There is a Growth Premium After All*

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Abstract

The conventional wisdom argues that the growth stocks are riskier to earn a higher premium. However, the empirical evidence points out that the value stocks, which are classified based on the book-to-market ratio, tend to have a higher premium. To solve this tension, this paper decomposes the book-to-market ratio into two components, a trend component, and a temporary (innovation) component. Both economic interpretation and empirical results show that the temporary component has a strong negative relationship with future cross-sectional stock returns even after controlling for main return predictors including Book-to-Market ratio, while the trend component is positively associated with the value premium. Therefore, consistent with conventional wisdom, our results confirm that there is growth premium captured by the temporary component of the book-to-market ratio.

JEL Classification: G12

keyword: Book-to-Market ratio, Temporary Component of B/M, Growth Option, Growth Premium

1 Introduction

Conventional wisdom suggests that growth stocks, characterized by low book-to-market ratios (B/M), should earn higher expected returns than value stocks because growth options, which are leveraged positions, are riskier than assets-in-place (e.g., Cox and Rubinstein (1985); Bernardo, Chowdhry, and Goyal (2007)). However, the empirical evidence overwhelmingly points the opposite: value stocks with high book-to-market ratios earn higher average returns than growth stocks (e.g., Fama and French (1993); Fama and French (1998)). The value premium counter-intuitively implies that assets-in-place are riskier than growth options (e.g., Lettau and Wachter (2007); Zhang (2005)).

In this paper, we reconcile the conventional wisdom and the empirical evidence by decomposing the B/M into two components, a temporary component, and a persistent trend component. We use the 8-quarter backward looking moving average of the book-to-market (B/M) ratio as the proxy for the trend component of B/M. The temporary component refers to the difference between current B/M and the persistent trend component. Our baseline results indicate that the temporary component of B/M ($\mathbf{I}_{(B/M)}$) captures the value of real options in firms and has a strong negative relation with cross–sectional stock returns even after controlling for various return predictors. The negative relation between $\mathbf{I}_{(B/M)}$ and stock returns indicates a growth premium. In contrast, the trend component of B/M (BM_{ave}) is positively associated with stock returns. In other words, the value premium concentrates in the BM_{ave} component while the growth premium concentrates in the $\mathbf{I}_{(B/M)}$ component.

Our decomposition of B/M into the trend and temporary components is motivated by the time–series properties of B/M and further strengthened by the real option approach of stock valuation. Our empirical evidence finds that the B/M is both persistent and time–varying. A decomposition of B/M into the trend and temporary components naturally fits the time–series properties of B/M. Our decomposition is further supported by the conjectures in recent literature such as Gerakos and Linnainmaa (2017), Golubov and Konstantinidi (2016), and Rhodes-Kropf, Robinson, and Viswanathan (2005).

More importantly, the temporary and trend components are corresponding to different elements in the real option valuation models. Specifically, the prior theory of real options decomposes the market equity of firms into two components: the present value of future cash flows from assets-in-place and the value of real options (e.g., Berk, Green, and Naik (1999); Bernardo, Chowdhry, and Goyal (2007); Cochrane (1991); Cochrane (1996); Gomes, Kogan, and Zhang (2003); Hillier, Grinblatt, and Titman (2011)). In the theoretical models, the sequential cash flows from the assets-in-place can be represented by a sequence of constants or a trajectory of cash flows with a fixed growth rate (e.g., Berk, Green, and Naik (1999); Bernardo, Chowdhry, and Goyal (2007)). Thus, the cash flows from assets-in-place can be represented by a drift term (or a deterministic trend) plus a random walk component, which is similar to the settings of a persistent trend component in the time series analysis. Therefore, the trend component of B/M mimics the cash flows from the assets-in-place since it captures the embedded cash flow growth path with the existing assets-in-place.

The empirical evidence also supports the relationship between the persistent trend component and assets-in-place. Specifically, we find a strong positive relationship between the trend component and various irreversibility measures. Given the composition of market equity, we can even back out that the temporary component of B/M is related to the value of growth option. The economic intuition on the association between the value of growth options and the temporary component of B/M can be illustrated through the properties of the growth options and B/M. First, the change in B/M is largely driven by the change in the market equity (e.g., Gerakos and Linnainmaa (2017)). A step further, because the elasticity of a growth option is larger than one, the component of growth opportunities of the market equity dominates the component of assets-in-place when the book value changes. Therefore, the "abnormal" changes in B/M is driven by the change in the value of growth options and well captured by the temporary component of B/M.

When a growth option is exercised, the book value increases but the market equity declines because the option is more valuable when it is alive than being exercised. As higher growth opportunities imply higher risk, we posit a negative cross-sectional predictive relation between $\mathbf{I}_{(B/M)}$ and future stock returns.

We check the return predictability power of $\mathbf{I}_{(B/M)}$ and BM_{ave} by using both portfolio sorts and Fama–MacBeth regressions. When stocks are sorted on $\mathbf{I}_{(B/M)}$ into decile portfolios, the equal–weighted average next–quarter portfolio return decreases from decile 1 to decile 10. The high minus low (H-L) spread between deciles 10 and 1 is -2.152% per quarter (an annualized spread of -8.608%) and statistically significant at the 1% level. Value–weighting stock returns and adjusting returns by the conventional risk factors can even make the results stronger. The evidence is corroborated by the estimates of Fama–MacBeth regressions, even in the presence of other return predictors including B/M itself. To further test the robustness of our results, we also include in our alternative sample only the non-microcap stocks and employ the value–weighted least square Fama–MacBeth regressions following Green, Hand, and Zhang (2017). Interestingly, in portfolios simultaneously sorted on both $\mathbf{I}_{(B/M)}$ and BM_{ave}, and in cross–sectional regressions of returns at the firm level, the negative $\mathbf{I}_{(B/M)}$ effect on returns and positive BM_{ave} effect on returns neither drive out nor dominate each other.

The growth premium of $\mathbf{I}_{(B/M)}$ has important implications on the migration between value and growth stocks. Fama and French (2007a) and Fama and French (2007b) among others find that the value premium can be attributed to the convergence of value and growth stocks using B/M as the benchmark. In other words, growth (value) stocks migrate to value (growth) category right after the classification of their value/growth types. The migration of growth stocks to value stocks can be caused either by the successful growth option conversion or by market value destruction (e.g., Piotroski (2000)). Successful growth option conversion leads to an increase in the B/M, i.e., an increase in book value and a relatively larger decrease in firm value. On the other hand, if growth stocks fail to live up to the expectation of investors, their market values decrease. However, using B/M as the benchmark cannot justify whether the increase in B/M is contributed to market value destruction or successful transformation of the market value to book value.

We find that our $\mathbf{I}_{(B/M)}$ measure can justify the growth option conversion or value destruction. Specifically, we have designed tests to track the future dynamics of fundamentals among different $\mathbf{I}_{(B/M)}$ portfolios. We find that the growth stocks with high $\mathbf{I}_{(B/M)}$ tend to have excess migration to value stocks, experiencing less growth option conversion and higher investors' over–extrapolation errors. Additionally, value stocks with high $\mathbf{I}_{(B/M)}$ are the ones with higher propensity to remaining in the value stock group. Our findings indicate that the growth premium is largely driven by firms' failure to convert growth options to assets-in-place and the failure to live up to investors' expectation.

Our findings even cast doubt on the recent argument (e.g., Golubov and Konstantinidi (2016)) that the value premium is a behavioral phenomenon. In our decomposition, $\mathbf{I}_{(B/M)}$ is highly correlated with behavioral measures while B/M_{ave} is associated with rational measures such as firm fundamentals. Our empirical test shows that the growth premium is driven by the $\mathbf{I}_{(B/M)}$ and the value premium is driven by the B/M_{ave}. Since $\mathbf{I}_{(B/M)}$ absorbs all the 'irrational' component of B/M, it is unlikely that a rational-based measure B/M_{ave} leads to a irrational value premium.

Our paper contributes to the literature from at least three aspects. First, our decomposition of B/M demonstrates that growth premium and value premium co–exists in the temporary component and the persistent trend component, respectively. Our decomposition adds a new dimension to the existing literature on the decomposition of B/M such as Gerakos and Linnainmaa (2017), Golubov and Konstantinidi (2016), and Rhodes-Kropf, Robinson, and Viswanathan (2005). Second, we demonstrate that to capture the migration between value and growth stocks, one needs to simultaneously consider the BM_{ave} corresponding to the value/growth convergence and the $\mathbf{I}_{(B/M)}$ component corresponding to the value/growth divergence. Third, the $\mathbf{I}_{(B/M)}$ is a novel and strong return predictor which has the potential to be designed for trading strategies.

Section 2 presents our decomposition of the book-to-market ratio into a persistent trend component and a temporary component. Section 3 illustrates the information contents of $\mathbf{I}_{(B/M)}$ and BM_{ave}. Section 4 reports the return predictive power of $\mathbf{I}_{(B/M)}$ and BM_{ave} by using both portfolio sorts and Fama-MacBeth regressions. Section 5 shows the relation between $\mathbf{I}_{(B/M)}$ and the firms future fundamentals. Section 6 concludes.

2 Decomposition of Book-to-Market Ratio

2.1 Classical Dividend Discount Model

Borrowing the terminology of Fama and French (2006), the dividend discount model says that the market value of a stock is the present value of expected dividends:

$$M_t = \sum_{\tau=1}^{\infty} \frac{E(D_{t+\tau})}{(1+r)^{\tau}}, \tag{1}$$

where M_t is the market price at t, $E(D_{t+\tau})$ is the expected dividend of period $t+\tau$, and r is the long-term average expected stock return. With clean surplus accounting, D_t is equal to earnings per share, Y_t, minus the change of book value per share, $\Delta B_t = B_t - B_{t-1}$. Using these notations to replace D_t and dividing market equity by book equity, we have:

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - \Delta B_{t+\tau})}{(1+r)^{\tau}}}{B_t}. \tag{2}$$

If expected earnings and expected changes in book equity (both measured relative to current book equity) are fixed, then a higher market-to-book ratio, M_t/B_t, implies a lower expected stock return, r. If we use the book-to-market ratio, B_t/M_t, then it implies a positive relation between r and B_t/M_t, which is consistent with the empirical evidence in the literature. Vuolteenaho (2002) also derives the same positive relation between r and B_t/M_t using the log-linear approximation.

2.2 A Model with Growth Opportunities

The above implied positive relation between book-to-market ratio and expected stock return is at odds with the conventional wisdom that low book-to-market stocks are riskier and should earn higher returns due to their higher growth opportunities. To reconcile the opposite views, we note that the classical dividend discount model does not incorporate growth opportunities and is best applicable to stocks with little growth prospect. When a firm has growth opportunities and takes those opportunities, the firm's earnings and book equity can change unexpectedly and significantly. Therefore, "controlling" expected earnings and change of book equity is not feasible in the presence of growth opportunities. We extend the classical dividend discount model by incorporating growth opportunities explicitly. The key insight is treating a firm's stock as a portfolio of an *ex-growth* stock supported only by the existing asset and some growth opportunities, which are treated as call options written on the *ex-growth* stock. Specifically, we write the stock price as the sum of the two components:

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

where V_t is the present value of cash flows generated only by the current book equity, B_t, and C_t is the present value of growth opportunities. In particular, C_t is the value of some call options written on V_t.[1] To differentiate growth opportunities from organic changes of V_t, we assume that the firm has to take certain actions such as new investments to realize growth opportunities. That is, C_t is based on some future projects that have not been taken and therefore not reflected in the current book equity. The expected next-period return of the stock is then the weighted sum of the expected returns of V_t and C_t:

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

[1] Treating growth opportunities as call options is widely used in the literature (e.g., Berk, Green, and Naik (1999); Bernardo, Chowdhry, and Goyal (2007)). Alternatively, we can model growth opportunities as call options written on book equity, B_t. In addition to V_t, the value of C_t can be related to other state variables.

where $w_t^V = V_t/(V_t + C_t)$ and $w_t^C = C_t/(V_t + C_t)$ 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 returns of V_t and C_t, respectively. A well-known result in option pricing theory is that the return of a call option is greater than that of the underlying (e.g., Cox and Rubinstein (1985); Bernardo, Chowdhry, and Goyal (2007)): $E(r_{t+1}^C) \geq E(r_{t+1}^V)$. Hence, the higher the option value relative to the *ex-growth* stock, the higher the expected return of the stock. The market-to-book ratio can be written as:

$$\frac{M_t}{B_t} = \frac{V_t}{B_t} + \frac{C_t}{B_t}. \tag{5}$$

By definition, V_t, the price of the *ex-growth* stock, which is the continuation of the current firm without any future growth opportunities. We can apply the classical dividend discount model to this "ex-growth" stock:

$$\frac{V_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau}^V - \Delta B_{t+\tau}^V)}{(1+r^V)^\tau}}{B_t}, \tag{6}$$

where Y_t^V is the earnings per share, ΔB_t^V is the change of book equity, and r^V is the average expected return of the stock. Clearly, there is a negative relation between r^V and V_t/B_t if Y_t^V and ΔB_t^V are fixed. Equation (5) says that the market-to-book ratio of a stock is equal to the sum of the market-to-book of the *ex-growth* stock and the ratio of growth options to the book equity of the firm. C_t/B_t is very different from V_t/B_t in that C_t is based on future earnings and changes of book value that are not *directly* related to the current book equity.

The generalized model can reconcile the contradiction between the classical dividend discount model and the conventional wisdom. Equation (5) says that a higher value of M_t/B_t can be caused by higher V_t/B_t, C_t/B_t, or both. First, controlling everything else, a higher value of V_t/B_t implies a lower value of r^V per (6) and therefore a lower value of expected stock return, r, following (4). Second, controlling everything else, a higher value of C_t/B_t implies higher value of C_t and therefore a higher value of the expected stock return as the weight of options is greater. Finally, when both V_t/B_t and C_t/B_t are higher, the net impact on the expected stock return depends on the relative magnitude of the individual effects of V_t/B_t and C_t/B_t.

The above discussion provides a potential explanation to why we do not find supporting evidence for higher returns for growth (low book-to-market) stocks. The right measure of growth opportunities is C_t/B_t, but the empirical evidence is based on M_t/B_t, which also contains V_t/B_t. The impact of V_t/B_t is probably so significant that it offsets the impact of C_t/B_t in portfolio sorts and regressions. In the next section, we propose a decomposition of M_t/B_t, which enables us to disentangle the opposite effects of V_t and C_t.

2.3 A Decomposition of Book-to-Market

While it is possible to construct a clean proxy of firm growth opportunities using the public accounting information, we take an econometric approach by exploiting the empirical implications of the decomposition (5). Empirical evidence indicates that M_t/B_t changes as growth stocks become value stocks and vice versa (e.g., Fama and French (2007b)). We will use the information content of the time-series data of M_t/B_t to separate V_t/B_t from C_t/B_t.

Intuitively, as the market-to-book ratio of the *ex-growth* stock, V_t/B_t should be more stable than the growth component C_t/B_t. In other words, the short-run variation of M_t/B_t should be mainly driven by C_t/B_t instead of V_t/B_t. As an extreme example, in the Gordon's growth model with constant dividend growth rate and expected stock return, V_t/B_t is constant. An alternative way of understanding this is that the elasticity of a call option is greater than 1 (e.g., Cox and Rubinstein (1985)).[2] In addition to changes of option as a result of changes of the underlying and other state variables, C_t/B_t can exhibit large variations as options are exercised or expire.

To exploit the difference in variation of V_t/B_t and C_t/B_t, we decompose M_t/B_t as the

[2] The elasticity of an option is the ratio of percentage change of the option value to that of the underlying.

sum of the time-varying mean and the innovation:

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

where μ_t is the mean, and ϵ_t is the innovation. μ_t is suppose to capture the slow-moving level process of of M_t/B_t driven by V_t/B_t while ϵ_t captures the temporary shocks to M_t/B_t caused by C_t/B_t. Because μ_t and ϵ_t are not observed, we construct their empirical proxies. In particular, we use the sample mean of rolling window to approximate μ_t and the difference between the mean and the current observation of M_t/B_t to approximate ϵ_t.

Since B_t/M_t is more often used in the asset pricing literature, we build the corresponding proxies for B_t/M_t for the rest of the paper. We follow Hou, Xue, and Zhang (2015) to use quarterly B/M, defined as the ratio of quarterly book equity to quarter-end market capitalization. The lagged rolling mean, BM_{ave}, and the innovation, $\mathbf{I}_{B/M}$ are defined as:

$$BM_{ave,t} = \frac{1}{s}\sum_{i=1}^{s}\frac{B_{t-i}}{M_{t-i}} \tag{8}$$

$$\mathbf{I}_{B/M,t} = \frac{B_t}{M_t} - BM_{ave,t}, \tag{9}$$

where s is the size of the rolling window. For the benchmark case shown in the paper, $s = 8$. By construction, $B_t/M_t = BM_{ave,t} + \mathbf{I}_{B/M,t}$. The trend component, which is the s-period backward looking moving-average of $\{B/M\}$, must be persistent. In contrast, the temporary component, which is the deviation of the current B_t/M_t from the trend, can exhibit large variations if there are significant changes to growth opportunities.

The idea of backing out the two underlying drivers of B_t/M_t is analogous to identifying two sources of signals with different frequencies. In this case, B_t/V_t is the low frequency source and B_t/C_t is the high frequency source while the two signals are $BM_{ave,t}$ and $\mathbf{I}_{B/M,t}$. Because the two signals are orthogonal by construction, they should be good proxies of the two sources.

2.3.1 $BM_{ave,t}$ and Return

The trend component, $BM_{ave,t}$, is the moving average of book-to-market ratio. Taking moving average smooths out the impact of temporary shocks caused by growth opportunities. Hence, $BM_{ave,t}$ should be highly correlated with B_t/V_t, the book-to-market ratio of the *ex-growth* stock. A higher value of $BM_{ave,t}$ implies higher B_t/V_t and consequently higher expected stock return.

2.3.2 $\mathbf{I}_{B/M}$ and Return

To see that $\mathbf{I}_{B/M,t}$ captures the component of growth opportunities of book-to-market ratio, we examine three basic types of change of book-to-market ratio that involve growth opportunities. Because we have argued that the variation of B_t/V_t is very low, we assume it is equal to its long-run mean at time $t-1$. Any change to B_t/M_t is a combination of the three base cases. In the first case, C_t changes as a result of changes in V_t and other state variables. B_t/M_t increases(decreases) if C_t decreases (increases). Therefore, $\mathbf{I}_{(B/M),t}$ is negatively associated with the change of growth opportunities. In the second case, consider a scenario where a new option is created without any changes to book equity. This is similar to the first case where C_t increases. So the same negative relation between $\mathbf{I}_{(B/M),t}$ and the change of growth opportunities holds.

Finally, assume that a growth opportunity is taken at time t. That is, a call option is exercised. We assume that the firm invests K to take the opportunity, W is the present value of the cash flows of the growth opportunity, and C_0 is the option value of the opportunity at time $t-1$. The growth option can be regarded as a European option with expiration at t. After the growth opportunity being taken, the book value becomes $B_t = B_{t-1} + K$, the value of growth opportunities is reduced to $C_t = C_{t-1} - C_0$, and the market value becomes $M_t = V_{t-1} + W - K + C_{t-1} - C_0$. Using the fact that $C_0 \geq W - K$ from the option pricing theory, it is straight forward to show that $B_t/M_t > B_{t-1}/M_{t-1}$. Once again, B_t/M_t changes in the opposite direction of growth opportunities. Interestingly, we have just showed that exercising growth options is a channel of migration.

Taken together, a higher value of $\mathbf{I}_{B/M}$ is likely caused by a decline in C_t/B_t and consequently implies lower expected stock return.

3 The Information Contents of $\mathbf{I}_{(B/M)}$ and BM_{ave}

3.1 Data and Sample

To form the main measures and other variables, we consider all NYSE, AMEX, and NASDAQ firms in the CRSP monthly stock return files up to December, 2015. In this study, stock return and accounting data are obtained from the CRSP and COMPUSTAT, except financial stocks (four digit SIC codes between 6000 and 6999) and stocks with end–of–quarter share price less than \$1. We further require a firm to have at least 16 quarters of B/M during 1971–2015 to be included in the sample. t is the year–quarter indicator such as "January 1996" and $t-1$ indicates "December 1995".

3.2 The Time Series Properties of $\mathbf{I}_{(B/M)}$ and BM_{ave}

To justify the needs for the decomposition of B/M into $\mathbf{I}_{(B/M)}$ and BM_{ave}, we first explore the time–series properties of B/M, specifically the persistence and the time variation of B/M. Our main argument is that the B/M contains two different components: a temporary and fast–moving component which is captured by $\mathbf{I}_{(B/M)}$ and a persistent and slow–moving component BM_{ave}.

We use the transition matrix for the two different quarters to detect the persistence and the time variation of B/M. Specifically, at the end of each quarter t, we sort all stocks into ascending B/M decile portfolios. We further sort stocks into deciles based on quarter $t+1$ $(t+8)$ B/M. The transition matrix in Panel A reports the percentage of stocks in quarter t that fall in each quarter $t+1$. If B/M is random but not persistent, the elements in the transition matrix should be all around 10%. The diagonal elements represents the average percentage of stocks falls in the same decile in quarter t and quarter $t+n$. Thus, if B/M process is persistent, we expect the diagonal elements are significantly larger than 10%.

Panel A in Table 1 presents the transition matrix of B/M from quarter t to quarter $t+1$. The results in Table 1 indicate that B/M is highly persistent. To gauge the degree of persistency, we look at the diagonal of the matrix. Around 77.1% (81.4%) of the stocks within the lowest (highest) B/M decile in quarter t still remain in the same decile. The persistence of B/M is confirmed by the Markov transition matrix using a much longer horizon. The Panel B in Table 1 report the Markov transition matrix for B/M from quarter t to quarter $t+8$. Even in a much longer horizon such as two years' time period, the B/M can still be classified as persistent. Specifically, the results in Table 2 indicate that 46.1% of the stocks with B/M classified within decile 1 in quarter t are still in decile 1 after eight quarters' evolution.

Even though highly persistent, the B/M still exhibits some degrees of time variation. In two years' time period, 54% (1-46%) of the stocks classified within the decile with lowest B/M migrates to other deciles. The time variation of B/M is further confirmed in the Appendix 1 using the variance ratio test. To sum up, the Markov transition matrix indicates that the B/M is both persistent and time–varying. Our finding also confirms the conjecture in Gerakos and Linnainmaa (2017) that the B/M contains both permanent and temporary components. Per Kamara, Korajczyk, Lou, and Sadka (2016), the value premium is priced over intermediate horizons such as 24 to 36 months. Thus, the value premium is priced for its slow–moving and persistent component in B/M corresponding to the intermediate horizons. Our decomposition of B/M into $\mathbf{I}_{(B/M)}$ and BM_{ave} can explore the different dynamics of the two components.

We first employ the Markov transition matrices to examine whether the $\mathbf{I}_{(B/M)}$ and BM_{ave} are the temporary and permanent components, respectively. Table 2 reports the Markov transition matrix for $\mathbf{I}_{(B/M)}$. Panel A (B) is the transition matrix for $\mathbf{I}_{(B/M)}$ from quarter t to quarter $t+1$ ($t+8$). We choose $t+8$ as a benchmark case for the transition matrix is because it corresponds to the horizon to construct our $\mathbf{I}_{(B/M)}$ and BM_{ave} measures. We find that the $\mathbf{I}_{(B/M)}$ is fast–moving and much less persistent than B/M. If one measure is not persistent at all, the elements on the diagonal of the transition matrix must be close to 10%, indicating one element has equal probability to fall in any deciles in the next period. Our finding is better illustrated in Panel B. Panel B of Table 2 indicates that 15.3% (15.8%) of stocks within the lowest (highest) $\mathbf{I}_{(B/M)}$ decile still remain in the same decile after eight quarters. The other diagonal elements are all close to 10%.

We then explore the time-series properties of BM_{ave}. The corresponding results are shown in Table 3. The BM_{ave} is even more persistent than B/M. For the decile with highest BM_{ave}, more than 90% (60%) of the stocks remains in the same decile after one (eight) quarter. The $\mathbf{I}_{(B/M)}$ and BM_{ave} successfully decompose the B/M into two components with different time–series properties: a fast–moving one and a persistent one.

3.3 The Correlation Matrix and Summary Statistics

To better understand the information content of $\mathbf{I}_{(B/M)}$ and BM_{ave}, we use correlation matrix to detect the interaction of $\mathbf{I}_{(B/M)}$, $BM_{ave}$and other control variables. Firm characteristics in our analysis include size (Size), the book–to–market ratio (B/M), momentum (MOM), return reversal (REV), gross profitability (GP), and standardized unexpected earnings surprises. All the variables are constructed following convention in the literature and are described as follows:

- Size: The logarithm of market capitalization at the end of each quarter. Market capitalization is the end–of–quarter share outstanding multiplied by the stock price.

- B/M: Book–to–market ratio is the ratio of quarterly book equity to quarter–end market capitalization. Quarterly book equity is constructed by following Hou, Xue, and Zhang (2015) (footnote 9), which is basically a quarterly version of book equity of Davis, Fama, and French (2000).

- MOM: Momentum for month t is defined as the cumulative return between month $t-12$ and month $t-1$. We following the convention in the literature by skipping month t when momentum is used to predict returns in month $t+1$. We have also use the cumulative return between month $t-6$ and $t-1$ and obtained similar results.

- REV: The return reversal in quarter t is the monthly return of the last month within the quarter.

- GP: Following Novy-Marx (2013), gross profitability is defined as quarterly revenue minus quarterly cost of goods sold scaled by quarterly asset total.

- SUE_1: SUE stands for the standardized unexpected earnings. SUE at time t is the quarter t–end price–scaled difference between realized earnings in quarter t and the earnings in quarter $t-1$.

- SUE_2: SUE stands for the standardized unexpected earnings. SUE at time t is the quarter t–end price–scaled difference between realized earnings in quarter t and the median of analyst earnings forecast.

- SUE_3: SUE stands for the standardized unexpected earnings. SUE at time t is the quarter t–end price–scaled difference between realized earnings in quarter t and the mean of analyst earnings forecast.

Table 4 reports the summary statistics and the correlation matrix for $\mathbf{I}_{(B/M)}$ and other control variables. Many interesting patterns show up.

First, we find that our $\mathbf{I}_{(B/M)}$ measure has low correlations with both B/M and BM_{ave}. Specifically, the correlation between $\mathbf{I}_{(B/M)}$ and B/M is only 0.33. Even though $\mathbf{I}_{(B/M)}$ is a transformation of B/M, the low correlation indicates that they have different information contents. Additionally, the correlation between $\mathbf{I}_{(B/M)}$ and BM_{ave} is significantly negative at -0.079. The correlation, on one hand, indicates that the temporary component and persistent trend component share different information contents. On the other hand, we demonstrate in the previous sections that the persistent trend component captures the cash flows from assets-in-place and the temporary component gauges the change in the value of growth options. The negative correlation between $\mathbf{I}_{(B/M)}$ and BM_{ave} justifies our decomposition since the correlation indicates that the firms deriving more values from assets-in-place tend to be not the ones deriving their values from growth options.

Second, Table 4 indicates that the correlation between $\mathbf{I}_{(B/M)}$ and past cumulative returns is high (-0.198). The high correlation is not surprising: if we take a second look at $\mathbf{I}_{(B/M)}$, we can find it captures the unexpected increase in B/M. The strongly negative correlation is straightforward given the connection between fundamentals and momentum (Liu and Zhang (2014); Novy-Marx (2015)).

Last, the correlations of $\mathbf{I}_{(B/M)}$ and other control variables are also consistent with our argument. For instance, the negative correlation between $\mathbf{I}_{(B/M)}$ and gross profitability indicates that value firms are less profitable than growth firms.

4 The Return Predictability

To detect the return–predictive power of $\mathbf{I}_{(B/M)}$ and BM_{ave}, we rely mostly on the portfolio sorts and cross–sectional regressions of Fama and Macbeth (1973) for our empirical investigation.

For single portfolio sorts, we rank stocks on $\mathbf{I}_{(B/M)}$ into decile portfolios and then consider both equal–weighted and value–weighted portfolio returns. If $\mathbf{I}_{(B/M)}$ is negatively related to stock returns, we expect a decreasing pattern of portfolio returns from decile 1 to decile 10. For double portfolio sorts, we first rank stocks into quintiles by a control variable such as size and then further sort stocks within each portfolio into quintiles by $\mathbf{I}_{(B/M)}$. If the control variable can explain the predictability of $\mathbf{I}_{(B/M)}$, we expect the increasing pattern of returns in $\mathbf{I}_{(B/M)}$ to be much less significant in each quintile of the control variable. To compute t–statistics of average portfolio returns, we use the Newey and West (1987) adjusted standard errors because of the persistence in the portfolio compositions[3].

For the Fama and MacBeth regression, we expected the average estimated coefficient of $\mathbf{I}_{(B/M)}$ to be negative and significant. The cross–sectional regressions allow us to examine the marginal effect of the $\mathbf{I}_{(B/M)}$ when controlling for other variables known to predict stock returns. In the most general specification, we include all control variables in the regression. If $\mathbf{I}_{(B/M)}$ captures information about expected stock returns beyond that in other variables, the coefficient of the $\mathbf{I}_{(B/M)}$ should be significant even in the presence of all control variables.

We show the results of portfolio sorts first and then the estimates of Fama and MacBeth regressions. After confirming the return–predictive power of $\mathbf{I}_{(B/M)}$, we turn to more specific tests for the real effect of $\mathbf{I}_{(B/M)}$.

4.1 Single Portfolio Sorts

Panel A of Table 5 reports the average returns and characteristics of the decile portfolios formed by sorting stocks on $\mathbf{I}_{(B/M)}$ for the full sample. When sorted on $\mathbf{I}_{(B/M)}$, the average equal–weighted quarterly return decreases from decile 1 (4.91%) to decile 10 (2.76%). The average high minus low (H-L) spread is -2.152% per quarter (or -8.608% per year) and highly significant (t=-4.56). To make sure the significant *H-L* spread is not driven by higher stock risk, we estimate the risk-adjusted α using the Fama and French (2016) five–factor model. The risk-adjusted *H-L* spread is even larger at -2.923%. The value–weighted *H-L* spreads are very similar to but slightly smaller than the equal–weighted *H-L* spreads, indicating that the results are not dominated by small stocks.

Next, we look at the characteristics of the equal–weighted decile portfolios. Low $\mathbf{I}_{(B/M)}$ stocks have lower B/M, higher past cumulative returns, and lower return reversal. To make sure that the return–predictive power of $\mathbf{I}_{(B/M)}$ is not driven by the firm characteristics, we will reexamine the return predictability by double portfolio sorts and Fama–MacBeth regressions.

[3]We use six lags to adjust the standard error. Using more lags does not change the results.

We then examine the return predictability of BM_{ave}. In untabulated results, we find that the difference between quarterly high BM_{ave} minus low decile portfolio returns is 1.824% and highly significant with a t statistics of 3.53. The positive association between BM_{ave} and returns indicates that the value premium is largely driven by the persistent trend component in the B/M. This finding also extends the findings in Kamara, Korajczyk, Lou, and Sadka (2016) which argue that the value premium is priced over intermediate horizons such as 24 to 36 months. The horizon to construct BM_{ave} coincides with the intermediate horizon in Kamara, Korajczyk, Lou, and Sadka (2016) and is the component in B/M capturing the value premium.

Overall, we find a negative relation between the $\mathbf{I}_{(B/M)}$ and future stock returns. The results are robust regardless whether the returns are equal–weighted or value–weighted, and unadjusted or risk–adjusted. We also find a positive relation between BM_{ave} and future stock returns. The above results indicate that the value premium is corresponding to the persistent trend component and the growth premium is corresponding to the temporary component. We then explore the marginal return–predictive power of $\mathbf{I}_{(B/M)}$ by using double portfolio sorts.

4.2 Double Portfolio Sorts

We now investigate whether the predictability of $\mathbf{I}_{(B/M)}$ are caused by firm characteristics. We use the double portfolio sort approach by first sorting stocks on firm characteristics and then sorting on $\mathbf{I}_{B/M)}$. Table 6 reports the average value–weighted returns and value–weighted adjusted returns for the characteristics reported in Table 5. We have also examined a number of other control variables and those results are available upon requests.

Since the return–predictive power of B/M is more concentrated in firms with small market capitalization, we first consider the impact of market capitalization on the return–predictive power of $\mathbf{I}_{(B/M)}$. When stocks are initially ranked by firm size, the H-L spreads of $\mathbf{I}_{(B/M)}$ quintiles show a hump–shaped pattern (in magnitude) from size quintile 1 (-0.1997%) to size quintile 3 (-3.318%) and then to size quintile 5 (-1.022%), suggesting the return–predictive power of $\mathbf{I}_{(B/M)}$ is stronger for medium to large stocks. Even though the return–predictive power of $\mathbf{I}_{(B/M)}$ is modest within the quintile portfolio of the smallest stocks, $\mathbf{I}_{(B/M)}$ has a strong negative relation with stock returns in portfolios of medium size to largest size. The results indicate that the return–predictive power of $\mathbf{I}_{(B/M)}$ is not a phenomenon for small capitalization stocks but works for stocks with medium to large stocks. The phenomenon that the return–predictive power of $\mathbf{I}_{(B/M)}$ is more pronounced in medium size firms indicates that medium size firms are the ones with more frequent migration across value and growth portfolios.

One may still concern the incremental explanatory of $\mathbf{I}_{(B/M)}$ against B/M since $\mathbf{I}_{(B/M)}$ is a simple transformation of B/M. We mitigate the concern by first sorting on book–to–market ratio and then on $\mathbf{I}_{(B/M)}$. Table 6 shows that the H-L spreads of $\mathbf{I}_{(B/M)}$ quintiles show an increasing pattern (in magnitude) from B/M quintile 1 to B/M quintile 5. The results indicate that the impact of $\mathbf{I}_{(B/M)}$ is stronger for value stocks. The H-L spreads across five B/M quintiles are all significant positive, suggesting that the return- predictive power of $\mathbf{I}_{(B/M)}$ is strong in all B/M quintiles. In other words, the B/M effect and $\mathbf{I}_{(B/M)}$ effect are different.

We also control for the effect of past return measures. Even though the correlation between $\mathbf{I}_{(B/M)}$ and past cumulative returns are extremely high, the return–predictive power of $\mathbf{I}_{(B/M)}$ is robust to both past cumulative returns and return reversal. The return–predictive power of $\mathbf{I}_{(B/M)}$ is more pronounced in the portfolios of past winner stocks. On the other hand, the return reversal has nonlinear impact on $\mathbf{I}_{(B/M)}$'s predictive power. The return–predictive power of $\mathbf{I}_{(B/M)}$ are more pronounced in high and low return reversal portfolios.

Given the concern that historical information of B/M is already incorporated in firm-s' current gross profitability, we control the effect of gross profitability. We find $\mathbf{I}_{(B/M)}$ has return–predictive power in all gross profitability portfolios. Beyond that, the return–predictive power of $\mathbf{I}_{(B/M)}$ is stronger in the highest and lowest gross profitability portfolios.

This nonlinear effect of gross profitability on the return–predictive power of $\mathbf{I}_{(B/M)}$ indicates that firms with extreme gross profit tend to change in type between value and growth.

Ang, Hodrick, Xing, and Zhang (2006) document a negative relation between $IVOL$ and stock returns. To make sure the negative relation between $\mathbf{I}_{(B/M)}$ and returns is not absorbed by the $IVOL$ effect, we perform the sequential portfolio sort first on $IVOL$ and then on $\mathbf{I}_{(B/M)}$. The $\mathbf{I}_{(B/M)}$ effect is still robust even after controlling for $IVOL$.

Standardized unexpected earnings are similar to our $\mathbf{I}_{(B/M)}$ measure. Specifically, SUE is the unexpected component of earnings while our $\mathbf{I}_{(B/M)}$ measure is the unexpected component of B/M. One may concern that $\mathbf{I}_{(B/M)}$ only captures the post-earnings announcement drift. We perform sequential portfolio sorts first on various SUE measures and then on $\mathbf{I}_{(B/M)}$. We find that the association between $\mathbf{I}_{(B/M)}$ and stock returns is still robust under different SUE measures.

To examine whether the BM_{ave} can provide independent information on stock returns against various firm characteristics, we perform sequential portfolio sorts first on different control variables and than on BM_{ave}. The corresponding results are presented in Table 8. The return predictive power of BM_{ave} is robust even controlling for firm size, gross profitability, and the idiosyncratic volatility. More interestingly, even though BM_{ave} is only one component of B/M, controlling for B/M cannot mitigate the return predictive power of BM_{ave}. However, the return predictive power of BM_{ave} is largely absorbed by past cumulative returns. The return predictive power is only pronounced in the second highest past-cumulative-return quintile. The potential reason is that if the share outstanding is fixed, past cumulative returns can be viewed as the average past market capitalization which is the denominator of BM_{ave}.

To sum up, the results of double portfolio sorts indicate that the return–predictive power of $\mathbf{I}_{(B/M)}$ is robust to different return predictors and is not restricted to small stocks. Even though BM_{ave} can provide additional information on stock returns when controlling for various return predictors, its predictive power is absorbed heavily by past cumulative returns.

4.3 Fama–MacBeth Regressions

We now examine the return predictability of $\mathbf{I}_{(B/M)}$ with the Fama–MacBeth regressions, which allow us to control for multiple return predictors simultaneously. We perform the Fama–MacBeth regression for both full sample and the reduce sample. The corresponding results are reported in Table 8. Panel A is for the normal Fama–MacBeth regressions and Panel B is for the Fama–MacBeth regressions using value–weighted least square estimation. We estimate four regression models. The first one uses $\mathbf{I}_{(B/M)}$ as the only explanatory variable. Model (2) examines the return–predictive power of $\mathbf{I}_{(B/M)}$ when controlling for the market capitalization and the B/M. Model (3) simultaneously control for $\mathbf{I}_{(B/M)}$, B/M and other control variables. Models (4) and (5) add in the two different SUE measures. Models (6) to (8) run regressions of returns on BM_ave. Models (9) to (12) include $\mathbf{I}_{(B/M)}$ and B/M simultaneously.

From Model (1), the average coefficient of $\mathbf{I}_{(B/M)}$ is negative and significant at the 1% level (-1.838 and t=-5.33). In Model (2), we include the market capitalization and B/M. The inclusion of B/M does not influence the return-predictive power of $\mathbf{I}_{(B/M)}$. When we include other control variables in Model (4) and (5), the return–predictive power of both $\mathbf{I}_{(B/M)}$ and B/M is not influenced. In sum, the incremental return–predictive power of $\mathbf{I}_{(B/M)}$ is stronger even after controlling for various return predictors.

Models (6) through (8) indicate that BM_{ave} is a robust return predictor even after controlling for major control variables. The pattern becomes more interesting when we include simultaneously the $\mathbf{I}_{(B/M)}$ and B/M_{ave} in Models (9) through (12). In Model (9) when we include only $\mathbf{I}_{(B/M)}$ and B/M_{ave} in the regression, the average coefficients of $\mathbf{I}_{(B/M)}$ and B/M are both significant at 1% level, indicating that the $\mathbf{I}_{(B/M)}$ effect and BM_{ave} effect on returns cannot dominate or absorb each other. Thus, the growth premium from $\mathbf{I}_{(B/M)}$ and the value premium from BM_{ave} co–exist. The coefficients of $\mathbf{I}_{(B/M)}$ effect and BM_{ave} are both significant at the level of 1% even after controlling for various control variables.

One concern of the Fama–MacBeth regression is that the coefficient could be boosted by outliers with small market capitalization. We mitigate this concern by performing a Fama–MacBeth regression with value–weighted least square as suggested by the literature such as Green, Hand, and Zhang (2017). The corresponding results are reported in Table 14. Not surprisingly, the return predictive power of all the variables decreases. Interestingly, even though B/M is not significant under the settings of value–weighted least square and multivariate regression, its two components, $\mathbf{I}_{(B/M)}$ and B/M_{ave} are robust return predictors. Besides $\mathbf{I}_{(B/M)}$ and B/M_{ave}, the other robust return predictors are the gross profitability, momentum, and the idiosyncratic volatility. The robustness of gross profitability and momentum is consistent with Fama and French (2006). The robustness of idiosyncratic volatility under value–weighted treatment is in line with the findings in Bali and Cakici (2008).

The return predictive power of $\mathbf{I}_{(B/M)}$ and B/M_{ave} lasts even more than one year. Specifically, we examine whether $\mathbf{I}_{(B/M)}$ and B/M_{ave} can predictive stock returns in quarters $t+2$, $t+3$, and $t+4$, respectively. Table 9 reports the average coefficient of the Fama–MacBeth regressions of returns in quarters $t+2$, $t+3$, and $t+4$ on $\mathbf{I}_{(B/M)}$, B/M_{ave}, and other control variables. For the returns in quarters $t+2$ and $t+3$, the coefficients of $\mathbf{I}_{(B/M)}$ and B/M_{ave} are highly significant at the 1% level. The coefficients of regression of returns in future quarter $t+4$ on $\mathbf{I}_{(B/M)}$ and B/M_{ave} are significant at the 5% level.

5 $\mathbf{I}_{(B/M)}$ and the Firms' Future Fundamentals

To detect the real effect of $\mathbf{I}_{(B/M)}$, we examine its predictability of firms' future fundamentals. Regarding firm fundamentals, we focus on gross profitability and B/M which are used to identify whether a stock belongs to value or growth stock. Prior research such as Fama and French (2007b) and Daniel and Titman (1997) use B/M as the indicator to identify value and growth stocks. They find that value and growth stocks tend to move to the other extreme after their identification. In other words, these studies state that growth (value) stocks with low (high) B/M tend to become value stocks by losing (gaining) profit and gaining (losing) increase in B/M. The value premium comes from the opposite migration between value and growth stocks (Fama and French (2007b)).

However, the empirical design in Fama and French (2007b) is *ex–post*. Specifically, they use B/M to classify value/growth stocks and examine their future B/M and gross profitability. Given the strong relation among B/M, $\mathbf{I}_{(B/M)}$, and stock returns, we explore whether $\mathbf{I}_{(B/M)}$ can be the other dimension to gauge the migration of B/M and help to explain the value premium. We perform a sequential portfolio sort for the universe of stocks first on $\mathbf{I}_{(B/M)}$ and then on B/M. In the previous section, we perform the double portfolio sort first on B/M and then $\mathbf{I}_{(B/M)}$ to examine the robustness of $\mathbf{I}_{(B/M)}$'s return predictive power. We switch the order of sorting in this section because we would like to detect whether controlling the effect of $\mathbf{I}_{(B/M)}$ can variate the value premium. Table 10 reports the return patterns of the double portfolio sorts. Panel A reveals that under sequential portfolio sorts first on $\mathbf{I}_{(B/M)}$, the value premium is largely mitigated and only marginally exists in the high $\mathbf{I}_{(B/M)}$ quintile. To further examine the interaction between the value premium and $\mathbf{I}_{(B/M)}$, we also perform an independent portfolio sort of $\mathbf{I}_{(B/M)}$ and B/M. The corresponding results in Panel C of Table 10 indicate that the value premium is strong in the quintiles with highest and second highest $\mathbf{I}_{(B/M)}$. Specifically, the quarterly return spread between high and low B/M quintiles is 2.569% within the highest $\mathbf{I}_{(B/M)}$ quintile.

Since BM_{ave} well captures the value premium, we also perform sequential portfolio sorts by ranking stocks based on $\mathbf{I}_{(B/M)}$ and on BM_{ave}. The findings are similar and reported in Panels B and D in Table 10. No matter using BM_{ave} or B/M, the value premium always concentrated in the high $\mathbf{I}_{(B/M)}$ quintiles. The value premium in the high $\mathbf{I}_{(B/M)}$ quintiles comes from the extremely low returns of stocks with low B/M and high $\mathbf{I}_{(B/M)}$ and the relatively high returns of high B/M and high $\mathbf{I}_{(B/M)}$. To better understand the low (high) returns of stocks with low (high) B/M and high $\mathbf{I}_{(B/M)}$, we examined whether B/M and $\mathbf{I}_{(B/M)}$ jointly determine the stocks' future migration across value and growth stock quintiles.

To determine the migration across value/growth quintiles, in each month we sequentially rank the stocks into quintiles based on $\mathbf{I}_{(B/M)}$ and then rank based on B/M. More importantly, we further sort the stocks into quintiles based on firms' future (quarter $t+1$) B/M. We report the average next–quarter (quarter $t+1$) quintiles of each $\mathbf{I}_{(B/M)}/B/M$ quintiles. Table 11 reports the corresponding results. The numbers reported in Table 11 are average quintiles ranging from 1 to 5. For instance, in Panel A of Table 11, the stocks fall in both lowest B/M and $\mathbf{I}_{(B/M)}$ tend to be in B/M quintile 1.43 in the quarter $t+1$. The most interesting pattern in this table is that the growth stocks (with the lowest B/M) with high $\mathbf{I}_{(B/M)}$ have a much larger propensity to migrate to value stocks. On average, the growth stocks (in the lowest B/M quintile) with the lowest $\mathbf{I}_{(B/M)}$ tend to fall in B/M quintile 1.43. But the growth stocks with the highest $\mathbf{I}_{(B/M)}$ tend to fall in B/M quintile 2.67. On the other hand, the stocks with both highest B/M and highest $\mathbf{I}_{(B/M)}$ have a higher propensity to remain in the highest B/M stocks.

The evidence in Table 11 indicates the value premium is caused by the excess migration of growth stocks with high $\mathbf{I}_{(B/M)}$ to the value stock group and the ability of value stocks with the high $\mathbf{I}_{(B/M)}$ to remain in the value groups. A step further, the inertia of those value stocks with high $\mathbf{I}_{(B/M)}$ indicates that the risk profiles of these stocks do not change.

On the other hand, the excess migration of growth stocks with high $\mathbf{I}_{(B/M)}$ can have two reasons. First, the excess migration of growth stocks with high $\mathbf{I}_{(B/M)}$ are 'bad' growth stocks that investors extrapolate the firms' future growth (e.g., Lakonishok, Shleifer, and Vishny (1994); Piotroski (2000); Skinner and Sloan (2002)). Second, the excess migration can also be caused by the change in risk profile of these growth firms. If growth stocks exercise their growth options and settle down their investment, the riskiness of growth stocks decreases. Consequently, the market values of these growth stocks with growth options exercised are decreased relative to the book equity of these stocks.

To examine the relationship between $\mathbf{I}_{(B/M)}$ and the amount of growth options exercised, we run a Fama–MacBeth regressions of growth option conversion on $\mathbf{I}_{(B/M)}$. Following Purnanandam and Rajan (2016), we measure the growth option conversion in quarter t by the difference between quarter–t capital expenditure and quarter–$t-1$ capital expenditure scaled by corresponding lagged quarterly total assets. A positive relation between $\mathbf{I}_{(B/M)}$ and the growth option conversion indicates that firms with high $\mathbf{I}_{(B/M)}$ are the ones exercising more growth options, which supports the change in risk profile hypothesis. Table 12 reports the average coefficients of future growth option conversion on $\mathbf{I}_{(B/M)}$ and B/M_{ave}. $\mathbf{I}_{(B/M)}$ has a strong negative relationship with future growth option conversion in quarters $t+2$ through $t+4$, indicating that stocks with high $\mathbf{I}_{(B/M)}$ are the ones with less growth option converted to assets-in-place.

To examine whether our $\mathbf{I}_{(B/M)}$ measure captures the investors' over- or under-extrapolation on the firms' sales growth, we follow Piotroski (2000) to define two dummies 'Good' and 'Bad'. 'Good' ('Bad') dummy in quarter t equals to 1 if the SUE in quarter $t+1$ is larger (smaller) than zero and equals to zero elsewhere. if 'Good' ('Bad') equals to one, the dummy indicates investors' under-extrapolation (over–extrapolation) of the firm.

We run Fama–MacBeth regressions of future stock returns on $\mathbf{I}_{(B/M)}$ and 'Good' and 'Bad' dummies. The Model (2) and Model (5) in Table 13 presents the corresponding results using different SUEs as the dependent variables. We find that the 'Good' dummy capturing the dynamics of future SUEs has a strong positive relation with future stock returns while the 'bad' dummy has a significantly negative relation with stock returns. The return predictive power of $\mathbf{I}_{(B/M)}$ is marginally significant once controlling for the investors' extrapolation. Since $\mathbf{I}_{(B/M)}$ can capture the degree of the extrapolation, we interact the 'Good' and 'Bad' dummies and $\mathbf{I}_{(B/M)}$. The results in Model (3) and Model (6) indicate that the return predictive power of $\mathbf{I}_{(B/M)}$ is mitigated by the interaction term of the 'Good' and 'Bad' dummies and $\mathbf{I}_{(B/M)}$. The empirical evidence in Table 13 indicates that the return predictive power of $\mathbf{I}_{(B/M)}$ is consistent with the hypothesis that the excess migration of growth stocks with high $\mathbf{I}_{(B/M)}$ are the ones with investors' more severe over-extrapolation.

6 Conclusions

The empirical evidence has shown that the value stocks, which are classified based on the B/M ratio, tend to have a higher premium than the growth stocks. This phenomenon conflicts the conventional wisdom, which argues that the growth stocks are riskier to earn higher premium. In this paper, we reconcile the conventional wisdom and the empirical evidence by decomposing the B/M into two components, a temporary component, and a persistent trend component. Our baseline results indicate that the temporary component of B/M ($\mathbf{I}_{(B/M)}$) captures the value of real options in firms and has a strong negative relation with cross–sectional stock returns even when controlling for various return predictors. The negative relation between $\mathbf{I}_{(B/M)}$ and stock returns indicates a growth premium. In contrast, the trend component of B/M (BM_{ave}) is positively associated with stock returns. In other words, the value premium concentrates in the BM_{ave} component while the growth premium concentrates in the $\mathbf{I}_{(B/M)}$ component.

The empirical evidence also supports the relationship between the persistent trend component and assets-in-place. Specifically, we find a strong positive relationship between the trend component and various irreversibility measures. We check the return predictability power of $\mathbf{I}_{(B/M)}$ and BM_{ave} by using both portfolio sorts and Fama–MacBeth regressions. Interestingly, in portfolios simultaneously sorted on both $\mathbf{I}_{(B/M)}$ and B/M, and in cross–sectional regressions of returns at the firm level, the negative $\mathbf{I}_{(B/M)}$ effect on returns and positive B/M effect on returns neither drive out nor dominate each other.

We have designed tests to track the future dynamics of fundamentals among different $\mathbf{I}_{(B/M)}$ portfolios. We find that $\mathbf{I}_{(B/M)}$ can predict future stock returns because it well captures the investors over- and under-extrapolation of firms' future earnings growth ((e.g., Daniel and Titman (1997); Lakonishok, Shleifer, and Vishny (1994))).

Table 1: The Transition Matrix for BM

This table reports the transition matrix for BM–sorted portfolios. At the end of each quarter t, all stocks are sorted into ascending BM decile portfolios. For each quarter t, BM decile, the table reports the time–series average of the percentage of stocks in the given quarter t, BM decile portfolio that fall in each quarter $t+s$, BM decile portfolio. Panel A reports the result when $s=1$, i.e. 1-quarter ahead, while Panel B reports the results when $s=8$, i.e. 8-quarter ahead.

Panel A: BM in Quarter t and $(t+1)$										
	Time (t+1)									
Time t	1	2	3	4	5	6	7	8	9	10
1	0.771	0.167	0.034	0.015	0.006	0.004	0.002	0.001	0.001	0.000
2	0.181	0.540	0.196	0.048	0.019	0.008	0.004	0.002	0.001	0.001
3	0.028	0.217	0.452	0.207	0.059	0.022	0.009	0.004	0.002	0.000
4	0.009	0.048	0.225	0.406	0.211	0.065	0.022	0.009	0.003	0.001
5	0.004	0.015	0.061	0.226	0.384	0.217	0.064	0.020	0.006	0.001
6	0.002	0.007	0.019	0.066	0.225	0.383	0.219	0.062	0.015	0.003
7	0.001	0.003	0.007	0.021	0.067	0.221	0.402	0.223	0.048	0.007
8	0.001	0.002	0.003	0.007	0.020	0.061	0.222	0.452	0.212	0.019
9	0.001	0.001	0.001	0.003	0.006	0.016	0.049	0.206	0.564	0.154
10	0.001	0.000	0.001	0.001	0.002	0.003	0.007	0.021	0.149	0.814
SUM	1	1	1	1	1	1	1	1	1	1

Panel B: BM in Quarter t and $(t+8)$										
	Time (t+8)									
Time t	1	2	3	4	5	6	7	8	9	10
1	0.461	0.210	0.108	0.069	0.046	0.035	0.026	0.020	0.015	0.009
2	0.217	0.261	0.179	0.112	0.075	0.054	0.039	0.030	0.021	0.010
3	0.111	0.190	0.204	0.160	0.114	0.081	0.058	0.041	0.027	0.014
4	0.066	0.120	0.176	0.178	0.152	0.116	0.082	0.053	0.038	0.018
5	0.042	0.075	0.119	0.165	0.174	0.153	0.112	0.082	0.053	0.023
6	0.030	0.051	0.080	0.120	0.158	0.173	0.153	0.122	0.080	0.034
7	0.024	0.037	0.054	0.084	0.123	0.155	0.183	0.168	0.122	0.052
8	0.018	0.025	0.039	0.057	0.080	0.120	0.169	0.207	0.191	0.093
9	0.017	0.020	0.028	0.036	0.054	0.077	0.124	0.191	0.265	0.190
10	0.012	0.011	0.015	0.020	0.024	0.035	0.053	0.086	0.187	0.557
SUM	1	1	1	1	1	1	1	1	1	1

Table 2: The Transition Matrix for $\mathbf{I}_{(B/M)}$

This table reports the transition matrix for $\mathbf{I}_{(B/M)}$–sorted portfolios. At the end of each quarter t, all stocks are sorted into ascending $\mathbf{I}_{(B/M)}$ decile portfolios. For each quarter t, $\mathbf{I}_{(B/M)}$ decile, the table reports the time–series average of the percentage of stocks in the given quarter t, $\mathbf{I}_{(B/M)}$ decile portfolio that fall in each quarter $t+s$, $\mathbf{I}_{(B/M)}$ decile portfolio. Panel A reports the result when $s = 1$, i.e. 1-quarter ahead, while Panel B reports the results when $s = 8$, i.e. 8-quarter ahead.

Panel A: $\mathbf{I}_{(B/M)}$ in Quarter t and $(t+1)$

	Time (t+1)									
Time t	1	2	3	4	5	6	7	8	9	10
1	0.647	0.191	0.052	0.023	0.016	0.014	0.012	0.013	0.013	0.020
2	0.149	0.363	0.216	0.095	0.050	0.034	0.030	0.025	0.022	0.016
3	0.045	0.174	0.270	0.203	0.113	0.067	0.047	0.035	0.029	0.018
4	0.025	0.079	0.174	0.234	0.189	0.120	0.078	0.050	0.033	0.018
5	0.016	0.045	0.099	0.172	0.220	0.189	0.121	0.075	0.044	0.019
6	0.016	0.035	0.063	0.106	0.177	0.218	0.182	0.118	0.060	0.026
7	0.016	0.032	0.047	0.071	0.111	0.175	0.217	0.189	0.104	0.039
8	0.019	0.029	0.035	0.047	0.067	0.107	0.179	0.238	0.203	0.076
9	0.023	0.027	0.028	0.031	0.038	0.055	0.100	0.190	0.306	0.202
10	0.046	0.026	0.018	0.018	0.018	0.021	0.033	0.067	0.185	0.567
SUM	1	1	1	1	1	1	1	1	1	1

Panel B: $\mathbf{I}_{(B/M)}$ in Quarter t and (t+8)

	Time (t+8)									
Time t	1	2	3	4	5	6	7	8	9	10
1	0.153	0.108	0.091	0.077	0.068	0.069	0.079	0.092	0.111	0.150
2	0.073	0.098	0.101	0.099	0.100	0.101	0.104	0.111	0.113	0.099
3	0.052	0.081	0.100	0.109	0.115	0.117	0.118	0.117	0.107	0.084
4	0.043	0.075	0.096	0.115	0.124	0.127	0.128	0.113	0.102	0.076
5	0.041	0.072	0.097	0.118	0.128	0.133	0.124	0.113	0.099	0.075
6	0.044	0.079	0.099	0.119	0.128	0.128	0.118	0.110	0.098	0.077
7	0.052	0.088	0.109	0.117	0.123	0.119	0.112	0.107	0.096	0.079
8	0.077	0.117	0.113	0.110	0.101	0.097	0.098	0.099	0.098	0.091
9	0.135	0.147	0.114	0.088	0.075	0.071	0.076	0.085	0.098	0.111
10	0.331	0.134	0.078	0.048	0.039	0.038	0.042	0.054	0.078	0.158
SUM	1	1	1	1	1	1	1	1	1	1

Table 3: The Transition Matrix for BM_{ave}

This table reports the transition matrix for BM_{ave}–sorted portfolios. At the end of each quarter t, all stocks are sorted into ascending BM_{ave} decile portfolios. For each quarter t, BM_{ave} decile, the table reports the time–series average of the percentage of stocks in the given quarter t, BM_{ave} decile portfolio that fall in each quarter $t+s$, BM_{ave} decile portfolio. Panel A reports the result when $s=1$, i.e. 1-quarter ahead, while Panel B reports the results when $s=8$, i.e. 8-quarter ahead.

Panel A: BM_{ave} in Quarter t and $(t+1)$

	Time (t+1)									
Time 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
SUM	1	1	1	1	1	1	1	1	1	1

Panel B: BM_{ave} in Quarter t and (t+8)

	Time (t+8)									
Time 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
SUM	1	1	1	1	1	1	1	1	1	1

Table 4: The Summary Statistics and the Correlation Matrix

This table reports the correlation matrix and the summary statistics for BM_{ave} and $\mathbf{I}_{(B/M)}$.

Panel A: Summary Statistics							
	$\mathbf{I}_{(B/M)}$	BM_{ave}	BM	ME	GP	MOM	IVOL
Mean	0.018	0.962	0.91	2033.55	0.09	0.15	13.42
Med	0.001	0.574	0.56	178.23	0.08	0.06	10.79
Stdev	0.824	2.261	1.96	12019.7	0.09	0.65	10.46
p25	-0.095	0.330	0.32	47.12	0.05	-0.2	7.03
p75	0.100	0.977	0.96	768.09	0.13	0.35	16.74

Panel B: Correlation Matrix							
	$\mathbf{I}_{(B/M)}$	BM_{ave}	BM	ME	GP	MOM	IVOL
$\mathbf{I}_{(B/M)}$	1	-0.079***	0.330***	-0.006***	-0.024***	-0.198***	0.057***
p-value		$\leq$.0001	$\leq$.0001	$\leq$.0001	$\leq$.0001	$\leq$.0001	$\leq$.0001
BM_{ave}	-0.079***	1	0.915***	-0.034***	-0.056***	-0.018**	-0.020***
p-value	$\leq$.0001		$\leq$.0001	$\leq$.0001	$\leq$.0001	0.012	$\leq$.0001
BM	0.330***	0.915***	1	-0.037***	-0.063***	-0.102***	0.010*
p-value	$\leq$.0001	$\leq$.0001		$\leq$.0001	$\leq$.0001	$\leq$.0001	0.084

Table 5: Single Portfolio Sort for $\mathbf{I}_{(B/M)}$

This table reports the average next-quarter returns and firm characteristics of decile portfolios formed by sorting stocks on the $\mathbf{I}_{(B/M)}$. EW and VW reports equal-weight and value-weight, respectively. R_{Raw} is the raw quarterly return and R_{α} is the risk-adjusted return. α, FF5, EW reports the equal-weighted abnormal return adjusted by the 5-factor model of Fama and French (2015). The row Diff reports the differences of average returns between decile 10 and decile 1, i.e. H-L, with the corresponding Newey-West t-statistics shown in the last row. The spreads followed by *, **, and *** are significant at the 10%, 5%, 1% confidence level based on their time–series standard error, respectively. The firm characteristics of the decile portfolios are equal-weighted. The unadjusted and adjusted returns, MOM, and $IVOL$ are reported in percentage. Specifically, Panel A reports the results for the full sample, while Panel B reports the results for the sample filtering out the observation falling in the same B/M and $\mathbf{I}_{(B/M)}$ deciles in each quarter.

Panel A: Full Sample

Decile	R^{EW}_{Raw}	$R^{EW}_{\alpha,FF5}$	R^{VW}_{Raw}	$R^{VW}_{\alpha,FF5}$	I_{BM}	ME	BM	MOM	GP	REV	IVOL	SUE_1	SUE_2
1	4.91	2.12	3.82	1.33	-0.655	$657.29	1.15	0.571	8.58	7.05	15.16	10.50	-0.74
2	4.69	2.16	3.57	2.18	-0.196	$1,444.16	0.71	0.443	9.08	5.35	12.79	1.09	-0.11
3	4.05	1.61	3.54	1.71	-0.105	$2,066.75	0.62	0.353	9.42	4.00	11.60	0.24	-0.10
4	3.91	1.53	3.44	1.73	-0.053	$2,736.38	0.58	0.270	9.89	2.89	11.16	1.31	-0.04
5	3.45	0.91	3.38	1.57	-0.015	$2,983.05	0.55	0.195	10.02	1.88	11.23	1.38	-0.05
6	3.14	0.55	3.32	1.31	0.019	$2,750.80	0.59	0.117	9.92	0.83	11.29	-0.82	-0.15
7	2.97	0.20	2.60	0.32	0.059	$2,437.82	0.65	0.042	9.70	-0.50	11.42	0.08	-0.30
8	2.70	-0.19	2.40	0.00	0.113	$1,983.83	0.78	-0.037	9.23	-1.63	12.16	-1.18	-0.21
9	2.82	-0.39	2.76	-0.01	0.210	$1,210.82	1.01	-0.136	8.44	-3.17	13.40	-0.61	-0.39
10	2.76	-0.80	1.96	-1.00	0.634	$514.52	1.98	-0.277	7.13	-6.24	16.43	-2.32	-1.15
Diff	-2.152***	-2.923***	-1.855***	-2.332***	1.289***	-142.77	0.837***	-0.847***	-1.456***	-13.29***	1.277**	-12.82***	-0.415*
t stats.	[-4.56]	[-5.36]	[-3.88]	[-4.23]	[12.38]	[-1.46]	[-21.40]	[-21.40]	[-6.53]	[-17.22]	[2.30]	[-3.13]	[-1.77]

Panel B: All But Microcap

Decile	R^{EW}_{Raw}	R^{EW}_{FF5}	R^{VW}_{Raw}	R^{VW}_{FF5}	I_{BM}	ME	BM	MOM	GP	REV	IVOL	SUE_1	SUE_2
1	4.62	1.99	3.98	2.02	-0.352	$1,889.98	0.89	60.96	8.22	6.93	10.61	5	-0.09
2	4.01	1.70	3.63	1.87	-0.145	$2,881.27	0.59	46.30	9.06	5.25	9.45	0.038	0.006
3	3.98	1.74	3.55	1.80	-0.083	$3,660.88	0.53	38.53	9.87	4.25	8.94	0.243	0.054
4	3.83	1.61	3.18	1.52	-0.046	$4,449.27	0.50	30.05	10.42	3.35	8.67	0.36	0.012
5	3.62	1.33	3.67	1.97	-0.017	$4,954.19	0.48	24.69	10.56	2.59	8.75	0.931	0.003
6	3.28	0.87	3.22	1.34	0.008	$4,570.82	0.50	17.75	10.70	1.77	8.78	-0.082	-0.004
7	3.08	0.54	2.88	0.83	0.035	$4,231.43	0.54	10.76	10.41	0.64	8.73	0.293	-0.085
8	2.80	0.09	2.52	0.25	0.070	$3,810.75	0.62	4.29	9.77	-0.51	8.96	-0.718	-0.325
9	2.73	-0.18	2.40	0.00	0.126	$3,061.25	0.75	-3.69	8.90	-1.56	9.35	-0.202	-0.045
10	2.74	-0.77	2.39	-0.12	0.301	$2,016.66	1.25	-15.24	7.51	-3.68	10.48	-0.189	-0.29
Diff	-1.883***	-2.752***	-1.589***	-2.139***	0.654***	126.67	0.363***	-76.20***	-0.71***	-10.61***	-0.129	-5.189	-0.20**
t stats.	[-4.19]	[-4.84]	[-3.22]	[-4.08]	[18.31]	[0.55]	[4.72]	[-15.53]	[-2.79]	[-13.91]	[-0.37]	[-1.32]	[-2.53]

Table 6: Double Portfolio Sorts for $\mathbf{I}_{(B/M)}$

This table reports the value-weighted average next-quarter returns of portfolios formed by double sorting stocks on the $\mathbf{I}_{(B/M)}$ and firm characteristics. For each firm characteristic, we first sort stocks into quintiles using the characteristic, and then within each quintile, we further sort stocks into quintiles based on the $\mathbf{I}_{(B/M)}$. The row Ret Diff shows the differences of average returns between quintile 5 and quintile 1. The row FF adj shows the Fama and French (2015) five-factor adjusted differences of average returns between quintile 5 and quintile 1, with the corresponding Newey-West t-statistics shown below. The spreads followed by *, **, and *** are significant at the 10%, 5%, 1% confidence level based their time–series standard error, respectively.

Panel A: Market Capitalization

$\mathbf{I}_{(B/M)}$ Quintile	Market Cap Quintile: Low	2	3	4	High
Low	4.81	5.54	5.12	4.44	3.56
2	4.01	4.40	4.20	3.90	3.04
3	3.48	3.48	3.05	3.47	3.44
4	3.07	2.36	2.77	3.02	2.46
High	2.83	2.22	2.46	2.75	2.54
Ret Diff	-1.977***	-3.318***	-2.660***	-1.697***	-1.022*
t stats.	[3.37]	[-4.19]	[-3.96]	[-2.74]	[-1.76]
FF adj	-2.614***	-4.225***	-3.310***	-2.637***	-1.701***
t stats.	[-5.49]	[-4.41]	[-4.15]	[-4.68]	[-2.97]

Panel B: BM

$\mathbf{I}_{(B/M)}$ Quintile	BM Quintile: Low	2	3	4	High
Low	3.98	3.89	3.54	4.15	4.06
2	3.46	2.92	3.63	3.66	3.74
3	3.19	3.05	3.60	3.65	4.23
4	2.93	2.98	3.31	3.17	2.36
High	1.85	2.27	2.86	3.19	1.52
Ret Diff	-2.131*	-1.619***	-0.683	-0.956	-2.539***
t stats.	[-1.92]	[-2.71]	[-1.13]	[-1.35]	[-3.26]
FF adj	-2.151**	-2.323***	-1.191*	-1.509**	-3.177***
t stats.	[-1.98]	[-3.67]	[-1.86]	[-2.05]	[-3.68]

Panel C: REV

$\mathbf{I}_{(B/M)}$ Quintile	REV Quintile: Low	2	3	4	High
Low	3.84	3.50	4.22	3.23	4.51
2	3.18	3.16	3.72	3.35	3.98
3	1.92	3.67	3.62	3.71	3.14
4	1.77	2.74	3.36	2.12	3.14
High	1.73	3.38	2.65	2.37	1.41
Ret Diff	-2.109***	-0.126	-1.565***	-0.860	-3.098***
t stats.	[-2.90]	[-0.23]	[-2.77]	[-1.53]	[-3.96]
FF adj	-3.381***	-0.490	-2.118***	-1.474***	-3.423***
t stats.	[-3.95]	[-0.85]	[-3.27]	[-2.78]	[-4.20]

Panel D: MOM

$\mathbf{I}_{(B/M)}$ Quintile	MOM Quintile: Low	2	3	4	High
Low	1.85	2.72	3.33	3.70	4.38
2	2.01	2.79	3.27	3.27	4.30
3	1.60	2.78	2.88	3.73	4.13
4	2.48	3.62	3.02	3.53	4.15
High	1.28	3.19	1.53	2.05	3.98
Ret Diff	-0.566	0.470	-1.799***	-1.648***	-0.400
t stats.	[-0.58]	[0.69]	[-2.96]	[-2.88]	[-0.60]
FF adj	-1.528**	-0.105*	-1.996***	-1.863***	-0.573
t stats.	[-2.11]	[-1.69]	[-3.03]	[-2.91]	[-0.79]

Panel E: GP

$\mathbf{I}_{(B/M)}$ Quintile	GP Quintile: Low	2	3	4	High
Low	3.26	3.40	4.12	4.31	5.40
2	3.37	2.94	3.01	3.50	4.19
3	2.09	2.91	3.08	3.29	4.11
4	1.46	2.08	2.74	3.41	4.19
High	0.65	3.03	3.62	4.16	3.28
Ret Diff	-2.611***	-0.376	-0.503	-0.148	-2.122***
t stats.	[-2.89]	[-0.50]	[-0.66]	[-0.14]	[-3.09]
FF adj	-3.202***	-1.605**	-1.399*	-1.033	-2.734***
t stats.	[-2.83]	[-2.51]	[-1.94]	[-1.09]	[-4.47]

Panel F: IVOL

$\mathbf{I}_{(B/M)}$ Quintile	IVOL Quintile: Low	2	3	4	High
Low	3.63	4.22	5.13	4.58	3.58
2	3.24	3.94	3.57	3.82	2.47
3	3.18	3.72	3.00	2.79	0.95
4	2.74	2.95	2.43	1.02	0.22
High	2.52	3.27	3.21	1.74	1.38
Ret Diff	-1.105**	-0.949	-1.924	-2.849***	-2.204***
t stats.	[-2.12]	[-1.37]	[-1.52]	[-2.72]	[-2.83]
FF adj	-1.827***	-1.872***	-3.281**	-4.640***	-4.304***
t stats.	[-3.74]	[-3.33]	[-2.20]	[-4.95]	[-3.19]

Table 6 – Continued

Panel G: SUE_1

$\mathbf{I}_{(B/M)}$		SUE_1 Quintile			
Quintile	Low	2	3	4	High
Low	4.37	3.29	3.64	4.66	5.57
2	2.47	2.79	3.36	3.92	3.99
3	2.71	2.72	3.59	4.27	3.73
4	3.25	2.44	3.09	3.63	3.33
High	2.06	2.79	2.56	2.83	3.52
Ret Diff	-2.318**	-0.507	-1.080	-1.836***	-2.058***
t stats.	[-2.55]	[-0.68]	[-1.53]	[-2.65]	[-2.99]
FF adj	-3.958***	-1.628**	-2.004***	-2.284***	-2.542***
t stats.	[-4.51]	[-2.41]	[-2.80]	[-3.02]	[-3.34]

Panel H: BM_{ave}

$\mathbf{I}_{(B/M)}$		BM_{ave} Quintile			
Quintile	Low	2	3	4	High
Low	3.54	3.45	4.07	3.83	4.07
2	3.36	3.13	3.11	3.65	3.72
3	3.01	3.01	3.72	3.63	3.60
4	1.91	3.22	3.39	2.99	3.93
High	1.37	2.46	3.36	3.17	2.22
Ret Diff	-2.170***	-0.99	-0.718	-0.663	-1.851***
t stats.	[-3.27]	[-1.45]	[-0.90]	[-0.79]	[-2.91]
FF adj	-2.998***	-1.987***	-1.635**	-1.631**	-2.355***
t stats.	[-4.17]	[-2.70]	[-2.14]	[-2.16]	[-4.31]

Panel I: SUE_2

$\mathbf{I}_{(B/M)}$		SUE_2 Quintile			
Quintile	Low	2	3	4	High
Low	3.96	3.46	3.54	4.44	5.48
2	2.15	2.87	3.34	4.09	4.02
3	2.69	2.80	3.45	4.43	4.24
4	2.78	2.52	3.36	3.30	3.51
High	1.63	3.04	2.76	2.52	3.65
Ret Diff	-2.325**	-0.429	-0.779	-1.928**	-1.833**
t stats.	[-2.48]	[-0.61]	[-1.11]	[-2.49]	[-2.22]
FF adj	-3.697***	-1.545**	-1.647**	-2.361***	-2.378***
t stats.	[-3.74]	[-2.42]	[-2.32]	[-2.83]	[-3.50]

Panel J: SUE_3

$\mathbf{I}_{(B/M)}$		SUE_3 Quintile			
Quintile	Low	2	3	4	High
Low	3.60	3.08	4.13	4.07	4.45
2	3.39	2.92	3.51	4.04	3.04
3	2.81	2.61	3.37	3.70	3.61
4	3.94	2.98	3.08	3.26	3.95
High	2.27	2.71	2.75	2.42	3.96
Ret Diff	-1.328**	-0.363	-1.381**	-1.653***	-0.488
t stats.	[-2.07]	[-0.47]	[-2.50]	[-2.94]	[-0.52]
FF adj	-2.615***	-1.114	-2.321***	-2.019***	-1.602
t stats.	[-3.37]	[-1.26]	[-2.99]	[-2.85]	[-1.63]

Table 7: Double Portfolio Sorts for BM_{ave}

This table reports the value-weighted average next-quarter returns of portfolios formed by double sorting stocks on the BM_{ave} and firm characteristics. For each firm characteristic, we first sort stocks into quintiles using the characteristic, and then within each quintile, we further sort stocks into quintiles based on the BM_{ave}. The row Ret Diff shows the differences of average returns between quintile 5 and quintile 1. The row FF adj shows the Fama and French (2015) five-factor adjusted differences of average returns between quintile 5 and quintile 1, with the corresponding Newey-West t-statistics shown below. The spreads followed by *, **, and *** are significant at the 10%, 5%, 1% confidence level based their time–series standard error, respectively.

Panel A: Market Capitalization

BM_ave		Market Cap Quintile			
Quintile	Low	2	3	4	High
Low	1.73	2.27	2.25	3.08	2.82
2	3.30	3.39	2.84	3.23	2.98
3	4.05	4.03	3.89	3.64	2.85
4	4.52	4.11	4.20	3.92	3.42
High	4.30	4.07	4.04	3.75	3.02
Ret Diff	2.575***	1.794**	1.788**	0.672	0.204
t stats.	[3.72]	[2.06]	[2.18]	[0.93]	[0.33]
FF adj	2.418***	1.881***	1.696***	0.613	-0.405
t stats.	[5.00]	[2.89]	[3.23]	[1.44]	[-0.96]

Panel B: BM

BM_ave		BM Quintile			
Quintile	Low	2	3	4	High
Low	3.07	1.94	2.78	3.15	2.62
2	2.59	2.96	3.58	3.58	3.84
3	2.91	3.05	3.21	3.49	3.86
4	3.13	3.12	3.86	3.58	3.08
High	3.65	3.51	3.41	4.01	3.59
Ret Diff	0.585	1.567***	0.633	0.863	0.965
t stats.	[0.83]	[2.68]	[0.98]	[1.32]	[1.38]
FF adj	0.467	1.590***	0.951	1.438**	2.109***
t stats.	[0.70]	[2.64]	[1.51]	[1.99]	[3.30]

Panel C: REV

BM_ave		REV Quintile			
Quintile	Low	2	3	4	High
Low	1.44	2.72	3.35	3.15	2.66
2	2.72	3.29	3.29	2.90	3.40
3	2.82	3.56	3.60	3.05	3.32
4	2.97	3.82	3.84	3.18	3.39
High	3.14	3.98	3.93	3.03	4.03
Ret Diff	1.703*	1.266**	0.581	-0.121	1.367**
t stats.	[1.96]	[2.01]	[0.79]	[-0.19]	[2.35]
FF adj	1.947***	0.839	-0.01	-0.771*	0.265
t stats.	[2.80]	[1.62]	[-0.02]	[-1.80]	[0.35]

Panel D: MOM

BM_ave		MOM Quintile			
Quintile	Low	2	3	4	High
Low	1.33	2.38	2.60	3.23	4.25
2	1.71	2.94	3.14	3.41	3.70
3	2.38	3.09	3.31	3.53	3.94
4	1.67	3.33	2.68	3.88	4.39
High	1.52	3.21	3.09	4.32	4.55
Ret Diff	0.19	0.826	0.492	1.097*	0.297
t stats.	[0.21]	[1.26]	[0.83]	[1.68]	[0.37]
FF adj	-0.534	0.087	0.111	1.695**	-0.147
t stats.	[-0.69]	[0.15]	[0.25]	[2.36]	[-0.22]

Panel E: GP

BM_ave		GP Quintile			
Quintile	Low	2	3	4	High
Low	1.76	1.73	2.16	2.49	3.72
2	1.83	2.99	3.14	4.07	3.60
3	2.38	3.21	3.69	3.40	4.19
4	2.66	3.42	3.91	4.30	4.42
High	2.32	3.65	4.78	4.98	4.72
Ret Diff	0.569	1.921***	2.617***	2.487***	1.002
t stats.	[0.62]	[2.93]	[3.73]	[3.41]	[1.33]
FF adj	-0.206	1.523***	2.270***	1.704***	-0.039
t stats.	[-0.27]	[2.95]	[3.94]	[3.73]	[-0.08]

Panel F: IVOL

BM_ave		IVOL Quintile			
Quintile	Low	2	3	4	High
Low	2.98	3.33	2.35	1.92	0.41
2	3.15	2.99	2.93	2.64	0.90
3	3.01	3.98	3.99	3.33	2.39
4	3.10	3.93	4.19	3.35	3.26
High	3.42	4.20	4.49	3.99	3.63
Ret Diff	0.444	0.872	2.140**	2.072**	3.223***
t stats.	[0.76]	[1.26]	[2.19]	[2.28]	[3.44]
FF adj	-0.255	-0.026	1.165	1.417**	1.926***
t stats.	[-0.56]	[-0.04]	[1.33]	[2.01]	[2.65]

Table 8: Fama and MacBeth Regression of Returns

This table reports the Fama and MacBeth regression result of returns. Each quarter from 1976–2014 we run a firm–level cross–sectional regression of returns on $\mathbf{I}_{(B/M)}$, BM_{ave} and lagged predictor variables. The table reports the time–series average of the cross–sectional regression coefficient, their associated Newey-West (1987) adjusted t-statistics (in parentheses), and the regression R^2s. The coefficients followed by *, **, and *** are significant at the 10%, 5%, 1% level based their time–series standard error, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbf{I}_{(B/M)}$	-1.838***	-1.836***	-1.459***	-1.368***	-1.326***				-1.433***	-1.472***	-1.494***	-1.388***
	[-5.33]	[-5.62]	[-4.28]	[-3.54]	[-3.46]				[-3.76]	[-3.49]	[-3.57]	[-3.12]
BM_{ave}						0.947***	0.879***	0.889***	0.714**	0.967***	0.886***	0.901***
						[3.22]	[2.84]	[2.88]	[2.24]	[2.76]	[2.79]	[2.84]
log(ME)		-0.087	-0.315**	-0.390***	-0.391***	-0.282**	-0.356**	-0.356**	-0.063	-0.291**	-0.362**	-0.362**
		[-0.63]	[-2.31]	[-2.72]	[-2.72]	[-2.11]	[-2.55]	[-2.55]	[-0.46]	[-2.16]	[-2.58]	[-2.58]
log(BM)		0.528**	0.799**	0.707**	0.717**							
		[2.32]	[2.57]	[2.13]	[2.17]							
REV			-3.148**	-2.550**	-2.524*	-2.899**	-2.305	-2.313*		-3.489***	-2.831**	-2.809**
			[-2.58]	[-1.98]	[-1.97]	[-2.23]	[-1.65]	[-1.66]		[-2.78]	[-2.13]	[-2.12]
MOM			1.509**	1.566**	1.534**	1.597**	1.644**	1.595**		1.388*	1.477**	1.442**
			[2.10]	[2.33]	[2.24]	[2.14]	[2.33]	[2.24]		[1.91]	[2.17]	[2.07]
GP			10.314***	9.769***	9.776***	10.566***	10.009***	10.002***		10.562***	10.002***	10.013***
			[5.96]	[5.38]	[5.37]	[6.10]	[5.52]	[5.50]		[6.10]	[5.53]	[5.52]
IVOL			-0.116***	-0.095***	-0.094***	-0.117***	-0.096***	-0.095***		-0.116***	-0.095***	-0.094***
			[-3.49]	[-2.87]	[-2.83]	[-3.49]	[-2.85]	[-2.81]		[-3.50]	[-2.86]	[-2.81]
SUE1				2.350**			2.681***	4.890***			2.464**	
				[2.48]			[2.77]	[3.92]			[2.56]	
SUE2					4.450***							4.423***
					[3.67]							[3.28]
R Square	0.008	0.024	0.055	0.057	0.059	0.054	0.055	0.056	0.023	0.056	0.059	0.059

Table 9: Long–Horizon Tests

This table reports the Fama and MacBeth regression result of returns in quarter $t+2$, $t+3$, and $t+4$ respectively on $\mathbf{I}_{(B/M)}$, BM_{ave}, and other control variables. The dependent variables in Model (1) through Model (4) are the returns in quarter $t+2$. The dependent variable in Model (5) through (8) are the returns in quarter $t+3$. The dependent variables in Model (9) through Model (12) are the returns in quarter $t+4$. Each quarter from 1976–2014 we run a firm–level cross–sectional regression of returns on $\mathbf{I}_{(B/M)}$, BM_{ave} and lagged predictor variables. The table reports the time–series average of the cross–sectional regression coefficient, their associated Newey-West (1987) adjusted t-statistics (in parentheses), and the regression R^2s. The coefficients followed by *, **, and *** are significant at the 10%, 5%, 1% level based their time–series standard error, respectively.

	RET(t+2)				RET(t+3)				RET(t+4)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbf{I}_{(B/M)}$	-2.626***	-3.085***	-1.572***	-1.255***	-1.405***	-2.051***	-1.454***	-1.143***	-1.508*	-2.102**	-1.317***	-0.854***
	[-3.16]	[-3.76]	[-4.55]	[-3.10]	[-2.81]	[-4.17]	[-5.47]	[-3.79]	[-1.69]	[-2.54]	[-4.19]	[-2.88]
BM_{ave}	0.546***			0.636***	0.690***			0.607***	0.421*			0.607***
	[2.65]			[2.75]	[3.53]			[2.89]	[1.72]			[2.74]
BM		0.806***	0.703**			0.940***	0.762***			0.831***	0.835***	
		[2.90]	[2.45]			[3.49]	[2.67]			[3.09]	[2.84]	
log(ME)			-0.232	-0.273**			-0.144	-0.197			-0.094	-0.161
			[-1.64]	[-2.00]			[-1.03]	[-1.46]			[-0.72]	[-1.25]
REV			3.239***	2.939***			1.963*	1.616			2.813***	2.470**
			[3.23]	[2.90]			[1.93]	[1.57]			[2.62]	[2.34]
MOM			0.058	-0.119			-0.544*	-0.750**			-0.996***	-1.188***
			[0.11]	[-0.21]			[-1.66]	[-2.22]			[-3.63]	[-4.55]
GP			8.628***	8.451***			7.779***	7.441***			6.651***	6.141***
			[4.99]	[5.09]			[4.27]	[4.22]			[3.94]	[3.78]
IVOL			-0.067**	-0.077**			-0.029	-0.041			-0.009	-0.022
			[-2.10]	[-2.27]			[-1.02]	[-1.32]			[-0.30]	[-0.70]
Adj R squares	0.015	0.014	0.043	0.041	0.014	0.015	0.036	0.034	0.013	0.013	0.032	0.033

Table 10: Sorts on $\mathbf{I}_{(B/M)}$ and BM_{ave}

This table reports the value-weighted average next-quarter return of portfolios formed by sorted stocks based on current period $\mathbf{I}_{(B/M)}$ and BM_{ave} or $\mathbf{I}_{(B/M)}$ and BM. For Panel A and Panel B, we first sort stocks into quintiles using $\mathbf{I}_{(B/M)}$ and then, within each quintile, we further sort stocks into quintiles based on either BM or BM_{ave}. For Panel C and Panel B report the same results with independent sorting. The row Ret Diff shows the differences of average returns between quintile 5 and quintile 1. The row FF adj shows the Fama and French (2015) five-factor adjusted differences of average returns between quintile 5 and quintile 1, with the corresponding Newey-West t-statistics shown below. The spreads followed by *, **, and *** are significant at the 10%, 5%, 1% confidence level based their time–series standard error, respectively.

Panel A: Sequential Sort First on $\mathbf{I}_{(B/M)}$ then on BM						Panel B: Sequential Sort First on $\mathbf{I}_{(B/M)}$ and then on BM_{ave}					
BM		$\mathbf{I}_{(B/M)}$ Quintile				BM_{ave}		$\mathbf{I}_{(B/M)}$ Quintile			
Quintile	Low	2	3	4	High	Quintile	Low	2	3	4	High
Low	3.89	3.56	3.35	2.53	1.93	Low	3.92	3.46	3.44	2.32	1.72
2	3.97	3.47	2.96	2.41	3.19	2	3.87	3.80	2.87	2.63	2.85
3	3.60	3.41	3.37	2.89	3.15	3	3.86	3.33	3.60	3.14	3.64
4	4.05	3.64	3.56	2.90	2.33	4	3.92	3.83	3.54	2.79	2.69
High	4.10	3.40	3.83	2.83	2.63	High	4.05	3.42	3.92	2.83	2.61
Ret Diff	0.202	-0.151	0.482	0.300	0.697	Ret Diff	0.13	-0.037	0.48	0.514	0.897*
t stats.	[0.26]	[-0.20]	[0.60]	[0.44]	[1.27]	t stats.	[0.18]	[-0.05]	[0.58]	[0.70]	[1.69]
FF adj	-0.004	-0.72	0.202	0.184	1.053*	FF adj	-0.298	-0.562	0.23	0.435	1.369**
t stats.	[-0.01]	[-1.40]	[0.32]	[0.35]	[1.86]	t stats.	[-0.58]	[-1.21]	[0.34]	[0.78]	[2.10]
Panel C: Independent Sort on $\mathbf{I}_{(B/M)}$ and on BM						**Panel D: Independent Sort on $\mathbf{I}_{(B/M)}$ and on BM_{ave}**					
BM		$\mathbf{I}_{(B/M)}$ Quintile				BM_{ave}		$\mathbf{I}_{(B/M)}$ Quintile			
Quintile	Low	2	3	4	High	Quintile	Low	2	3	4	High
Low	3.54	3.60	3.44	1.40	-0.17	Low	3.46	3.93	3.37	2.24	1.21
2	3.82	3.06	3.01	3.04	1.20	2	3.53	3.23	3.12	3.43	2.72
3	3.49	3.87	3.54	3.31	2.18	3	3.89	3.45	3.65	3.28	3.62
4	4.46	3.69	3.92	2.67	3.32	4	3.65	3.62	4.10	2.60	3.13
High	4.28	3.56	3.68	3.48	2.39	High	4.01	3.67	3.85	3.84	2.66
Ret Diff	0.737	-0.047	0.244	2.080**	2.569***	Ret Diff	0.668	-0.256	0.472	1.597**	1.317*
t stats.	[0.87]	[-0.05]	[0.28]	[2.24]	[2.97]	t stats.	[0.49]	[-0.31]	[0.55]	[1.93]	[1.76]
FF adj	0.411	-1.021	-0.386	1.754**	2.431***	FF adj	0.959	-0.924	-0.096	1.554***	2.065**
t stats.	[0.66]	[-1.59]	[-0.56]	[2.09]	[2.85]	t stats.	[0.89]	[-1.43]	[-0.14]	[2.95]	[2.43]

Table 11: BM migration across BM_{ave} and $\mathbf{I}_{(B/M)}$ quintiles

This table reports the average next-quarter quintiles of book-to-market ratio,BM, and gross profitability, GP, of portfolios formed by sorted stocks based on current period BM and $\mathbf{I}_{(B/M)}$ or BM_{ave} and $\mathbf{I}_{(B/M)}$. Panel A and C report the results related with future BM, while Panel B and D report the results related with future GP. The row Diff shows the differences of average values between quintile 5 and quintile 1, with the corresponding Newey-West t-statistics shown below. The spreads followed by *, **, and *** are significant at the 10%, 5%, 1% confidence level based their time–series standard error, respectively. The column $H-L$ shows the differences of average values between quintile High and quintile Low.

Panel A: Future BM Under Independent Sort on BM and on $\mathbf{I}_{(B/M)}$						
BM		$\mathbf{I}_{(B/M)}$ Quintile				$\mathbf{I}_{(B/M)}$
Quintile	Low	2	3	4	High	H-L
Low	1.43	1.11	1.06	1.42	2.67	1.24
2	2.29	1.56	1.44	2.08	3.66	1.37
3	3.13	2.33	2.17	2.79	4.30	1.17
4	3.99	3.12	3.02	3.55	4.80	0.81
High	4.81	4.23	4.15	4.47	4.96	0.15
Diff	3.381***	3.128***	3.089***	3.047***	2.290***	-1.09***
t stats.	[108.63]	[69.27]	[79.50]	[52.65]	[23.90]	[56.24]
Panel C: Future BM Under Independent Sort on BM_{ave} and on $\mathbf{I}_{(B/M)}$						
BM_{ave}		$\mathbf{I}_{(B/M)}$ Quintile				$\mathbf{I}_{(B/M)}$
Quintile	Low	2	3	4	High	H-L
Low	1.60	1.12	1.07	1.42	2.67	1.07
2	2.54	1.59	1.44	2.05	3.59	1.05
3	3.29	2.34	2.17	2.77	4.17	0.88
4	3.96	3.12	3.01	3.53	4.74	0.77
High	4.67	4.22	4.14	4.46	4.97	0.30
Diff	3.067***	3.098***	3.076***	3.035***	2.302***	-0.77***
t stats.	[72.71]	[69.54]	[79.49]	[51.24]	[23.50]	[41.12]

Panel B: Future GP Under Independent Sort on $\mathbf{I}_{(B/M)}$ and on BM						
$\mathbf{I}_{(B/M)}$		BM Quintile				BM
Quintile	Low	2	3	4	High	H-L
Low	3.35	2.94	2.57	2.44	2.28	-1.07
2	3.69	2.99	2.63	2.39	2.11	-1.58
3	4.03	3.12	2.62	2.33	2.09	-1.94
4	4.08	3.21	2.73	2.44	2.11	-1.97
High	3.82	3.19	2.75	2.37	2.09	-1.73
Diff	0.474***	0.258***	0.179**	-0.07	-0.192**	-0.67***
t stats.	[5.22]	[3.27]	[2.02]	[-1.19]	[-2.31]	[-4.88]
Panel D: Future GP Under Independent Sort on BM_{ave} and $\mathbf{I}_{(B/M)}$						
$\mathbf{I}_{(B/M)}$		BM_{ave} Quintile				$\mathbf{I}_{(B/M)}$
Quintile	Low	2	3	4	High	H-L
Low	3.76	3.21	2.86	2.63	2.41	-1.35
2	4.00	3.12	2.75	2.44	2.29	-1.71
3	4.08	3.08	2.60	2.33	2.12	-1.96
4	3.77	3.01	2.59	2.31	2.05	-1.72
High	3.34	2.81	2.46	2.25	2.06	-1.28
Diff	-0.419***	-0.397***	-0.396***	-0.380***	-0.352***	0.07
t stats.	[-4.98]	[-4.36]	[-5.49]	[-6.23]	[-4.94]	[1.02]

Table 12: Growth Option Conversion Tests

This table reports the Fama and MacBeth regression result of future growth option conversion on $\mathbf{I}_{(B/M)}$, BM_{ave}, and other control variables. Growth option conversion in quarter t (GOC) is the different between quarter–t capital expenditure scaled by lagged total assets and the quarter–$t-1$ capital expenditure scaled by lagged total assets. Each quarter from 1976–2014, we run a firm–level cross–sectional regression of growth option conversion on $\mathbf{I}_{(B/M)}$ and lagged predictor variables. The table reports the time–series average of the cross–sectional regression coefficient, their associated Newey-West (1987) adjusted t-statistics (in parentheses), and the regression R^2s. The coefficients followed by *, **, and *** are significant at the 10%, 5%, 1% level based their time–series standard error, respectively.

	GOC(t+1)				GOC(t+2)				GOC(t+4)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbf{I}_{(B/M)}$	-0.184***		-0.161***	-0.192***	-0.172***		-0.161***	-0.171***	-0.116**		-0.134**	-0.109**
.	[-5.51]		[-3.38]	[-3.80]	[-4.36]		[-3.52]	[-4.19]	[-2.54]		[-2.47]	[-2.50]
BM_{ave}		0.007	0.062*	0.065*		0.018	-0.041**	-0.038		0.012	0.004	0
		[0.37]	[1.94]	[1.93]		[1.04]	[-2.13]	[-1.14]		[0.41]	[0.18]	[-0.02]
log(ME)			0.004	0.001			0	-0.001			0.008	0.008
.			[0.51]	[0.05]			[0.02]	[-0.12]			[0.73]	[0.70]
log(BM)			-0.033	-0.042			0.043	0.052			0.054**	0.071***
.			[-0.68]	[-0.77]			[1.39]	[1.45]			[2.48]	[3.20]
REV			0.368***	0.345**			0.714***	0.740***			0.302**	0.353**
.			[2.82]	[2.36]			[4.03]	[4.19]			[2.51]	[2.57]
MOM			0.146***	0.131***			0.174***	0.168***			0.087***	0.111***
.			[3.77]	[3.19]			[4.20]	[4.22]			[3.14]	[3.13]
GP			0.237	0.239			0.052	0.071			0.383***	0.387***
.			[1.40]	[1.37]			[0.24]	[0.31]			[2.76]	[2.65]
IVOL			-0.001	0			-0.002	-0.001			0.005**	0.004*
.			[-0.37]	[0.13]			[-0.72]	[-0.43]			[2.25]	[1.80]
SUE_1				0.231				0.131				0.065
.				[1.40]				[0.96]				[0.55]
Adj R square	0.004	0.001	0.015	0.013	0.004	0.001	0.015	0.015	0.004	0.001	0.019	0.02

Table 13: Expectation Error Tests

This table reports the Fama and MacBeth regression result of future returns and SUE. Each quarter from 1976–2014, we run a firm–level cross–sectional regression of returns on $\mathbf{I}_{(B/M)}$ and lagged predictor variables. Specially, ‘Good’ and ‘Bad’ are two dummy variables. ‘Good’ (‘Bad’) dummy in quarter t equals to 1 if the SUE in quarter t + 1 is larger (smaller) than zero and equals to zero elsewhere. The table reports the time–series average of the cross–sectional regression coefficient, their associated Newey-West (1987) adjusted t-statistics (in parentheses), and the regression R squares. The coefficients followed by *, **, and *** are significant at the 10%, 5%, 1% level based their time–series standard error, respectively.

	(1)	(2)	(3)		(4)	(5)	(6)
	$SUE_1(t+1)$	$RET(t+1)$	$RET(t+1)$		$SUE_2(t+1)$	$RET(t+1)$	$RET(t+1))$
$\mathbf{I}_{(B/M)}$	-0.056***	-0.735*	0.553	$\mathbf{I}_{(B/M)}$	-0.038***	-0.731*	0.737*
	[-10.07]	[-1.86]	[1.43]		[-9.79]	[-1.87]	[1.93]
Good	0.103	3.449***	3.465***	Good		3.454***	3.391***
		[13.24]	[12.88]			[12.32]	[11.44]
Bad		-2.189***	-2.526***	Bad		-2.226***	-2.513***
		[-7.55]	[-9.00]			[-7.03]	[-8.18]
Good*SUE_1*NegShock			17.093***	Good*SUE_2*NegShock			31.056***
			[6.39]				[8.60]
Bad*SUE_1*PosShock			14.657***	Bad*SUE_2*PosShock			22.304***
			[7.72]				[9.15]
BM	-0.004***	0.773***	0.984***	BM	-0.003***	0.785***	0.982***
	[-2.96]	[2.73]	[3.18]		[-3.33]	[2.77]	[3.18]
Ln(ME)	-0.001***	-0.556***	-0.554***	Ln(ME)	-0.000*	-0.570***	-0.565***
	[-2.91]	[-4.08]	[-3.91]		[-1.82]	[-4.18]	[-4.00]
REV	-0.010*	-3.758***	-5.235***	REV	-0.001	-3.764***	-5.343***
	[-1.67]	[-2.83]	[-3.69]		[-0.12]	[-2.83]	[-3.76]
MOM	-0.003*	0.471	0.355	MOM	-0.002	0.419	0.3
	[-1.67]	[0.66]	[0.49]		[-1.22]	[0.58]	[0.41]
GP	0.006	6.985***	6.081***	GP	0.003	6.968***	6.092***
	[1.39]	[4.01]	[3.41]		[1.12]	[4.00]	[3.43]
IVOL	-0.001**	-0.092***	-0.057	IVOL	-0.001**	-0.092***	-0.060*
	[-2.15]	[-2.71]	[-1.60]		[-2.04]	[-2.70]	[-1.69]
SUE_2	0.158***	0.44	-2.563**	SUE_2	0.236***	0.948	-3.605***
	[6.84]	[0.51]	[-2.02]		[10.20]	[0.81]	[-2.80]
R square	0.112	0.071	0.08	R square	0.129	0.071	0.088

Table 14: Fama–MacBeth Regressions with Value-Weighted Least Square

This table reports the Fama and MacBeth regression result of returns. Each quarter from 1976–2014 we run a firm–level cross–sectional regression of returns on $\mathbf{I}_{(B/M)}$, BM_{ave} and lagged predictor variables. The table reports the time–series average of the cross–sectional regression coefficient, their associated Newey-West (1987) adjusted t-statistics (in parentheses), and the regression R^2s. The coefficients followed by *, **, and *** are significant at the 10%, 5%, 1% level based their time–series standard error, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbf{I}_{(B/M)}$	-1.756***	-1.681***	-1.071**	-0.947**	-0.824*				-1.569**	-1.480**	-1.19*	-1.035**
	[-2.98]	[-2.74]	[-2.25]	[-2.03]	[-1.91]				[-2.17]	[-2.04]	[-1.86]	[-1.79]
BM_{ave}						0.37	0.515*	0.517*	-0.043	0.513*	0.621*	0.632*
						[1.64]	[1.92]	[1.93]	[-0.13]	[1.68]	[1.79]	[1.82]
log(ME)		-0.106	-0.198	-0.173	0.956	-0.254*	-0.225	-0.224	-0.114	-0.242*	-0.215	-0.213
		[-0.89]	[-1.44]	[-1.26]	[1.42]	[-1.81]	[-1.61]	[-1.60]	[-0.94]	[-1.74]	[-1.55]	[-1.53]
log(BM)		0.04	0.577**	0.623**	-0.171							
		[0.12]	[2.08]	[2.08]	[-1.24]							
REV			-0.531	-1.371	0.629**	-1.295	-2.217	-2.258		-0.641	-1.493	-1.505
			[-0.26]	[-0.67]	[2.10]	[-0.64]	[-1.10]	[-1.11]		[-0.31]	[-0.72]	[-0.73]
MOM			2.596***	2.654***	-1.387	2.083**	2.079**	2.053**		2.509***	2.536***	2.524***
			[3.04]	[3.13]	[-0.67]	[2.48]	[2.52]	[2.50]		[2.95]	[3.01]	[3.01]
GP			7.346***	7.989***	2.646***	5.713**	6.588**	6.621**		5.818**	6.600**	6.629**
			[3.00]	[3.22]	[3.13]	[2.18]	[2.50]	[2.50]		[2.26]	[2.54]	[2.54]
IVOL			-0.096*	-0.091*	8.025***	-0.107**	-0.100*	-0.098*		-0.104*	-0.098*	-0.096*
			[-1.82]	[-1.72]	[3.21]	[-2.00]	[-1.85]	[-1.81]		[-1.96]	[-1.84]	[-1.81]
SUE_1				-0.668	-0.089*		-0.37				-0.239	
				[-0.31]	[-1.69]		[-0.16]				[-0.11]	
SUE_2					2.837			3.066				3.652
					[0.94]			[0.97]				[1.17]
R Square	0.008	0.572	0.135	0.132	0.136	0.116	0.119	0.112	0.0524	0.123	0.127	0.127

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Appendix 1: The Time Series Properties of B/M

In this section, we discuss the time–series properties of B/M: both B/M and the volatility of B/M are persistent and time–varying. We propose the $\mathbf{I}_{(B/M)}$ to simultaneously capture the dynamics of B/M.

Variance ratio test and Markov transition matrix are the two methods we use to explore the time–series properties of B/M. To detect the persistency of B/M, we mainly rely on the transition matrix for B/M. To create the transition matrix for B/M, we sort the stocks into deciles by B/M in both quarter t and $t+n$. For each quarter t, the transition matrix presents the time–series average of the percentage of stocks in a given quarter t B/M decile portfolios that fall in $t+n$ B/M deciles. If B/M is persistent, the average percentage of stocks that fall in the same decile in quarter t and quarter $t+n$ must be high. Comparing with autocorrelation, transition matrix is more fitful for our research on the cross sectional of stocks: autocorrelation can only capture the persistency of a single time series but transition matrix can simultaneously capture the dynamics of stocks over time across the large cross section of stocks. To explore the time–variation of B/M and the volatility of B/M, we use both variance ratio test and transition matrix. Before going to the main tests, we first describe our sample selection rule and the definition for B/M.

We then turn to the time-varying volatility of B/M. First, we employ the variance ratio test (Campbell, Lo, MacKinlay, et al. (1997)) to investigate the time–varying volatility of B/M. The variance ratio test in this paper is performed at the firm level on each firm's realized volatility of B/M innovations. We only include in our sample the firms with more than 16 continuous B/M observations. First, we obtain residuals, $\epsilon_{\Delta d,t}$, from an AR(8) regression of B/M. Using 8 lags matches the two–year horizon for B/M and is more than adequate to account for the autocorrelation. Then, for each stocks, we compute the variance ratios for the absolute value of the residuals based on Equation (A.1)

$$VR_J = \frac{var[\Sigma_{j=0}^{J-1}|\epsilon_{\Delta d,t+j}|]}{J \times var[|\epsilon_{\Delta d,t+j}|]}, \tag{A.1}$$

where J is the horizon in quarter.

For statistical inference, we generate for each stock 10,000 bootstrap samples and compute the variance ratio for each sample. Here, the resampling procedure treats each data point in the time series as independent. Hence, the bootstrap samples and the percentiles are obtained under the null hypothesis of serial independence. As stated in Bansal and Yaron (2004), Campbell, Lo, MacKinlay, et al. (1997), and Yang (2011), without the time–varying volatility, the variance ratios in Equation (A.1) should be close to 1 with respect to different horizons.

We calculate the B/M variance ratios for individual stocks and report the summary statistics in Table A.1. With the increase in horizons from 8 quarters to 32 quarters, the percentage of individual stocks' variance ratios above 1 monotonically increases. For the horizon of eight quarters, based on the bootstrap percentile for each stock, we reject the null hypothesis of no time–varying volatility at 5% level for 46% of stocks. The rejection rate at 5% level then climbs up from 62% for 16–quarter horizon to 95% for 32–quarter horizon. In other words, the variance ratio test implies that at least 95% of the stocks in our sample have time–varying volatility in B/M in 32–quarter horizon.

To further understand the time variation of B/M, we manually go over B/M time series process for many stocks. We find that similar to the process of many asset classes, the time variation of B/M clusters. In other words, the B/M for many stocks changes dramatically in a certain period of time but becomes relatively smooth in other period.

Table A.1: The Variance Ratio Tests for B/M

The VR, of the realized volatility of $IVOL$ in the empirical data for each individual stock is calculated. This table reports the summary statistics of VR across stocks. Bootstrap percentiles are computed under the null hypothesis of no serial correlation by resampling the realized volatility series for 10,000 times. We also report the average 95% percentile for VR and the rejection rate.

	1st Pctl	10th Pctl	Q1	Median	Q3	90th Pctl	99th Pctl	Ave 95th Pctl Rej	Rej. Rate
Horizon (in Quarter)									
8	0.352	0.834	0.902	1.246	1.452	1.731	2.195	1.25	46%
16	0.417	0.931	1.355	1.683	1.894	2.082	2.414	1.47	62%
24	1.200	1.522	1.815	2.044	2.287	2.599	2.973	1.64	84%
32	1.473	1.886	2.008	2.293	2.571	2.89	3.306	1.78	95%

Table A.2: Single Portfolio Sort for $\mathbf{I}_Q$

This table reports the average next-quarter returns and firm characteristics of decile portfolios formed by sorting stocks on the $\mathbf{I}_Q$. EW and VW reports equal-weight and value-weight, respectively. R_{Raw} is the raw quarterly return and R_α is the risk-adjusted return. α, FF5, EW reports the equal-weighted abnormal return adjusted by the 5-factor model of Fama and French (2015). The row Diff reports the differences of average returns between decile 10 and decile 1, i.e. H-L, with the corresponding Newey-West t-statistics shown in the last row. The spreads followed by *, **, and *** are significant at the 10%, 5%, 1% confidence level based on their time–series standard error, respectively. The firm characteristics of the decile portfolios are equal-weighted. The unadjusted and adjusted returns, MOM, and $IVOL$ are reported in percentage.

Decile	R^{EW}_{Raw}	$R^{EW}_{\alpha,FF}$	R^{VW}_{Raw}	$R^{EW}_{\alpha,FF}$	I_Q	ME	BM	MOM	GP	REV	$IVOL$	SUE_1	SUE_2
1	4.37	1.66	3.73	1.70	-0.182	$878.98	0.70	0.76	9.80	1.74	13.57	4.44	-0.51
2	4.36	1.82	4.01	2.19	-0.092	$1,815.79	0.74	0.46	9.67	1.59	11.82	0.73	-0.17
3	4.08	1.57	3.72	1.92	-0.053	$2,433.08	0.78	0.32	9.56	1.53	11.31	0.46	-0.10
4	3.65	1.08	3.22	1.37	-0.026	$2,713.09	0.85	0.22	9.43	1.26	11.13	0.75	-0.50
5	3.63	1.02	3.13	1.29	-0.005	$2,569.66	0.90	0.14	9.22	1.12	11.47	-0.44	-0.12
6	3.65	0.97	2.63	0.56	0.015	$2,565.10	0.95	0.08	9.13	1.13	11.63	1.47	-0.15
7	3.33	0.53	2.64	0.51	0.037	$2,278.15	0.96	0.01	9.18	0.86	11.94	-0.40	-0.19
8	3.23	0.24	2.69	0.46	0.066	$1,904.98	0.98	-0.06	9.00	0.78	12.59	1.61	-0.21
9	2.76	-0.29	2.48	0.05	0.110	$1,353.06	1.06	-0.15	8.78	0.54	13.92	-0.43	-0.42
10	2.48	-0.74	1.99	-1.01	0.215	$588.69	1.25	-0.30	8.10	0.22	16.65	-0.86	-0.66
Diff	-1.891***	-2.407***	-1.743***	-2.703***	0.398***	-290.30**	0.549***	-1.057***	-1.703***	-1.518***	3.081***	-5.30**	-0.149
t stats.	[-4.27]	[-4.95]	[-3.74]	[-4.51]	[19.22]	[-2.08]	[9.34]	[-18.23]	[-5.69]	[-3.93]	[4.96]	[-2.08]	[-0.59]

Table A.3: Double Portfolio Sorts for $\mathbf{I}_Q$

This table reports the value-weighted average next-quarter returns of portfolios formed by double sorting stocks on the $\mathbf{I}_Q$ and firm characteristics. For each firm characteristic, we first sort stocks into quintiles using the characteristic, and then within each quintile, we further sort stocks into quintiles based on the $\mathbf{I}_Q$. The row Ret Diff shows the differences of average returns between quintile 5 and quintile 1. The row FF adj shows the Fama and French (2015) five-factor adjusted differences of average returns between quintile 5 and quintile 1, with the corresponding Newey-West t-statistics shown below. The spreads followed by *, **, and *** are significant at the 10%, 5%, 1% confidence level based their time–series standard error, respectively.

Panel A: Market Capitalization						Panel B: BM					
$\mathbf{I}_Q$	Market Cap Quintile					$\mathbf{I}_Q$	BM Quintile				
Quintile	Low	2	3	4	High	Quintile	Low	2	3	4	High
Low	4.09	4.75	4.30	4.39	3.59	Low	3.77	3.36	3.94	4.54	3.56
2	4.18	4.02	3.96	3.86	3.33	2	3.40	3.42	3.88	3.73	4.04
3	3.59	3.84	3.83	3.74	2.87	3	3.20	2.83	3.09	3.63	3.59
4	3.21	3.50	3.04	3.19	2.49	4	2.64	2.51	2.87	3.24	3.03
High	2.86	1.88	2.32	2.51	2.48	High	2.04	2.37	2.34	2.43	2.62
Ret Diff	-1.227**	-2.871***	-1.973***	-1.880***	-1.108	Ret Diff	-1.736***	-0.987	-1.596***	-2.110***	-0.935
t stats.	[-2.08]	[-4.49]	[-3.16]	[-2.78]	[-1.65]	t stats.	[-2.56]	[-1.33]	[-2.87]	[-3.09]	[-0.95]
FF adj	-1.610***	-3.410***	-2.465***	-2.503***	-1.542**	FF adj	-1.811***	-1.289	-2.034***	-2.694***	-2.542***
t stats.	[-3.02]	[-4.39]	[-3.67]	[-4.09]	[-2.37]	t stats.	[-2.71]	[-1.65]	[-2.86]	[-3.10]	[-2.64]
Panel C: REV						Panel D: MOM					
$\mathbf{I}_Q$	REV Quintile					$\mathbf{I}_Q$	MOM Quintile				
Quintile	Low	2	3	4	High	Quintile	Low	2	3	4	High
Low	4.08	4.03	4.34	3.36	4.18	Low	2.36	3.15	3.39	4.13	4.01
2	2.38	3.29	3.73	3.32	3.39	2	2.19	2.74	2.92	3.68	4.49
3	2.47	2.80	3.40	3.27	3.27	3	1.44	3.14	2.93	3.43	4.16
4	2.01	2.88	3.39	2.26	2.66	4	1.72	3.05	2.40	3.25	4.26
High	1.50	2.67	2.85	2.18	1.90	High	1.06	2.65	2.90	2.68	3.99
Ret Diff	-2.573***	-1.365*	-1.487*	-1.178*	-2.281***	Ret Diff	-1.301**	-0.502	-0.492	-1.450***	-0.022
t stats.	[-2.94]	[-1.69]	[-1.92]	[-1.97]	[-3.72]	t stats.	[-2.42]	[-0.90]	[-0.74]	[-2.92]	[-0.03]
FF adj	-3.435***	-2.095**	-1.958**	-1.798***	-3.118***	FF adj	-1.718***	-0.524	-0.503	-1.944***	0.028
t stats.	[-4.03]	[-2.42]	[-2.51]	[-3.05]	[-4.67]	t stats.	[-2.80]	[-1.00]	[-0.70]	[-3.87]	[0.04]

Table A.3 – Continued

Panel E: GP						Panel F: IVOL					
$\mathbf{I}_Q$		GP Quintile				$\mathbf{I}_Q$		IVOL Quintile			
Quintile	Low	2	3	4	High	Quintile	Low	2	3	4	High
Low	4.07	3.45	3.44	4.07	4.63	Low	3.86	4.21	5.07	4.35	2.74
2	3.34	2.73	3.49	3.46	4.24	2	3.14	4.07	3.49	2.56	2.96
3	1.61	2.52	2.84	3.02	4.23	3	3.33	3.35	2.53	3.08	0.94
4	1.20	2.27	2.95	3.06	3.68	4	2.41	3.13	2.38	1.40	0.91
High	0.78	1.85	3.01	3.45	3.45	High	2.62	2.65	2.89	2.13	0.43
Ret Diff	-3.289***	-1.599*	-0.43	-0.624	-1.175	Ret Diff	-1.232*	-1.558**	-2.181**	-2.219*	-2.311**
t stats.	[-3.14]	[-1.90]	[-0.48]	[-0.78]	[-1.30]	t stats.	[-1.91]	[-2.10]	[-2.33]	[-1.79]	[-2.08]
FF adj	-4.322***	-2.433***	-1.005	-1.184	-1.806**	FF adj	-1.783***	-2.357***	-3.055***	-3.743***	-3.589***
t stats.	[-3.82]	[-3.14]	[-1.23]	[-1.54]	[-2.15]	t stats.	[-2.97]	[-3.44]	[-2.94]	[-3.09]	[-2.93]
Panel G: SUE_1 and $\mathbf{I}_Q$						Panel H: SUE_2 and I_Q					
$\mathbf{I}_Q$		SUE_1 Quintile				$\mathbf{I}_Q$		SUE_2 Quintile			
Quintile	Low	2	3	4	High	Quintile	Low	2	3	4	High
Low	4.33	3.60	4.04	4.66	4.67	Low	3.61	3.38	4.01	4.62	4.82
2	3.33	2.70	3.60	4.03	3.42	2	2.94	2.72	3.60	4.09	3.91
3	2.41	2.52	3.33	4.10	3.48	3	2.01	2.79	3.31	3.92	3.92
4	2.76	2.16	2.84	2.86	3.49	4	2.66	2.48	2.86	2.94	3.50
High	1.90	2.21	2.76	3.29	3.01	High	1.95	2.24	2.60	3.22	3.05
Ret Diff	-2.431***	-1.389*	-1.279	-1.377	-1.652*	Ret Diff	-1.660***	-1.143	-1.413	-1.400	-1.763***
t stats.	[-2.72]	[-1.84]	[-1.36]	[-1.59]	[-1.76]	t stats.	[-2.71]	[-1.63]	[-1.58]	[-1.39]	[-2.87]
FF adj	-3.696***	-2.190***	-1.627**	-1.775**	-2.239**	FF adj	-2.795***	-1.725***	-1.839**	-1.909**	-2.543***
t stats.	[-5.02]	[-3.21]	[-2.16]	[-2.18]	[-2.45]	t stats.	[-3.84]	[-2.82]	[-2.55]	[-2.13]	[-2.95]