\log BM_{ave}$		0.325***		0.276**		0.245**		0.212***
		[2.83]		[2.13]		[1.97]		[3.10]
$\log ME$		-0.039		0.270***		-0.472***		-0.090
		[-0.52]		[3.49]		[-5.08]		[-1.51]
REV		0.800*		1.812***		-1.541***		-0.746**
		[1.70]		[3.14]		[-2.96]		[-2.40]
MOM		-0.711		3.985		1.225		-2.067
		[-0.42]		[1.56]		[1.26]		[-1.49]
GP		0.490***		0.890***		0.744***		0.544*
		[4.12]		[3.78]		[3.11]		[1.88]
$IVOL$		-0.024*		-0.006		0.046***		0.007
		[-1.80]		[-0.32]		[3.58]		[0.68]
$ILLIQ$		0.154***		-0.021		0.096**		0.063*
		[2.87]		[-0.41]		[2.37]		[1.72]
CSI		-0.248***		-0.172**		-0.054		0.026
		[-3.26]		[-2.54]		[-1.62]		[1.08]
INV		-0.031**		-0.026**		-0.010		-0.020
		[-2.50]		[-2.39]		[-1.47]		[-1.37]
Adj. R^2	0.010	0.031	0.009	0.024	0.008	0.020	0.006	0.017