The Value Premium Puzzle, Behavior versus Risk: New Evidence from China

Abstract

This paper investigates the value premium puzzle in the Chinese stock market. After establishing that the value premium does exist in the Chinese stock market, it uses an innovative technique based on stochastic dominance theory to test the behavior based versus risk based explanations for the puzzle. We find no evidence of a systematic behavioral factor, such as over/under-reaction, that is driving this premium. This finding is robust with respect to negative and positive return regimes. We do, however, find strong evidence that the value premium reflects compensation for bearing more risk associated with financial inflexibility.

***JEL Classification*:** C14 ; G11; G12

Keywords: Value premium puzzle; Risk; Financial inflexibility; Stochastic dominance

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1. Introduction

The “value premium puzzle” refers to the well documented anomaly where stocks with high B/M ratios (i.e., value stocks) earn higher average returns than stocks with low B/M ratios (i.e., growth stocks) (e.g., Fama and French, 1992 and 1993; Lakonishok et al., 1994; Daniel and Titman, 1997; etc.). Although much of the research focuses on the US market, other studies show that the value premium is not confined to the US stock market, but exists in many foreign markets as well (e.g. Fama and French, 1998). Financial economists have struggled for decades to explain this puzzle. The current, ongoing debate of why value stocks earn higher average returns than growth stocks pits the behavioral-based explanations against the more conventional risk-based explanations. For example, researchers such as DeBondt and Thaler (1987), Lakonishok et al. (1994), and Daniel and Titman (1997) attribute the value premium to behavioral finance and argue that naive investors’ extrapolation of the future trend from the past is the reason the value premium exists. In particular, investors might overreact by naively extrapolating past corporate performance, resulting in stock prices that are “too high” for growth stocks and “too low” for value stocks. This point of view is also supported by Chan and Lakonishok (2004) among others. In contrast to the behavioral-based explanation of the value premium, there is an alternative explanation that attributes the value premium to risk compensation. For example, Fama and French (1992, 1993 and 1996) argue that value stocks are fundamentally riskier than growth stocks, and the value premium is simply a compensation for bearing more risk. Chen and Zhang (1998) use a set of risk characteristics including firm distress, financial risk, and the riskiness of future cash flows that provide support for the risk compensation argument. Petkova and Zhang (2005) find that betas of value stocks are positively correlated with the expected market premium, while betas of growth stocks are negatively correlated with the expected market premium and conclude that time-varying risk can partially explain the value premium.[1] Up to now, there is no consensus on what is driving the value premium.

In this study, we look at the Chinese market to shed some light on these conflicting explanations for the premium puzzle. The Chinese stock market is an interesting case in point because, although it only began in the early 1990s, by the end of 2014 it had grown to become the second largest in the world by market capitalization based on the statistics of the World Federation of Exchanges. It also has some interesting characteristics that lend themselves to a study of the value premium. First of all, retail investors account for 85% of all trades in the Chinese equity market, 70% of whom hold three stocks or less.[2] Consequently, the potentially biased behaviors of individual investors are likely to have a more important impact on Chinese stock returns and anomalies than one observes in developed markets dominated by sophisticated institutional investors (e.g., Ng and Wu, 2006; Feng and Seasholes, 2008; Lee et al., 2010). For example, several studies have documented strong behavioral biases among Chinese investors, such as over-confidence, the disposition effect, representativeness bias, and herding.[3] Secondly, Chinese retail investors seem to have an attitude towards risk that differs radically from what is observed in the US. Chiang et al. (2011) have documented, that in contrast to the US market where the negative return regime is accompanied by higher volatility, in the Chinese market it is the positive regime that is associated with higher stock volatility while the negative regime is associated with decreasing volatility.

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[1] Focusing on business cycle risk, Fong (2012) uses a measure of expected business conditions based on real GDP growth forecasts in the Livingston Survey published by the Federal Reserve Bank of Philadelphia. He finds that the value premium cannot be explained by business cycle risk in the US.

[2] This is based on a market survey conducted through a survey platform "Investors Voice" under Shanghai Stock Exchange in 2016. http://m.sohu.com/n/467240289/?wscrid=95360_5

[3] See, for example, Feng and Seasholes (2005), Kim and Nofsinger (2008), and Tan et al. (2008).

Research on the value premium puzzle in the Chinese stock market is also very limited and the empirical evidence is inconclusive. Cai and Wu (2003), Wu and Xu (2004), Wang (2004) and Eun and Huang (2007) show that the value premium exists in the Chinese stock market, while Drew et al. (2003) and Wang and Xu (2004) do not support this finding. Wu and Xu (2004) and Wang (2004) find evidence that supports the risk-based explanation of the value premium while Cai and Wu (2003) find evidence that rejects it in favor of the behavior based explanation. Otherwise, the literature is silent on the value premium puzzle in the Chinese stock market.

This paper aims to fill this gap in the literature. We begin by using stochastic dominance theory (Hanoch and Levy, 1969; Whitmore, 1970; etc.) to determine the plausibility of risk based versus behavioral based explanations for the value premium puzzle. Stochastic dominance (SD) is a general approach to expected utility maximization, the cornerstone of modern investment theory and practice. In contrast to the popular but restrictive mean-variance framework,[4] the stochastic dominance framework requires neither a specific utility function nor a specific return distribution. Under the general assumption that investors are risk averse, SD provides the probabilistic conditions under which all non-satiating, risk-averse investors prefer one risky asset to another. The most commonly used SD rules are first, second, and third-order SD for risk-averse investors, denoted as FSD, SSD, and TSD, respectively. Under FSD all investors prefer more to less. Under SSD, they prefer more to less and are risk-averse. Under TSD they prefer more to less, they are

[4] Within the comprehensive framework of utility maximization mean-variance (MV) optimization, based on a single measure of risk, is the special case that is most widely accepted throughout the financial profession. MV, however, has a major shortcoming in that the conditions for it to be analytically consistent with expected utility maximization, such as quadratic utility functions or normally distributed returns, seldom hold in practice. See, for example, Mandelbrot (1963). Furthermore, it has been shown that risk measures other than variance, such as the third and the fourth moments of return distributions - skewness and kurtosis respectively - do matter to investors, who show a preference for positive skewness and an aversion to kurtosis (see, Kraus and Litzenberger (1976), Dittmar (2002), Post et. al. (2008)).

risk averse and they are prudent, meaning that the third derivative of their utility function is greater than or equal to 0.

Using these very general rules of dominance, we test for evidence of systematic incremental utility associated with value stocks compared to growth stocks. The absence of SD would suggest that there is no systematic incremental utility associated with value stocks compared to growth stocks. Any differences in returns would be explained by tradeoffs across the various risk measures (moments) of the two return distributions. For example, in mean-variance space a higher return for the value portfolio would be offset by a higher variance. In mean-variance-skewness space higher returns would be offset by higher variance, lower skewness, or a combination of the two. The presence of SD, however, would suggest that something besides the return distributions, such as misvaluation of the capital markets, is driving the value premium. Our results reject the presence of SD at any order over the whole sample. To control for behavioral characteristics specific to different market states, such as overreaction in the positive regimes or under-reaction in the negative regimes, we extend the SD analysis to look independently at positive and negative regimes. Again, our results reject the presence of SD at any order over both the positive and negative domains of the sample. We conclude that there is no systematic phenomenon, such as misvaluation of the capital markets, that is driving the value premium.

Following a number of papers that have focused on the link between financial inflexibility and the value premium (Carlson et al., 2004; Garlappi and Yan, 2007; Zhang, 2005; Cooper, 2006; Livdan et al., 2009), we pursue the risk based arguments for the value premium by developing and testing an index of financial inflexibility. Financial inflexibility refers to a firm's inability to alter investment expenditure to mitigate exogenous shocks, so as to generate a smooth dividend stream and it stems from operating leverage, financial leverage, costly reversibility and financial constraints. Carlson et al. (2004) model the relation between expected returns and endogenous corporate investment decisions and find that the value premium is driven by operating leverage. Garlappi and Yan (2007) explicitly consider financial leverage in a simple equity valuation model and show that financial leverage amplifies the magnitude of the value premium. Zhang (2005) demonstrates that costly reversibility, which is another source of financial inflexibility, can generate the observed value premium. Cooper (2006) builds on the work of Zhang (2005) and develops a real options model that accounts for the observed value premium. He shows that the irreversibility of investment is the driving force behind the value premium. Livdan et al. (2009) propose another inflexibility mechanism, which stems from collateral constraints. Based on their model, value firms are less flexible, are more correlated with economic downturns, and are riskier than growth firms. Novy-Marx (2007) provides empirical evidence that supports the model of Carlson et al. (2004). He finds a positive relation between operating leverage and stock returns and between operating leverage and loadings on the value factor (Fama and French, 1993). Using portfolios based on operating leverage and financial leverage, respectively, García-Feijóo and Jorgensen (2010) show that there is a positive relation between the B/M ratio and operating leverage and between operating leverage and stock returns as well as a positive relation between the B/M ratio and financial leverage and between financial leverage and stock returns. They conclude that, compared with financial leverage, operating leverage seems to be the main cause of the value premium. More recently, Poulsen et al. (2013) show that the value premium in the US market can be partially explained by financial inflexibility measured as a composite index of the foregoing factors.

This paper makes two interesting contributions to the literature on the value premium puzzle. First, after establishing that the value premium does, in fact, exist in the Chinese market, we provide evidence that it is not behavioral based. Testing over the whole sample we find that value stocks do not dominate growth stocks in FSD, SSD or TSD. This means that even though investing in value stocks does provide investors with higher profits, it does not increase their expected utilities. The implication is that it is the risk profile (distribution) of the returns that is driving the investor utility and that the value premium is compensation for bearing more risk. When the sample is broken down into its positive and negative regimes, the results are similar. There is no FSD, SSD or TSD. This suggests that there is no over or under-reaction on the part of Chinese investors that is driving the value premium. In the second contribution of this paper we show that the risk of financial inflexibility is a major determinant of the value premium. We find there is a positive relationship between financial inflexibility and the B/M ratio, between financial inflexibility and stock returns, and between the returns of inflexible firms and value firms.

The remainder of this paper is organized as follows. Section 2 describes our data and methodology. Section 3 presents and discusses our empirical findings. Conclusions are provided in Section 4.

2. Data and methodology

2.1. Data and portfolio construction

We collect all data used in this study from the China Stock Market and Accounting Research (CSMAR) database. The data set contains monthly stock returns of A-share stocks for a period of 20 years from July 1995 to June 2014. Following the previous studies, we exclude financial firms, ST/PT firms, and firms whose relevant data are missing. We use value-weighted

A-share market return data as a proxy for market return (R_m). The one-year fixed deposit rate is converted into its monthly equivalent, which is used as the risk-free rate (R_f) in this study.

Following the literature, we construct value and growth portfolios by sorting firms into five groups based on the B/M ratio. The B/M ratio is computed as the ratio between a firm's book equity at the fiscal year-end in calendar year t-1 and its market value at the end of December in year t-1. To avoid the so-called look-ahead bias, all accounting data for the fiscal year-end in calendar year t-1 are matched to stock returns for the period between July of year t to June of year t+1. We then compute the equal-weighted monthly returns for each portfolio. As a robustness test in this study, we also compute the value-weighted monthly portfolio returns. All the portfolios are rebalanced annually.

2.2. Stochastic dominance rules

SD theory provides a general framework for ranking risky prospects based on utility theory. Hanoch and Levy (1969) and Whitmore (1970) lay the utility foundations of SD analysis. The theoretical attraction of SD is its nonparametric orientation. Comparing investments using the SD approach is equivalent to choosing investments based on expected-utility maximization. One advantage of the SD approach is that the SD theory makes only minimal assumptions about investors' utility functions. SD rules are relevant for any well-defined Von Neumann and Morgenstern (1944) set of utility functions. For example, SD rules for risk averters, which apply to the general class of non-decreasing, concave utility functions, offer consistent rankings for all members of this class. Starmer (2000) show that the SD criteria also apply to a range of non-expected utility theories of choice under uncertainty. Another advantage is that the SD approach does not require any assumption about the nature of the distribution and, therefore, can be used for any type of distribution. In addition, since SD uses the entire empirical return distribution, it has the potential to recover all of the information from the return distribution. As a result, the SD approach is superior to and less restrictive than the traditional parametric asset pricing models.

Let F and G be the cumulative distribution functions (CDFs) of X and Y, for the portfolio returns of value stocks and growth stocks, respectively, with common support $[a,b]$, where a < b. We define the integral H_j to be the j^{th} order cumulative distribution function (CDF) for $H = F$ and G (j = 1, 2 and 3):

$$H_j(x) = \int_a^x H_{j-1}(t)\,dt \tag{1}$$

where $H_1 = H$.

The most commonly used SD rules associated with three broadly defined utility functions are first-, second-, and third-order SD for risk-averse investors, denoted as FSD, SSD, and TSD, respectively. All investors are non-satiated (prefer more to less) under FSD, non-satiated and risk-averse under SSD, and non-satiated, risk-averse, and possessing prudence (the third derivative of the utility function is greater than or equal to zero) under TSD. The SD rules are defined as follows (see, for example, Quirk and Saposnik, 1962):

Definition: X dominates Y by FSD (SSD, TSD), denoted by $X \succ_1 Y$ $\left(X \succ_2 Y, X \succ_3 Y\right)$ if and only if $F_1(x) \le G_1(x) \left(F_2(x) \le G_2(x), F_3(x) \le G_3(x) \right)$, for all possible returns x and the strict inequality holds for at least one value of x, where X is the portfolio return of value stocks and Y *is the portfolio return of growth stocks.*

We note that a hierarchical relationship exists in SD: FSD implies SSD, which in turn implies TSD. However, the converse is not true: the existence of SSD does not imply the existence of FSD. Likewise, the existence of TSD does not imply the existence of SSD or FSD. Jarrow (1986) and Falk and Levy (1989) claim that under FSD, investors will increase their wealth and expected utilities when they switch from holding the dominated asset to the dominant one; under SSD, this switch will increase risk-averse investors' expected utilities; under TSD, this switch will increase the expected utilities of risk-averse investors with DARA.

2.3. The LMW Test for stochastic dominance

The early work of Beach and Davidson (1983) examines dominance at the first order. More recently, several methods have been proposed for testing for SD of other orders (see, for example, Anderson, 1996; Davidson and Duclos, 2000; Barrett and Donald, 2003). Importantly, Linton et al. (2005) (hereafter LMW) have provided a comprehensive theory of inference for a class of test statistics for the standard pairwise comparison of prospects. One particular advantage of the LMW test over other SD tests is that this test is well suited for financial data because it does not require the data to be identically and independently distributed (i.i.d.). In particular, the LMW test is particularly suited to financial time series that exhibit dependence, such as GARCH or stochastic volatility and serial correlations (Fong, 2010).[5]

[5] Abhyankar et al. (2009) apply a SD test developed by Barrett and Donald (2003) to investigate the SD relationship between value stocks and growth stocks in stock markets of the G7. They find that value stocks dominate growth stocks only in the US, Canada, and Japan. However, the SD test we use here is superior to their test.

The LMW SD test is based on sub-sampling, and the resulting tests are consistent and powerful against some $N^{-1/2}$ local alternatives, where N is the sample size. The LMW SD test statistic is:

$$T_j = \sup_x \sqrt{N}\left[\hat{F}_j(x) - \hat{G}_j(x)\right] \tag{2}$$

where $\hat{H}_j(x) = \frac{1}{N(j-1)!}\sum_{i=1}^{N}(x - z_i)_+^{j-1}$, $H = F, G$, j=1, 2 and 3.

Linton et al. (2005) show that the asymptotic null distribution of this statistic is non-standard. They propose using sub-sampling bootstrap simulations to compute the empirical p-values of the test. The idea of the sub-sampling bootstrap procedure is to sample blocks of data without replacement to account for non-i.i.d. features of the data. Politis and Romano (1994) prove that the sub-sample bootstrap consistently estimates the distribution of a statistic under very weak conditions. In the case of the LMW test, the sub-sampling method requires computing N-b+1 times the following test statistic for a sub-sample of size b such that:

$$T_{j,i} = \sup_x \sqrt{b}\left[\hat{F}_{j,i}(x) - \hat{G}_{j,i}(x)\right] \quad \text{for } i = 1, 2, \ldots, N - b + 1. \tag{3}$$

The distribution of this sub-sample test statistic is then used to approximate the distribution of Equation (2). Since each sub-sample taken without replacement is, in fact, a sample of size b from the true sampling distribution of the original data, the procedure has the asymptotically correct size (Theorem 2, Linton et al., 2005). In addition, by sampling blocks of observations (rather than individual observations), the procedure allows for general dependence in the data.

Let $\hat{p}_j$ denote the corresponding empirical p-value. We reject the null hypothesis at the α significance level if:

$$\hat{p}_j = \frac{1}{N-b+1} \sum_{i=1}^{N-b+1} 1\left(T_{j,i} - T_j > 0\right) < \alpha. \tag{4}$$

Specifically, the following two sets of null and alternative hypotheses are tested:

$$\begin{aligned} &H_{0j} : F_j\,(x_i) \le G_j\,(x_i) \text{ for all } x; \text{ and} \\ &H_{1j} : F_j\,(x_i) > G_j\,(x_i) \text{ for some } x. \end{aligned} \tag{5}$$

$$\begin{aligned} &H^{'}_{0j} : G_j\,(x_i) \le F_j\,(x_i) \text{ for all } x; \text{ and} \\ &H^{'}_{1j} : G_j\,(x_i) > F_j\,(x_i) \text{ for some } x. \end{aligned} \tag{6}$$

For j=1, 2 and 3, the null hypothesis of H_{0j} states that the value stock portfolio dominates the growth stock portfolio (not strictly) at order j, denoted by $F \succeq_j G$, while the null hypothesis of $H^{'}_{0j}$ states that the growth stock portfolio dominates the value stock portfolio (not strictly) at order j, denoted by $G \succeq_j F$. The alternative hypothesis is that the SD relationship fails at some points.

We test the SD relationships between the value stock and growth stock portfolios based on the following two-step procedure. First, we test whether the value stock portfolio dominates (not strictly) the growth stock portfolio (i.e., H_{0j}: $F \succeq_j G$). Second, we test the reverse hypothesis (i.e., $H^{'}_{0j}$: $G \succeq_j F$). The statistical test results can be interpreted as follows: if we fail to reject H_{0j} ($H^{'}_{0j}$) but we reject $H^{'}_{0j}$ (H_{0j}), we could conclude that the value (growth) stock portfolio strictly dominates the growth (value) stock portfolio at order j, denoted by $F \succ_j G$ ($G \succ_j F$). On the other hand, if we reject or fail to reject both H_{0j} and $H^{'}_{0j}$, we could conclude that there is no SD relationship between the value stock and growth stock portfolios.

2.4. Measuring financial inflexibility

Financial inflexibility represents a firm's inability to adjust its investment program to engender a smooth dividend stream when facing exogenous shocks. There are three alternative but related sources of financial inflexibility, which are total leverage, costly reversibility, and financial constraints.

The degree of total leverage (DTL) is the product of the degree of operating leverage (DOL) and the degree of financial leverage (DFL). Operating leverage refers to the sensitivity of a firm's operating income to changes in its sales. Financial leverage refers to the sensitivity of a firm's net income to changes in its operating income. Firms with high total leverage are regarded as inflexible firms, since they are less able to alter investment when their cash flows are volatile. For example, Gulen et al. (2008) argue that firms with high DOL and DFL are inflexible because they are less able to adjust investments to meet the relatively higher volatility of their cash flows. In addition, firms with higher financial leverage have more debt and must repay more interest expenditures. This would lower their future borrowing capacity to finance new investments, which make them more inflexible (Gulen et al., 2008; Rapp et al., 2014). In the literature, two econometric methods have been proposed to estimate DOL and DFL (Mandelker and Rhee, 1984). However, both of them suffer from similar estimation biases.[6] In addition, the application of these two approaches requires choosing the length of an overlapping time window, which is arbitrary. Therefore, in this study, we use the DTL data provided by the CSMAR database, where DTL equals (EBIT + fixed cost)/(EBIT-interest expense).

[6] For a detailed discussion, please refer to Dugan and Shriver (1992).

Costly reversibility refers to the higher cost firms face when reducing productive assets (Abel and Eberly, 1994). Firms with high costly reversibility are regarded as inflexible firms, since costly reversibility deprives firms of flexibility in adjusting capital when they are facing an unexpected shock, which causes them to be riskier. Zhang (2005) argues that firms with a high fixed assets ratio (defined as total property, plant, and equipment (PPE) divided by total assets) find it costly to reduce capital stock in bad times and may even have incentives not to do so. Cooper (2006) further proposes that firms with a high fixed assets ratio would also benefit from this excess installed capacity in good times, because they need not undertake significant new investment. Moreover, Gulen et al. (2008) argue that because costly reversibility primarily applies to investment in PPE, a higher fixed assets ratio suggests less real flexibility. Following these literatures, we use the fixed assets ratio as a proxy for costly reversibility in this study.

Financial constraints are frictions that prevent firms from funding all desired and profitable investments. Livdan et al. (2009) show that constrained firms are more sensitive to exogenous shocks, since they have less ability to adjust investments in response. In the literature, some researchers use firm characteristics, such as firm size, firm age, cash flow, and firm bond rating, to measure financial constraints (Almeida et al., 2004; Hennessy and Whited, 2007; etc.). In addition, a few financial constraint indices have been constructed using US stock market data (such as the KZ index (Kaplan and Zingales, 1997); the WW index (Whited and Wu, 2006) and the SA index (Hadlock and Pierce, 2010)). Beck and Demirguc-Kunt (2006) show that transaction costs and the risk premium are higher for small firms, since they are more opaque and have fewer assets to be offered as collateral. Hennessy and Whited (2007) document that small firms face higher indirect external financing costs compared with big firms. Furthermore, Hadlock and Pierce (2010) find that, compared with other measures of financial constraints, firm size and age are particularly useful predictors of financial constraint levels. In this study, we use the reciprocal of the natural logarithm of firm size as the proxy for financial constraints instead of directly using the aforementioned financial constraints indices designed for the US stock market.

After obtaining these three proxies for total leverage, costly reversibility, and financial constraints, we combine them into a composite financial inflexibility index ($FII_{i,t}$), which captures firm i's financial inflexibility in year t. To calculate the $FII_{i,t}$, we use the variance-equal weight method, a common technique in the literature.[7] Specifically, we first normalize the firm-year measure of a given proxy $x_{i,t}$ by computing the difference between $x_{i,t}$ and the time series average of the proxy across all observations $\bar{x}$. Then we divide the difference by the time series standard deviation of the proxy across all observations σ_x (i.e., the normalized proxy $x_{i,t}^* = (x_{i,t} - \bar{x})/\sigma_x$) (Poulsen et al., 2013). The $FII_{i,t}$ is a sum of the above three normalized proxies. A low FII value suggests that a firm is financially flexible, while a high FII value suggests that a firm is financially inflexible.

2.5. Testing the relationship between the value premium and financial inflexibility

To investigate whether the value premium is compensation for bearing more financial inflexibility risk in the Chinese stock market, we proceed by following a three-step test procedure described below. As a preliminary analysis, we first examine the relationship between financial inflexibility and average stock returns. If financial inflexibility is the risk factor underlying the value premium, we expect to observe that inflexible firms earn higher average returns than flexible

[7] As a robustness test, we tried to apply the principle component analysis technique, but, since the three proxies do not move together, it does not yield meaningful results.

firms. To calculate the average returns of portfolios with different inflexibility levels, at the end of year t-1, all stocks are sorted into five portfolios based on the FII constructed in the preceding section. We then calculate the equal-weighted and value-weighted monthly returns for each portfolio from July of year t to June of year t+1. The portfolios are rebalanced every year.

In step 2, we test whether financial inflexibility risk can be captured by the standard CAPM. To do this, we run the following regression:

$$R_{i,t} - R_{f,t} = a_i + b_i(R_{m,t} - R_{f,t}) + u_{i,t} \tag{7}$$

where $R_{i,t}$ is the monthly equal-weighted or value-weighted return for portfolio i calculated above. $R_{f,t}$ is the monthly risk-free rate, which is converted from the one-year fixed deposit rate; $R_{m,t}$ is the value-weighted market return for the A-share stock market. If financial inflexibility is a risk factor omitted by the CAPM, we expect the abnormal return measured by the intercept in the regression above will increase with the financial inflexibility level.

Finally, in step 3, we follow Fama and French (1993), Poulsen et al. (2013) and Cheuk (2015) to formally examine whether financial inflexibility is a risk factor underlying the value premium. To this end eight portfolios are formed as follows. For each year from July of year t to June of year t+1, stocks are sorted into big and small groups by their market sizes. The stocks are then independently sorted by the B/M ratio in year t-1 and similarly divided into high and low B/M groups. An independent sorting is also carried out to split the stocks into inflexible and flexible groups based on the FII in year t-1. The resulting eight portfolios are: 1) big, high B/M, flexible portfolio; 2) big, high B/M, inflexible portfolio; 3) big, low B/M, flexible portfolio; 4) big, low B/M, inflexible portfolio; 5) small, high B/M, flexible portfolio; 6) small, high B/M, inflexible portfolio; 7) small, low B/M, flexible portfolio; 8) small, low B/M, inflexible portfolio. All the portfolios are rebalanced annually. The value-weighted and equal-weighted portfolio returns of these eight portfolios form the dependent variables of the Fama and French (1993) three-factor model (Equation 8) and a financial inflexibility-augmented four-factor model (Equation 9) shown below:

$$R_{i,t} - R_{f,t} = a_i + b_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + u_{i,t} \tag{8}$$

$$R_{i,t} - R_{f,t} = a_i + b_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + f_i IMF_t + u_{i,t} \tag{9}$$

where SMB (small minus big) is the size factor, which is the average of the returns on the small-stock portfolios minus the returns on the big-stock portfolios; HML (high minus low) is the book-to-market factor, which is the average of the returns on the high-B/M portfolios minus the returns on the low-B/M portfolios;[8] $\mathrm{IMF_t}$ (inflexible minus flexible) is the inflexibility mimicking factor. This new factor is constructed as follows: for each year from July of year t to June of year t+1, we sort stocks into two groups (small (S) and big (B)) based on their sizes; then we sort the same stocks into three groups based on their FII (F1 (flexible) and F3 (inflexible)) in year t-1, independently; six portfolios (S/F1, S/F2, S/F3, B/F1, B/F2 and B/F3) are formed and the value-weighted monthly returns of each portfolio are calculated. These portfolios are rebalanced every year. The IMF is the average of the returns on the inflexible portfolios minus the returns on the flexible portfolios:

$$\mathrm{IMF} = \frac{(\mathrm{S/F3}-\mathrm{S/F1}) + (\mathrm{B/F3}-\mathrm{B/F1})}{2} \tag{10}$$

[8] We follow Fama and French (1993) to construct these factors in this paper.

A comparison between the estimated results obtained from equations (8) and (9) provide us with information on the relationship between the value premium and financial inflexibility. If, after the IMF is included in the estimation, we find a statistically less significant (or insignificant) value factor, this would suggest that the value premium is compensation for financial inflexibility risk in the Chinese stock market. Furthermore, adjusted R^2 values could provide information on the role of financial inflexibility in asset-pricing models suitable for the Chinese stock market more generally.

3. Empirical results

Table 1 presents both equal-weighted and value-weighted portfolio returns formed on the B/M ratio. We can see that, as the B/M ratio increases, the portfolio return increases monotonically. For example, the equal-weighted return of the portfolio with the lowest B/M ratio (i.e., the growth portfolio) is 1.11%, while the corresponding return of the portfolio with the highest B/M ratio (i.e., the value portfolio) is 1.89%. The return spread between these two portfolios is 0.78%, which is highly significant. In addition, we obtain the same finding for the value-weighted portfolios. This evidence indicates that the value premium exists in the Chinese stock market and investors could obtain higher returns by investing in the value stocks.

[Table 1 here]

We now turn to the test results for the SD relationships between value and growth portfolios. We start by conducting two sets of tests. First, the Jarque-Bera test is used to determine whether the value and growth portfolio returns are normally distributed. Next, we perform the Brock, Dechert, Scheinkman (BDS) test (Brock et al., 1996), which essentially tests for deviations from identically and independently distributed (i.i.d.) behavior in the time series of portfolio returns. The Jarque-Bera statistics reported in Table 2 indicate that neither the value nor the growth portfolio returns are normally distributed, which suggests that the SD approach used in this study is well adapted to the analysis we propose. In Table 2, we also report the BDS test results. The evidence indicates that all of the portfolio return series are non-i.i.d, which highlights the importance of using the LMW SD test instead of other SD tests in this study.

[Table 2 here]

Table 3 presents the results of the LMW tests for stochastic dominance. Following the test procedures introduced in Section 2, we find that for both the equal-weighted and the value-weighted portfolios, we cannot reject the hypothesis that the value stock portfolio dominates the growth stock portfolio for all three orders (i.e., $H_{0j}: F \succeq_j G$). On the other hand, we find that we also cannot reject the reverse hypothesis that the growth stock portfolio dominates the value stock portfolio for all three orders (i.e., $H_{0j}^{'}: G \succeq_j F$). This is preliminary evidence that attention to risk rather than a systematic behavioural anomaly is driving the value premium.

Since there is evidence outlined in the introduction that the reaction of Chinese investors to upside and downside risk is different from that of investors in the US, we break our sample into its positive and negative regimes, and conduct the LMW test for each regime independently. This makes it possible to examine whether there is a behavioural anomaly of the Chinese investors in one or both regimes that is driving the value premium. The results reported in Table 3 are qualitatively the same: there is no FSD, SSD or TSD between value stocks and growth stocks. This suggests that there is no over or under-reaction on the part of Chinese investors that is driving the value premium. Overall, we conclude that value stocks do not stochastically dominate growth stocks and it is plausible to explain the value premium puzzle from the perspective of risk compensation in the Chinese stock market.[9]

[Table 3 here]

With this evidence in hand, we extend our analysis to examine whether the value premium is compensation for the financial inflexibility risk in the Chinese stock market. We first look at the relationship between the B/M ratio and financial inflexibility proxies as well as the FII we constructed in this study. Table 4 presents our results. As shown in Table 4, the financial inflexibility proxies almost all strictly increase monotonically with the B/M ratio. For example, total leverage increases from 1.7459 for growth firms to 2.5674 for value firms, and the difference in total leverage between these two types of firms is 0.8215, which is statistically significant. As for the fixed ratio, which measures costly reversibility, it is 0.2403 for growth firms and 0.3051 for value firms. In addition, the difference in the fixed ratio between value firms and growth firms is highly significant. As for the relation between financial constraints and the B/M ratio, we do not find that firms with higher B/M ratios always have higher levels of financial constraints. Nevertheless, we find that the FII we constructed still strictly increases monotonically with the B/M ratio. We find that value firms have higher FIIs than growth firms, and the difference in the FII between these two types of firms is statistically significant. These results suggest that there is a strong relationship between the B/M ratio and financial inflexibility and that value firms are more financially inflexible than growth firms in the Chinese stock market.

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[9] Our SD test results also imply that, even though investing in value stocks brings higher returns to investors, it does not improve their expected utilities in the Chinese stock market.

[Table 4 here]

We then quantify the relation between financial inflexibility and returns. If financial inflexibility is a risk factor underlying the value premium, we would expect to find that firms with high FIIs (i.e., inflexible firms) earn higher average returns than firms with low FIIs (i.e., flexible firms). In addition, we would expect to find that the estimated intercept item in the CAPM (Equation (7)) increases with inflexibility. The results shown in Table 5 support our expectations. The equal-weighted returns shown in Panel A of Table 5 increase monotonically with financial inflexibility. The average return is 0.0221 for the highest quintile, compared with an average return of 0.0128 for the lowest quintile. The spread of the average returns between inflexible firms and flexible firms is 0.0093, which is significant at the 1% level. In addition, the estimated CAPM alpha reported in Panel B is highly statistically significant in all regressions except for the lowest inflexibility quintile, and again it increases monotonically with the financial inflexibility quintile. We also report our robustness test results using value-weighted returns in Table 5. The results are consistent with those using equal-weighted returns discussed above. Overall, the combined results reported in Tables 4 and 5 indicate that there is a positive relation between financial inflexibility and the B/M ratio, between financial inflexibility and stock returns, and between the returns of inflexible firms and value firms in the Chinese stock market.

[Table 5 here]

To further explore the role played by financial inflexibility in asset-pricing models and its relationship to the value premium for the Chinese stock market, we estimate a standard Fama and French three-factor model (i.e., Equation (8)) and an inflexibility-augmented four-factor model (i.e., Equation (9)). We report our results in Table 6. Panels A and C report the estimated results for Equation(8), while Panels B and D report our estimated results for Equation(9), respectively. First, we analyze the results using equal-weighted portfolio returns (i.e., Panel A and Panel B). In Panel A, we can see that, holding the size and B/M portfolio constant, the size of the value factor increases with inflexibility. For example, the coefficient of HML is 0.262 for big, high and inflexible firms, in contrast to 0.112 for big, high and flexible firms. Next we look at our estimated results for the inflexibility-augmented four-factor model. Three aspects of the results shown in Panel B are worthy of our notice. First, six out of eight inflexibility factors are statistically significant. Second, we find that, after adding the inflexibility factor IMF, the significance of the value factor decreases: among the eight value factors, which are all significant without including the inflexibility factor, as shown in Panel A, three of them become insignificant, as shown in Panel B. One additional finding deserves our attention: for these three insignificant value factors, their corresponding financial inflexibility factors are all significant. Third, compared with values of the adjusted R^2 displayed in Panel A, we find that the adjusted R^2 for the four-factor model are higher (adjusted R^2 for the four-factor model range from 91.20% to 95.87%; adjusted R^2 for the three-factor model range from 87.43% to 95.34%). When we use value-weighted portfolio returns, we get very similar findings from Panel C and Panel D. Overall, these results indicate that financial inflexibility is a significant determinant of the value premium puzzle in the Chinese stock market.

[Table 6 here]

4. Conclusion

This paper investigates the value premium puzzle in the Chinese stock market. We find that the value premium does exist in the Chinese stock market. Using stochastic dominance theory, we also find that there is no systematic behavioral factor, such as over/under-reaction, that is driving this premium. This finding is robust with respect to negative and positive return regimes and suggests that explaining the value premium puzzle from the perspective of risk compensation is plausible in the Chinese stock market.

To test this proposition we look at financial inflexibility and analyze its effect on the value premium. We find there is a significant, positive relationship between financial inflexibility and the B/M ratio, between financial inflexibility and stock returns, and between the returns of inflexible firms and value firms. This suggests that the value premium reflects compensation for bearing more risk for financial inflexibility and is strong evidence for the risk based argument to explain the value premium puzzle in the Chinese stock market.

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Table 1

Monthly return of portfolios sorted by B/M ratio

	Low	2	3	4	High	H-L
Panel A: Equal-weighted						
average return	0.0111	0.0142	0.0169	0.0188	0.0189	0.0078
t-statistics	1.8784	2.2890	2.6592	2.8622	2.8854	2.8903
Panel B: Value-weighted						
average return	0.0081	0.0095	0.0124	0.0141	0.0152	0.0071
t-statistics	1.4276	1.6343	2.0374	2.2482	2.5379	2.1119

Notes: This table reports the average returns of value and growth portfolios for a period of 20 years from July 1995 to June 2014. We construct value and growth portfolios by sorting firms into 5 groups based on the B/M ratio. The value portfolio is the highest-B/M portfolio and the growth portfolio is the lowest-B/M portfolio. The B/M ratio is computed as the ratio between a firm's book equity at the fiscal year-end in calendar year t-1 and its market value at the end of December in year t-1. To avoid the so-called look-ahead bias, all accounting data for the fiscal year-end in calendar year t-1 are matched to monthly stock returns for the period between July of year t to June of year t+1. All portfolios are rebalanced annually. We then compute the equal-weighted and value-weighted returns for each portfolio. H-L is the difference between the average returns of value and growth portfolios.

Table 2

Normality test and BDS test results for growth and value portfolios

	Growth stock portfolio	Value stock portfolio
Panel A: Equal-weighted		
Jarque-Bera test	9.9893 (0.0068) ***	20.6619 (0.0000)***
BDS test (Dimension)		
2	1.6090 (0.1076)	2.5566 (0.0106)***
3	2.1677 (0.0302)**	3.4706 (0.0005)***
4	2.5792 (0.0099)***	4.4337 (0.0000)***
5	2.7923 (0.0052)***	5.0004 (0.0000)***
6	2.7831 (0.0054)***	5.3417 (0.0000)***
7	2.8104 (0.0049)***	5.5852 (0.0000)***
8	2.7796 (0.0054)***	5.6098 (0.0000)***
Panel B: Value-weighted		
Jarque-Bera test	18.3852 (0.0001)***	20.2327 (0.0000)***
BDS test (Dimension)		
2	2.2407 (0.0250)**	2.4436 (0.0145)**
3	2.9301 (0.0034)***	3.7530 (0.0002)***
4	3.4490 (0.0006)***	4.8914 (0.0000)***
5	3.5878 (0.0003)***	5.7301 (0.0000)***
6	3.5605 (0.0004)***	6.3057 (0.0000)***
7	3.6365 (0.0003)***	6.8287 (0.0000)***
8	3.7290 (0.0002)***	7.1715 (0.0000)***

Notes: This table reports the results of Jarque-Bera test statistics and the normalized BDS test statistics proposed by Brock *et al.* (1996) for returns of growth and value portfolios. Under the null hypothesis of a normal distribution, the Jarque-Bera test statistic is distributed as $\chi^2$with 2 degrees of freedom. The BDS approach essentially tests for deviations from identically and independently distributed (i.i.d.) behavior in the time series of portfolio returns. The test is applied for common lag lengths of two to eight lags. A common scale parameter of $e = 1.5\sigma$, where $\sigma = 1$ denotes the standard deviation of standardized series is used. For other settings of scale parameters, such as $e = 1.0\sigma$, the results are qualitatively no different. Numbers in parentheses are p-values. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 3

LMW stochastic dominance test results for value and growth portfolios

	$H_{0j}: F \succeq_j G$			$H'_{0j}: G \succeq_j F$		
	FSD(*j*=1)	**SSD(*j*=2)**	**TSD(*j*=3)**	**FSD(*j*=1)**	**SSD(*j*=2)**	**TSD(*j*=3)**
Panel A: Equal-weighted						
Full sample	0.3919	0.4900	0.2974	0.3350	0.3069	0.7010
Positive domain	0.7933	0.5611	0.5132	0.1220	0.2649	0.3027
Negative domain	0.6208	0.3704	0.2313	0.4342	0.8301	0.9503
Panel B: Value-weighted						
Full sample	0.8326	0.5112	0.3026	0.1456	0.2399	0.5545
Positive domain	0.5965	0.6046	0.5800	0.2814	0.3373	0.2502
Negative domain	0.2537	0.3450	0.2345	0.2417	0.6331	0.9690

Notes: This table reports the median of sub-sampling p-values of the LMW SD tests for value and growth portfolios for two null hypotheses: $H_{0j}: F \succeq_j G$ and $H'_{0j}: G \succeq_j F$, here j =1, 2 and 3. F and G are the CDFs of portfolio returns of value stocks and growth stocks, respectively. Median p-values are generated using a sequence of 20 sub-samples. The sample period is from July 1995 to June 2014. We construct value and growth portfolios by sorting firms into 5 groups based on the B/M ratio. The value portfolio is the highest-B/M portfolio and the growth portfolio is the lowest-B/M portfolio. The B/M ratio is computed as the ratio between a firm's book equity at the fiscal year-end in calendar year t-1 and its market value at the end of December in year t-1. To avoid the so-called look-ahead bias, all accounting data for the fiscal year-end in calendar year t-1 are matched to monthly stock returns for the period between July of year t to June of year t + 1. All portfolios are rebalanced annually. We then compute the equal-weighted and value-weighted returns for each portfolio.

Table 4

B/M ratio quintiles and financial inflexibility

B/M quintile	Total leverage	Costly reversibility	Financial constraints	FII
Low	1.7459	0.2403	0.0465	-0.2062
2	1.8479	0.2521	0.0466	-0.0372
3	1.9930	0.2670	0.0467	0.1678
4	2.0994	0.2838	0.0467	0.2884
High	2.5674	0.3051	0.0463	0.4257
H-L	0.8215	0.0647	-0.0001	0.6319
Z (H-L)	3.4742	3.7661	0.2336	2.4816
	(0.0005)	(0.0003)	(0.8153)	(0.0131)

Notes: This table presents time series medians for three financial inflexibility proxies and the financial inflexibility index (FII) sorted by the B/M ratio. The B/M ratio is computed as the ratio between a firm's book equity at the fiscal year-end in calendar year t-1 and its market value at the end of December of year t-1. The degree of total leverage is calculated as (EBIT + fixed cost)/(EBIT-interest expense). Costly reversibility is measured by the fixed assets ratio, which is calculated as fixed assets divided by total assets. Financial constraint is measured by the reciprocal of the natural logarithm of firm size. The FII is calculated as described in Section 2. Z is the Wilcoxon-Mann-Whitney test statistics and numbers in parentheses are corresponding p-values.

Table 5

Portfolios formed on the FII

	Flexible	2	3	4	Inflexible	I-F (t-statistics)
Panel A: average return						
equal-weighted	0.0128	0.0183	0.0185	0.0200	0.0221	0.0093 (3.4780)
value-weighted	0.0089	0.0159	0.0164	0.0169	0.0178	0.0089 (2.6803)
Panel B: abnormal return (CAPM alpha)						
equal-weighted	0.0016	0.0068	0.0071	0.0084	0.0103	
t-statistics	0.7353	2.5354	2.3495	2.7447	2.9357	
value-weighted	-0.0019	0.0046	0.0051	0.0056	0.0060	
t-statistics	-1.2170	2.1048	2.1566	2.1620	1.9005	

Notes: This table reports average returns and abnormal returns using the CAPM for firms sorted into 5 groups based on the FII. Firms with the lowest FII are "flexible" firms and firms with the highest FII are "inflexible" firms. "I-F" is the spread of returns between inflexible firms and flexible firms. Numbers in parentheses are t-statistics.

Table 6

Fama and French three-factor model and financial inflexibility-augmented four-factor model regressions.

Size	B/M	FII	α	Rm-Rf	SMB	HML	IMF	Adj.R^2
Panel A: equal-weighted (Fama-French three-factor model)								
B	**H**	**FLX**	-0.0003	1.0486	0.4749	0.1120		91.56%
t			-0.1510	45.7313	10.7667	2.4307		
B	**H**	**INFLX**	-0.0018	1.0415	0.6112	0.2620		90.47%
t			-0.8069	41.0980	12.5372	5.1473		
B	**L**	**FLX**	0.0002	1.0200	0.3831	-0.4720		92.29%
t			0.1178	49.8030	9.7242	-11.4717		
B	**L**	**INFLX**	-0.0013	1.1199	0.6151	-0.4509		87.43%
t			-0.5150	36.9431	10.5479	-7.4039		
S	**H**	**FLX**	0.0007	1.0536	1.0186	0.1021		93.63%
t			0.3588	48.0144	24.1296	2.3168		
S	**H**	**INFLX**	0.0016	1.0265	1.1752	0.2683		95.34%
t			0.9922	53.3768	31.7674	6.9445		
S	**L**	**FLX**	0.0021	1.0319	0.9709	-0.4105		93.22%
t			1.1063	47.8779	23.4183	-9.4810		
S	**L**	**INFLX**	0.0007	1.0091	1.0803	-0.3249		95.23%
t			0.4415	55.8435	31.0772	-8.9497		
Panel B: equal-weighted (financial inflexibility-augmented four-factor model)								
B	**H**	**FLX**	0.0001	1.0466	0.3353	0.0243	0.4061	92.08%
t			0.0459	47.1120	6.0615	0.4883	3.9773	
B	**H**	**INFLX**	-0.0010	1.0373	0.3234	0.0814	0.8364	92.63%

t			-0.5023	46.5262	5.8260	1.6290	8.1609	
B	**L**	**FLX**	0.0003	1.0196	0.3535	-0.4906	0.0860	92.29%
t			0.1639	49.7502	6.9273	-10.6837	0.9130	
B	**L**	**INFLX**	-0.0003	1.1141	0.2199	-0.6990	1.1481	91.20%
t			-0.1151	43.9118	3.4812	-12.2959	9.8452	
S	**H**	**FLX**	0.0009	1.0526	0.9522	0.0604	0.1929	93.71%
t			0.4581	48.2456	17.5256	1.2366	1.9233	
S	**H**	**INFLX**	0.0020	1.0244	1.0332	0.1791	0.4127	95.77%
t			1.2893	55.9249	22.6505	4.3640	4.9014	
S	**L**	**FLX**	0.0022	1.0311	0.9218	-0.4413	0.1426	93.26%
t			1.1807	47.9472	17.2134	-9.1583	1.4442	
S	**L**	**INFLX**	0.0011	1.0068	0.9207	-0.4251	0.4636	95.87%
t			0.7786	59.8950	21.9966	-11.2868	6.0010	

Panel C: value-weighted (Fama-French three-factor model)

B	**H**	**FLX**	0.0000	1.0012	-0.0590	0.3178	91.25%
t			0.0132	46.2430	-1.4168	7.3067	
B	**H**	**INFLX**	-0.0012	1.0046	0.4169	0.3659	88.75%
t			-0.5050	37.9792	8.1932	6.8868	
B	**L**	**FLX**	-0.0000	1.0066	0.0679	-0.4441	93.59%
t			-0.0164	56.8992	1.9954	-12.4958	
B	**L**	**INFLX**	-0.0020	1.1123	0.5123	-0.4319	87.31%
t			-0.7683	37.3142	8.9345	-7.2121	
S	**H**	**FLX**	0.0002	1.0513	0.9951	0.0977	93.16%
t			0.0874	46.3981	22.8313	2.1475	
S	**H**	**INFLX**	0.0007	1.0215	1.1435	0.2826	95.13%
t			0.4354	52.4004	30.4923	7.2172	

S	**L**	**FLX**	0.0029	1.0246	0.8626	-0.4209		91.30%
t			1.4119	42.7575	18.7115	-8.7433		
S	**L**	**INFLX**	0.0003	1.0148	1.0330	-0.3489		94.46%
t			0.1700	52.2966	27.6737	-8.9521		

Panel D: value-weighted (financial inflexibility-augmented four-factor model)

B	**H**	**FLX**	0.0002	1.0001	-0.1325	0.2717	0.2134	91.39%
t			0.1230	46.5582	-2.4762	5.6447	2.1615	
B	**H**	**INFLX**	-0.0002	0.9998	0.0887	0.1599	0.9535	91.80%
t			-0.1248	44.2636	1.5778	3.1595	9.1839	
B	**L**	**FLX**	0.0000	1.0064	0.0539	-0.4529	0.0407	93.57%
t			0.0091	56.7772	1.2208	-11.4038	0.5001	
B	**L**	**INFLX**	-0.0010	1.1069	0.1439	-0.6632	1.0706	90.73%
t			-0.4339	43.4256	2.2666	-11.6129	9.1377	
S	**H**	**FLX**	0.0004	1.0502	0.9201	0.0506	0.2181	93.25%
t			0.1950	46.6930	16.4279	1.0046	2.1095	
S	**H**	**INFLX**	0.0011	1.0195	1.0038	0.1949	0.4059	95.56%
t			0.6958	54.7311	21.6407	4.6705	4.7411	
S	**L**	**FLX**	0.0031	1.0238	0.8089	-0.4546	0.1559	91.33%
t			1.4852	42.8097	13.5828	-8.4834	1.4178	
S	**L**	**INFLX**	0.0008	1.0122	0.8568	-0.4596	0.5120	95.25%
t			0.4980	56.3403	19.1511	-11.4175	6.2000	

Notes: This table reports the results from the regressions of the Fama and French three-factor model (Panels A and C) and financial inflexibility-augmented four-factor model (Panels B and D) for monthly equal-weighted and value-weighted returns of eight portfolios, which are constructed as follows. For each year from July of year t to June of year t+1, stocks are sorted into big and small groups by their market sizes. Independently, the stocks are sorted by the B/M ratio in year t-1 and similarly divided into high and low B/M groups. The B/M ratio is computed as the ratio between a firm's book equity at the fiscal year-end in calendar year t-1 and its market value at the end of December in year t-1. An independent sorting is also carried out to split the stocks into inflexible and flexible groups based on the FII in year t-1. All portfolios are rebalanced annually. The equal-weighted and value-weighted returns of these eight portfolios form the dependent variables of the Fama and French (1993) three-factor model (Equation 8) and a financial inflexibility-augmented four-factor model (Equation 9).