Does mispricing drive the value effect? Evidence from Japan

Naoya Shiomi*

Faculty of Economics, Hosei University, 4342 Aihara, Machida, Tokyo 194-0298, Japan

Hidetomo Takahashi

Faculty of Economics, Hosei University, 4342 Aihara, Machida, Tokyo 194-0298, Japan

Peng Xu

Faculty of Economics, Hosei University, 4342 Aihara, Machida, Tokyo 194-0298, Japan.

Abstract

This paper shows that the residual book-to-market, which is free of the effects of investment factors and distress risk, can predict future stock appreciation. In addition, we find that the tendency is stronger among stocks with higher idiosyncratic volatility and lower investor sophistication. Our findings indicate that mispricing is the main driver of the value effect.

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*Corresponding author

Email addresses: naoya.shiomi.9y@stu.hosei.ac.jp (Naoya Shiomi), htak@hosei.ac.jp (Hidetomo Takahashi), pxu@hosei.ac.jp (Peng Xu)

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1. Introduction

The tendency that stocks with high book-to-market ratios (BM) earn substantially higher returns than do those with low BMs is one of well-known anomalies in the stock market. It is called the value effect. In the literature, there exist two competing explanations for this phenomenon: the risk-based explanation and the mispricing hypothesis. The former argues that the BM reflects the relative distress risk of a firm and the risk of a firm's investment activities (Fama and French, 2006; Griffin and Lemmon, 2002; Zhang, 2005). The latter states that investors tend to overvalue (undervalue) firms with low (high) BMs, which results in mean-reverting in the subsequent periods (Lakonishok, Shleifer, and Vishny, 1994).

In this paper, we examine whether the value effect is due to systematic risks or whether it occurs because of behavioral reasons. First, we test whether the value effect disappears after eliminating the effects of systematic risks on the BM. After estimating residuals (RedBM) by regressing BMs on proxies for financial distress and investment activities (i.e., asset growth, investment to asset, new stock issue), we form quintile portfolios according to RedBM and evaluate monthly return spreads between the highest RedBM portfolio and the lowest RedBM portfolio (RedBM hedging portfolio). We find that the RedBM hedging portfolio yields positive returns with statistical significance. The return is not different from that of the BM hedging portfolio. Our results indicate that the relative distress risk of a firm and the risk of the firm's investment activities do not seem to be a main driver of the value effect, which means that the value effect is due to mispricing.

Second, we test whether the value effect is driven by misevaluation by investors. To test this prediction, we examine the effect of limit-to-arbitrage on the value effect. As suggested by Shleifer and Vishny (1997), when arbitrages are costly, risky, and limited, there is a possibility that mispricing may not be corrected quickly. By employing two proxies for limit-to-arbitrage, we form 15 portfolios with RedBM and each limit-to-arbitrage proxy. Following Ali, Hwang, and Trombley (2003), we use idiosyncratic volatility and investor sophistication as proxies for limit-to-arbitrage. Then, we evaluate the monthly return spreads between the highest RedBM portfolio and the lowest RedBM portfolio on the subsample splits by using a given limit-to-arbitrage proxy. We find that the returns of RedBM hedging portfolios take larger values among the subsamples that have higher idiosyncratic volatility and lower investor sophistication. The results lend support for the prediction that the value effect is due to mispricing.

Our findings contribute to the literature on the value effect, in which it is still controversial whether the value effect is driven by systematic risks or mispricing. Xing (2008) finds that the value effect disappears after controlling for investment factors, which is consistent with the q-theory suggested by Zhang (2005). However, Ali, Hwang, and Trombley (2003) find that the value effect is stronger among stocks with higher idiosyncratic risk, higher transaction costs, and lower analyst following, which is consistent with Shleifer and Vishny (1997). We provide robust evidence supporting the mispricing hypothesis by using residual BMs that are not affected by systematic risks.

The remainder of this paper is organized as follows. The next section describes the primary data and calculates the book-to-market equity residuals used in our tests. Section 3 describes the results of comprehensive analysis whether the value effect is due to risk or mispricing. Section 4 presents the conclusion of this study.

2. Data

2.1. Primary data

Our sample consists of firms listed in the first section of the stock exchanges in Japan from the period of 1980 to 2010, based on market and financial data available from the Nikkei Economic Electronic Databank System. We exclude financial institutions and firms with negative book values. We also winsorize firms with highest and lowest 0.5% of BMs to alleviate the effect of outliers. Under these data requirements, the number of firms in our sample ranges from 846 firms in 1980 to 1,523 firms in 2010, with an average of 1,195 firms per year.

2.2. Definition of variables

We define variables used in our tests as follows. BM is defined as the ratio of book value of equity to market value of equity (MCAP). We employ asset growth (AG), investment to asset (IA), and net stock issue (NSI) as proxies for the systematic risk of investment activities. Following Cooper, Gulen, and Schill (2008), we measure AG as the change in total assets. Following Lyandres, Sun, and Zhang (2008), IA is measured as the change in gross property, plant, and equipment (PPE) plus the change in inventories.[1] To standardize AG and IA, both values are divided by the total assets at the previous fiscal year end. Following Li and Zhang (2010), net stock issue (NSI) is defined as the natural log of the ratio of the shares outstanding divided by the shares outstanding at the end of the previous fiscal year. Variables from financial data are used as of the most recent fiscal year end. The variables

[1] Gross PPE are calculated as the sum of the net PPE plus depreciation plus impairment loss. Because the impairment loss on the Nikkei NEEDS database includes both impairment loss on PPE and intangibles, we allocate the impairment loss for PPE in proportion to the amount of net PPE divided by the sum of net PPE plus intangibles.

are revised a month after the release of financial statements. We also employ a proxy for financial distress. We calculate probability of financial distress (Pnaive) following Bharath and Shumway (2008).

Panel A of Table 1 presents time-series averages of the mean, standard deviation, minimum, and maximum of firm characteristics. The mean of BM is 0.699, which indicates that, on average, the firm's market value exceeds its book value. The mean of AG is 0.044, with a standard deviation of 0.110; the mean of IA is 0.039, with a standard deviation of 0.073; and the mean of NSI is 0.015, with a standard deviation of 0.043. These values indicate that there are significant variations in investment-related variables both across firms and over time.

2.3. Residual book-to-market ratios (RedBMs)

To calculate RedBMs, we regress BM on AG, IA, NSI, Pnaive, and the natural logarithm of MCAP (LnMCAP) and obtain residuals. Panel B of Table 1 reports the results of time-series average of annual regressions (Fama-MacBeth regression results). The t-statistics are adjusted using Newey and West's (1987) robust standard errors with a one-month lag. Panel B shows the multiple regression result with all risk-related variables. As shown in Panel B, the slope coefficients of AG and NSI are negative (-0.313 and -1.018) and are statistically significant ($t = -10.03$ and -16.36). However, the slope coefficient of IA is slightly positive (0.041) and is not statistically significant ($t = 1.24$). This result indicates that the slope coefficient of IA is subsumed. Panel B also shows that the slope coefficient of Pnaive is positive (0.392), with a t-statistic of 2.81, and that the slope coefficient of LnMCAP is negative (-0.095), with a t-statistic of -14.66. Overall, the above results imply that risks of investment activities and financial distress affect BM.

3. Empirical results

3.1. Portfolios sorted by BM and RedBM

In this section, by using RedBM predicted in formula Panel B of Table 1, we evaluate the value effect after controlling for the effect of systematic risks on BM. For each month, we form quintile portfolios with the latest RedBM and construct a hedging portfolio that longs the highest RedBM portfolio and shorts the lowest RedBM portfolio. Then, we calculate time series average of monthly equal- and value-weighted returns of quintile and hedging portfolios. We also estimate alphas by regressing the monthly excess returns on Fama and French (1993) three-factors plus a momentum factor (Carhart, 1997).[2] Table 2 reports the results of alphas. After controlling for four factors, the equal-weighted alpha is 0.51% and statistically significant ($t = -4.51$); the value-weighted alpha is 0.51% and is statistically significant ($t = 4.52$). These results show that the mispricing is still a strong driver of the value effect, even after controlling for traditional factors.

3.2. Portfolios sorted by BM/RedBM and proxies for limit-to-arbitrage

The mispricing hypothesis suggests that the value effect reflects mispricing due to the market participant's behavioral biases. If mispricing is a main driver of the value effect, the value effect is expected to be stronger among firms with a stricter limit-to-arbitrage. To test this prediction, we employ two proxies for limit-to-arbitrage. The first one is idiosyncratic volatility (IVOL). Because arbitrageurs are poorly diversified, idiosyncratic risk adds substantially to the total risk of their portfolios. Therefore, arbitrageurs tend to avoid investing in firms with high IVOL, which leads to difficulty in hedging (Shleifer and Vishny, 1997).

[2]These factors are calculated using the Japanese market data following the description in the Kenneth R. French Data Library Web site.

Following Ali, Hwang, and Trombley (2003), IVOL is defined as the standard deviation of the residuals obtained from regressions of excess returns of individual stocks over the past 36 months on the 4-factor, Fama-French three factors and a momentum factor. The second proxy is foreign investors ownership (FORGN), which is defined as the percentage of outstanding shares held by foreign investors. According to Hamao and Mei (2001), foreign investors have more sophisticated investment technology than do their domestic investors in Japan.

Using proxies for the degree of limit-to-arbitrage, we examine the return predictability of RedBM. First, we divide all stocks into three groups according to each proxy for limit-to-arbitrage. We employ the top three and bottom three deciles based on each proxy for limit-to-arbitrage as breakpoints. Then, we form quintile portfolios with the latest RedBM and construct a hedging portfolio. Table 3 reports four-factor model-adjusted alphas of the portfolios in each subsample with t-statistics using Newey and West's (1987) robust standard errors.

Panel A of Table 3 shows that when we employ equal-weighted portfolios, the RedBM hedging portfolio with high IVOL yields larger returns than does a portfolio with a low IVOL. The spread between the RedBM hedging portfolio with a high IVOL and that with a low IVOL is 0.48%, and this difference is statistically significant ($t = 2.83$). Panel B of Table 3 presents, when we employ equal-weighted portfolios, the RedBM hedging portfolio with low FORGN yields larger returns than does that with high FORGN. The spread between high FORGN and low FORGN is -1.07% and is statistically significant ($t = -5.36$).[3] The

[3]In the case of both proxies, when we employ value-weighted portfolios, we obtain similar empirical results.

above findings indicate that the degree of limit-to-arbitrage affects the magnitude of the value effect, which means that mispricing is a strong driver of the value effect.

4. Conclusion

In this paper, we show that the effect of mispricing on the value effect persists, even after we control for the effect of risks such as investment factors and financial distress. Using BMs free of investment factors and financial distress (RedBM), we find that RedBM can predict future price appreciations. We also find that the tendency is stronger among stocks with higher degrees of limit-to-arbitrage. Our findings provide supportive evidence for the hypothesis that the behavioral biases of investors drive the value effect. We contribute to the literature on the value effect in that we provide more robust empirical evidence than do Ali, Hwang, and Trombley (2003). We obtain similar results to Ali, Hwang, and Trombley (2003), even after eliminating the effect of investment factors and distress risks.

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Table 1: Summary statistics of firm characteristics. Panel A reports descriptive statistics of firma characteristics and Fama-MacBeth (annually) regression results of book-to-market ratios on firm characteristics from 1980 to 2010. BM is defined as the ratio of book value of equity to market value of equity (MCAP). Asset growth (AG) is the change in total assets. Investment-to-asset (IA) is measured as the change in gross property, plant, and equipment (PPE) plus the change in inventories. Net stock issue (NSI) is defined as the natural log of the ratio of the shares outstanding divided by the shares outstanding at the previous fiscal year. Probability of financial distress (Pnaive) is calculated following Bharath and Shumway (2008). Panel B reports time-series average of regressions of BM on AG, IA, NSI, Pnaive, and MCAP. t-statistics are adjusted for the Newey and West (1987) robust standard errors with one year lag.

Panel A: Descriptive statistics of firm characteristics						
	BM	AG	IA	NSI	Pnaive	MCAP ($*10^6$)
Mean	0.699	0.044	0.039	0.015	0.041	211,411
SD	0.378	0.110	0.073	0.043	0.102	639,804
Min	0.045	-0.281	-0.229	-0.027	0.000	4,855
Max	2.555	0.657	0.457	0.355	0.780	14,120,658
Panel B: Fama-MacBeth regression of BM on firm characteristics						
	Intercept	AG	IA	NSI	Pnaive	MCAP
coef.	1.649	-0.225	-0.004	-0.980	0.443	-0.089
t-stat.	5.43	-3.06	-0.04	-5.78	3.05	-4.28

Table 2: Alphas of BM/RedBM quintile and hedging portfolios. This table reports the 4-factor model (Fama and French three-factors plus momentum factor) adjusted alphas of BM/RedBM quintile and hedging portfolios. For each month, we construct a hedging portfolio that has a long position in the highest BM/RedBM portfolio and a short position in the lowest BM/RedBM portfolio, using the latest BM/RedBM. This table report equal- and value-weighted returns of portfolios with t-statistics, which are adjusted using Newey and West (1987) robust standard errors with one month lag.

Sorting by	EW/VW	1 (low)	2	3	4	5 (high)	5–1	t(5-1)
BM	EW	-0.205%	-0.200%	-0.094%	-0.120%	0.046%	0.251%	2.53
BM	VW	-0.168%	-0.191%	-0.094%	-0.126%	0.044%	0.212%	2.12
RedBM	EW	-0.449%	-0.135%	-0.096%	0.050%	0.059%	0.508%	4.51
RedBM	VW	-0.444%	-0.130%	-0.087%	0.057%	0.062%	0.506%	4.52

Table 3: Alphas of hedging portfolio sorted by RedBM in subsamples sorted by proxies for limit-to-arbitrage. This table reports 4-factor model adjusted alphas of quintile and hedging portfolio sorted by RedBM on subsamples that were first sorted by proxies for limit-to-arbitrage: Idiosyncratic volatility (IVOL) and foreign investor ownership (FORGN). IVOL is defined as the standard deviation of residuals estimated by regressing e individual returns on Fama and French three-factors plus momentum factor over the past 36 months. FORGN is defined as the percentage of outstanding shares held by foreign investors at the previous fiscal year end. First, all stocks are divided into three groups according to each proxy for limit-to-arbitrage. The top three and bottom three deciles based on each proxy for limit-to-arbitrage are employed as breakpoints. Then, in each subsample, quintile and hedging portfolios are constructed using the latest RedBM. Panels A and B report the results when IVOL is employed as a proxy for limit-to-arbitrage. Panels C and D report the results when FORGN is employed as a proxy for limit-to-arbitrage. t-statistics are adjusted using Newey and West (1987) robust standard errors with one month lag.

Panel A: Equal-weighted returns of portfolio sorted by RedBM in subsamples sorted by IVOL							
	1(low RedBM)	2	3	4	5(high RedBM)	5–1	t(5-1)
1(low IVOL)	-0.091%	-0.050%	0.080%	0.142%	0.191%	0.282%	2.36
2	-0.181%	-0.040%	-0.104%	0.070%	0.100%	0.281%	2.29
3(high IVOL)	-0.914%	-0.378%	-0.255%	-0.270%	-0.154%	0.760%	4.74
3(high)-1(low)						0.477%	2.83
Panel B: Value-weighted returns of portfolio sorted by RedBM in subsamples sorted by IVOL							
	1(low RedBM)	2	3	4	5(high RedBM)	5–1	t(5-1)
1(low IVOL)	-0.091%	-0.056%	0.086%	0.150%	0.199%	0.290%	2.40
2	-0.190%	-0.054%	-0.099%	0.062%	0.085%	0.275%	2.25
3(high IVOL)	-0.928%	-0.371%	-0.223%	-0.247%	-0.152%	0.776%	4.84
3(high)-1(low)						0.486%	2.92
Panel C: Equal-weighted returns of portfolio sorted by RedBM in subsamples sorted by FORGN							
	1(low RedBM)	2	3	4	5(high RedBM)	5–1	t(5-1)
1(low FORGN)	-0.888%	-0.253%	-0.208%	0.008%	0.227%	1.116%	6.59
2	-0.237%	-0.245%	-0.085%	-0.118%	0.021%	0.259%	2.03
3(high FORGN)	-0.029%	-0.031%	0.100%	0.060%	0.015%	0.044%	0.31
3(high)-1(low)						-1.071%	-5.36
Panel D: Value-weighted returns of portfolio sorted by RedBM in subsamples sorted by FORGN							
	1(low RedBM)	2	3	4	5(high RedBM)	5–1	t(5-1)
1(low FORGN)	-0.924%	-0.266%	-0.214%	-0.001%	0.226%	1.149%	6.86
2	-0.247%	-0.255%	-0.083%	-0.106%	0.023%	0.270%	2.12
3(high FORGN)	-0.012%	-0.023%	0.116%	0.070%	0.026%	0.038%	0.26
3(high)-1(low)						-1.111%	-5.54