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The Aumann-Serrano Risk Factor and Asset Pricing: Evidence from the Chinese A-Share Market *

By **GANG JIANHUA, QIAN ZONGXIN and CHEN FAN***

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Abstract

Classic CAPM has long been criticized for errors in explaining the equity premium. This paper shows that one part of the inaccuracy comes from the quality of the risk measurement. Empirical evidence from the Chinese A-share stock market shows a single-factor model using the Aumann-Serrano riskiness index (the AS index) dominates both the CAPM and Fama-French three-factor model. This is because the AS index captures information of higher-order moments in the systematic risk that is neglected in traditional asset pricing models. This paper also suggests that the momentum factor is significantly correlated to the AS index and this relationship is of complementary nature rather than perfect substitutes.

JEL Classification: C1; C12; G30; G32

Keywords: Premium, Aumann-Serrano Riskiness Index, CAPM, Stock

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1. Introduction

The Capital Asset Pricing Model (CAPM) introduced by Treynor (1961, 1962), Sharpe (1964) and Lintner (1965) is one of the most important asset pricing models in finance. Welch (2008) finds that 75% of professors in finance recommend the CAPM for asset pricing. Graham and Harvey (2001) find that 73.5% of CFOs use it to calculate the financial cost. The CAPM focuses on the sensitivity of risky assets' premia against market excess returns and uses beta to measure the systematic risk of a given asset. By design, the CAPM intends to be mathematically straightforward and economically meaningful. However, the empirical performance of the CAPM is far from satisfactory. Major challenges against the CAPM come from market anomalies. Evidence of such anomalies that undermines the original CAPM rationality can be frequently found in practice. Academic literature on relevant topics is also extensive. Examples of anomalies include: the size effect identified by Banz (1981), who finds evidence that small companies tend to have higher risk-adjusted return than big companies; the excessive volatility phenomenon by Shiller (1980), who indicates that the stock price is simply too volatile if the market is efficient and the CAPM holds; the overreaction effect by De Bondt (1985); the book-to-market anomaly documented by Fama and French (1993); the momentum effect by Jegadeesh and Titman (1993). Additionally, Stambaugh et al. (2012) summarized all 11 well-documented anomalies that survive the adjustment of the Fama-French three factor model, which includes the financial distress, net stock issues and composite equity issues, total accruals, net operating assets, momentum, gross profitability premium, asset growth, ROA and Investor-to-assets.

To address these problems, researchers have been trying to modify the original CAPM by adding more risk factors. The three-factor model by Fama and French (1993) and four-factor model by Carhart (1997) are the most famous ones. Specifically, Fama and French (1993) add two more factors, the SMB (Small company minus big company) and HML (high book-to-market ratio minus low book-to-market ratio), to the original CAPM and Carhart (1997) adds another factor, the prior one-year return (PR1YR), which represents the momentum effect, into the Fama-French three-factor model. However, although the three-factor and four-factor models perform well in the American market in the 1990s, their performance in the global market is not as satisfactory. Griffin (2002) finds that the Fama-French three-factor model performs better in the American market than the international market, as the error of the model is relatively larger in the international market. Fama and French (2012) also investigate the effect of market size, value, and momentum in the international market, and find that their regional models perform poorly on the size-momentum portfolios of Europe and Asia Pacific. Da et al. (2012) argue that the CAPM failed to consider the value of options of a firm to modify current projects and undertake new ones and contend that beta in the CAPM could be adjusted by the option proxies. More specifically, they propose that the return and beta are functions of current asset risk and future growth potential. Da et al. (2012) show that using option-adjusted equity premium and betas for estimation substantially improves the performance of popular stock pricing models for the US market.

A common focus of the various extended forms of CAPM is trying to find satisfactory factors which precisely capture tractable information on the risk premium, and there have been many techniques in building these ingredients linearly in equity return which helps improve the model. Therefore, documented extensions of the CAPM are to add relevant factors. Hence, the thread of literature which put efforts in augmenting the original CAPM has been based on firstly acknowledging the soundness of the CAPM. Thus, the classic beta coefficient, which represents the systematic risk of a given asset, should be intuitively correct. As we shall see in this paper, beta as a risk factor has its limitations. Particularly, it does not satisfy the duality axiom of Aumann and Serrano (2008). Therefore, a better risk measurement than beta could potentially improve the empirical performance.

The reason that the classic CAPM is empirically flawed could also be attributed to its limited capability of measuring higher moments of the excess returns, therefore the systematic risk itself indicated by beta[1] can only proxy lower-moment risk for an individual asset, and ignore the risk of higher moments that is also hard to be diversified. This paper shows that it is possible to improve the performance of asset pricing models by simply revising the risk factors to include higher moments of returns.

Any measurement of risk should be clearly defined and meet certain criteria. Aumann and Serrano (2008) provide two critical axioms, the duality axiom, and the homogeneity positive axiom, that riskiness index should satisfy and give a sample economic index of riskiness that satisfies those criteria. Homm and Pisgorsch (2012) recommend an estimation method to calculate the Aumann-Serrano riskiness index (the AS index, hereafter) under normal inverse Gaussian distribution. They show that one advantage of their estimated riskiness index over the traditional risk measurement is that it contains information on the third and fourth moments of asset returns. Therefore, the estimated AS index carries information not only on volatility but also on tail risk. This paper tries to identify and quantify additional information delivered by the AS index. Our study also considers the possibility that the AS index performs as an alternative risk factor to replace the beta coefficient in the conventional CAPM. We focus our research on Chinese equity market, which has long been considered as irrational, extremely volatile and strongly influenced by policies. Properties as such can be interpreted as excessive kurtosis and heavy skew in econometric terms. The paper, therefore, extends factor models in an international context, especially explains markets with a risk profile of higher-orders being a norm. Tests are based on classic asset pricing models, option-adjusted equity premium and the AS factor. Corresponding evaluation and comparison on the performance of the AS factor in augmented asset pricing model and other model settings are subsequently conducted. Empirical evidence suggests that even a single-factor pricing model using the AS index to proxy the risk exhibits superior performance in Chinese A-Share stock

[1] The beta coefficient for each asset is calculated as the excess return of the asset as per unit of market excess return in the classic CAPM.

market. It fits the equity premium better than the CAPM and Fama-French three-factor models. By comparing explanatory powers of the AS factor and the momentum factor on equity premia, our study also shows the two are complementary to each other and partly correlated as well, which implies that part of the momentum effect can be rationalized as risk (of higher-order) compensation rather than pure irrational overreaction. But there is still momentum effect that cannot be explained by rational expectations.

The rest of the paper is structured as follows: Section 2 introduces the institutional background; Section 3 describes the methodology to estimate a risk measure using the AS index; Section 4 describes the dataset and variables; Section 5 shows the empirical results; Section 6 concludes the paper.

2. Institutional background

In the past decade, as a fast-growing developing country, Chinese capital market also expands dramatically. As is well documented, the Chinese government started partially privatizing state-owned enterprises (SOEs) in 1978, but before 2005, a large part of the SOE shares are not allowed to trade in the stock market. In 2005, the China Securities Regulatory Commission implemented the Non-tradable Share Reform. In essence, the reform enables all shares of the SOEs to be publically tradable.[2] By the end of 2017, the capitalization value of the Chinese stock market totalled at 56.7 trillion RMB (about 9 trillion US dollars), down from its peak of 62.7 trillion RMB in mid-2015, over six-folded as it was in 2006 (8.9 trillion RMB) and only seconded to the US stock market among all others. The Chinese A-Share stock market is also extremely active, liquid and volatile. Its cumulative turnover stayed at 112.4 trillion RMB by the end of 2017, also seconded to the US market (315.5 trillion RMB). There are currently 3,512 listed companies, up from only 1,421 public companies in 2006.

3. Riskiness index and risk factors

3.1 Characteristics of the Aumann-Serrano riskiness index

Aumann and Serrano (2008) give an axiomatic characterization of the riskiness index. More specifically, they require a riskiness index to satisfy two axioms: the Duality and Positive Homogeneity. The duality axiom says that the more risk-averse of two agents accepts the riskier of two gambles. The positive homogeneity axiom says that if g is a gamble, 2g is "twice as" risky as g.

Accordingly, Aumann and Serrano (2008) propose to measure a project's riskiness by the AS index defined by the following equation:

$$E(e^{-\frac{R_g}{AS}}) = 1. \tag{1}$$

Aumann and Serrano (2008) proved that the riskiness index as in Equation (1) satisfies both the duality and positive homogeneity. Note that a person with constant absolute risk aversion (CARA) is indifferent between accepting and not accepting the

[2] For details of the reform and its implications, see Jiang et al. (2008), Ahn and Cogman (2007) and Hung et al. (2015).

gamble g if his level of risk tolerance is AS. Therefore, anyone who has a higher risk tolerance will accept this gamble. This definition is consistent with the idea that less risk-averse agents accept riskier assets. In addition, the higher the AS index is, the riskier the asset is.

As argued by Homm and Pigorsch (2012), stock returns do not follow a normal distribution and higher moments are particularly informative on tail risks. Therefore, a normal inverse Gaussian (NIG) distribution can be used to match the empirical distribution of stock returns. Parametric approach as such is well-established in the field of financial econometrics and statistics. The NIG distribution is implemented widely to model unconditional as well as conditional return distributions[3]. In this case, the AS index is given by Equation (2):

$$AS_{nig} = \frac{3\kappa\mu - 4\mu\chi^2 - 6\chi\sigma + 9\sigma^2 / \mu}{18} \tag{2}$$

where χ represents the skewness and κ represents the kurtosis of the return distribution.[4] These two higher-order parameters help capture information about tail risks. Following methods as shown above by Homm and Pigorsch (2012), we construct the empirical AS index. However, this parameter estimation method requires the positive average return. Thus, we implemented the cumulative AS index rather than on a rolling basis. We will further discuss this issue in subsection 3.3.

3.2 Further discussion on risk factors

Beta of CAPM

In the traditional CAPM, a measure of riskiness, termed as beta, is an asset's correlation with the market portfolio. According to Aumann-Serrano axiomatic definition, we can verify if the beta meets the requirements of duality or positive homogeneity.

Duality: Consider two rational individuals i and j whose CARA utility functions are defined as:

$$U_k(r) = 1 - e^{-\alpha_k \omega (1+r)} \tag{3}$$

where ω stands for the initial wealth of the investor, α_k (*k* = *i*, *j*) represents the degree of risk aversion. A higher α_k represents a higher degree of risk aversion. Without the loss of generality, we set the initial wealth ω to 1, $\alpha_i = 2$ for investor *i*, and $\alpha_j = 1$ for investor *j* (Henceforth, *i* is more risk averse.). By considering two

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[3] Homm and Pigorsch (2012) give a brief review on the NIG distribution, readers could also resort to Andersson (2001), Bollerslev et al. (2009), Eriksson et al. (2009) and Zakamouline and Koekebakker (2009) for further reference.

[4] Homm and Pigorsch (2012) also provides a non-parametric estimator for the AS index. Our baseline results are robust if the AS index is calculated with the non-parametric estimator. These further results are available upon request.

risky assets g and h, and market return r_m in three equally probable situations in Table 1, we obtain the expected utility for investor i and j as presented in Table 2.

Table 1. Asset Returns and Utilitie

	r_g	$U_i((1+r_g)\omega)$	$U_j((1+r_g)\omega)$	r_h	$U_i((1+r_h)\omega)$	$U_j((1+r_h)\omega)$	r_m
1	-1.0%	0.86193	0.62842	-4%	0.85339	0.61711	0.10%
2	-1.0%	0.86193	0.62842	0	0.86466	0.63212	-0.60%
3	1.8%	0.86945	0.63868	4%	0.87507	0.64655	0.20%

Note: The numbers 1, 2 and 3 in the first column correspond to the three different situations and each has an equal probability of 1/3

Table 2. Expected Utility of Investors

	Asset g	**Asset h**
$E(U_i)$	**0.86444**	0.86438
$E(U_j)$	0.63184	**0.63192**
Beta	**2.21**	1.05

Note: Beta is calculated by a linear regression of the asset returns on the market returns as shown in Table 1.

According to the numerical levels of the expected utility, as reported in Table 2, investor i will choose asset h and investor j will choose asset g. However, given the scenario as described in Table 1, the beta of asset g is 2.21 while 1.05 of asset h according to the definition of the beta in the CAPM. This means that a more risk-averse investor i will choose a riskier asset measured by beta. Clearly, beta violates the duality axiom of the riskiness index.

Positive Homogeneity: Because the definition of beta is defined by the return of an asset, the positive homogeneity is satisfied.

In summary, the beta in CAPM does not satisfy the duality axiom of riskiness. Therefore, it may introduce mistakes if one uses it to measure risk.

Adjusted Beta

This study also adopts the approach by Da *et al*. (2012) to adjust equity returns and betas. According to Da *et al*. (2012), both equity returns and betas are influenced by project beta/return and other factors which are related to the option values of equities. Taylor expansions of equity returns and betas around their market counterparts can be done so as to separate the effects of other factors and project beta/return. Specifically, the return and the CAPM beta are defined in the following equations:

$$\begin{aligned} \mu_i &= f(\mu_i^p, OF_i) = f(\mu_M^p, OF_M) + f_1(\mu_i^p - \mu_M^p) + f_2(OF_i - OF_M) + \varepsilon_i \\ \beta_i &= g(\beta_i^p, OF_i) = g(\beta_M^p, OF_M) + g_1(\beta_i^p - \beta_M^p) + g_2(OF_i - OF_M) + \varepsilon_i \end{aligned} \quad (4)$$

In Equation (4), μ_i and β_i are the unadjusted equity premium and beta on stock i, μ_i^p and β_i^p are equity premium and beta on the project of firm i, respectively. The OF_i represents a vector of variables which are related to the option value of the stock i, μ_M^p, β_M^p and OF_M are the market risk premium, market beta and market option value, respectively. f_1, f_2, g_1 and g_2 are the corresponding partial derivatives. Based on Equation (4), Da *et al*. (2012) show that the option-adjusted equity returns and beta can be obtained by the following OLS regressions:

$$\mu_i = a(OF_i - OF_M) + \mu_i^{Adjusted}$$
$$\beta_i = b(OF_i - OF_M) + \beta_i^{Adjusted} \quad (5)$$

where a and b are regression coefficients, $\mu_i^{Adjusted}$ and $\beta_i^{Adjusted}$ are the option-adjusted return and beta. To implement the option adjustments, we need to find proxies for $(OF_i - OF_M)$. Da et al. (2012) use the idiosyncratic volatility, return on asset (ROA) and the book-to-market ratio (BM) of firm *i* as proxies for the option value. Recent literature (Cao et al., 2008 and Bekaert et al., 2010) link growth options to firms' idiosyncratic risks. The idiosyncratic volatility is then a common measure for the idiosyncratic risk. However, it ignores the higher moments which would imply potential tail risk. As shown by Homm and Pisgorsch (2012), compared with traditional volatility measures, the AS index can be a more informative risk indicator because it captures higher moments of the return. Therefore, in this paper, two types of adjusted betas are considered: beta that is defined as Da *et al*. (2012) with adjusted option value (hereafter, the "growth-adjusted beta"); the "risk-adjusted beta", which is obtained by introducing the AS index of firm *i* as the regressor instead of $(OF_i - OF_M)$ in Equation (5).[5]

3.3 Cumulative Statistics

In fact, in Homm and Pisgorsch (2012)'s paper, Equation (2.2) holds based on the assumptions as follows:

$$\mu > 0, \sigma^2 > 0, \kappa > 0, |\chi| < \sqrt{3\kappa - 5}$$

Then, if we choose to construct the AS index using a rolling window, it is likely that the average mean return is a negative value, which violates the assumption of this parameter estimation and makes this model flawed theoretically.[6] Instead of calculating the AS index on a rolling window, our paper proposes to use a cumulative calculation, so that the AS index is based on the information from time 0 to time t:

$$Cum\_AS_t = AS_t(r_0, r_1, \ldots, r_t)$$

The HS300 index and its corresponding cumulative AS index are plotted in Figure 1.

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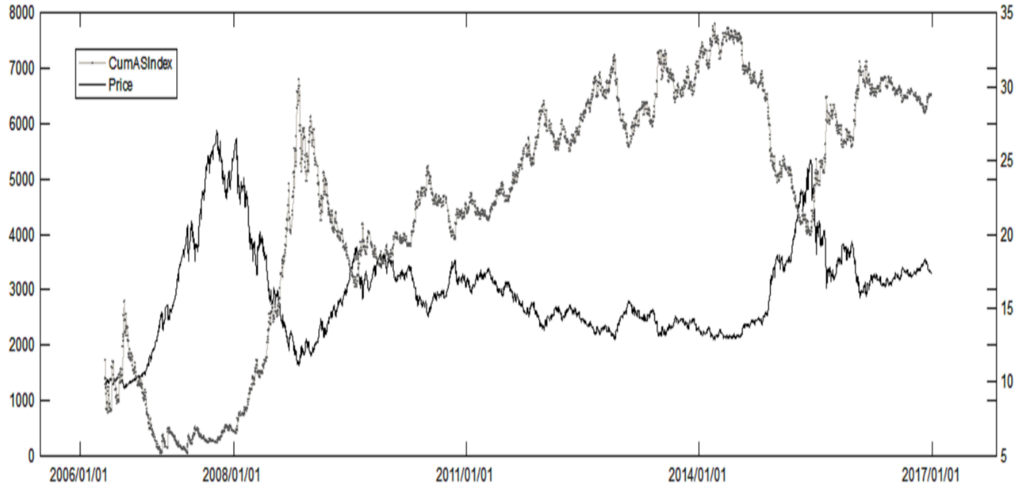
[5] Note that although the adjusted betas preclude the effect of real option values, they are still constructed based on the CAPM beta of firm i. As we have discussed, it does not satisfy the duality axiom and hence may cause potential measurement errors as a risk indicator.

[6] One simple example for this argument is the US stock market return during the financial crisis starting from mid-2007. The values of SPX returns based on a 20-day rolling window in November of 2007 are all negative.

Figure 1. Relationship between cumulative Aumann-Serrano Index and Price Series



Notes: The x-axis is the date; the left y-axis is HS300 index and the right is the corresponding cumulative AS index of the HS300 index. The estimation of the cumulative AS index starts from May 2006

Figure 1 shows the cumulative AS index is negatively correlated with the price and persistent. This is not surprising since the difference between the AS_t and AS_{t-1} comes from the new information which arrives at time t. The difference, ΔCum_AS_t, can be interpreted as the "unexpected" change of risk.

4. Data description and variables

We collect time series dataset of daily frequency for each stock that is publicly traded in Chinese A-share stock market from the year 2005 to the end of 2016. The A-share stocks are officially termed as the "RMB-denominated common stocks", and traded in Shanghai and Shenzhen Stock Exchange. A-share stocks may only be initiated by China-based companies and traded in domestic currency[7]. Among all the stock markets in mainland China, the A-share stock market is the dominant one in terms of the total number of listed companies and gross market value. Our cross-sectional test period starts from May, 2005 (just after the non-tradable stock reform) until the end of 2016.

A brief description of our variables is as follows: the beta estimates are calculated as the slope coefficient of CAPM regressions; the Beta_MKT, Beta_SMB, Beta_HML are calculated as the slope coefficients in the Fama-French three-factor model; all estimates are based on the cumulative method. To calculate the growth-adjusted beta, we apply the approach of Da et al. (2012) to remove the effects of option value on the stock return and beta. The idiosyncratic volatility is calculated

[7] As opposed to the A-share stocks, there is also a B-share stock market in mainland China (excluding Hong Kong), which is denominated in RMB but shares can only be traded using US dollar or Hong Kong dollar. Besides the A- and B-share stocks, there is also a H-share stocks, which refers to the shares of companies incorporated in mainland China but are traded in the Hong Kong Stock Exchange.

using the approach by Ang et al. (2006). The ROA and BM data are retrieved from the CSMAR database. The Fama-French three factors for the Chinese A-share market are retrieved from CSMAR as well. The risk-adjusted beta is constructed by removing the effect of the AS Index on the original beta. The first-order difference of the cumulative AS index is used in all regressions. Stock price momentum (hereafter, Momt) is calculated using the prior 20 days returns (including day t)[8]. All variables are defined in Table 3.

Table 3. Variable Definition

Variables	Definition
Beta	Capital asset pricing model beta
Beta_RA	Risk-adjusted beta
Beta_PA	Potential growth-adjusted beta
AS_nig	Aumann-Serrano index estimated by assuming the return distribution of normal inverse Gaussian distribution
AS_normal	Aumann-Serrano index estimated by assuming the return distribution of normal distribution
CumAS_nig	Aumann-Serrano index estimated using cumulative method by assuming the return distribution of normal inverse Gaussian distribution
Ivol	Idiosyncratic volatility estimates using the approach of Ang et al. (2006)
ROA	Return on total asset
BM	Book-to-market ratio
MKT	Market excess return of the Fama-French(1993) three-factor model
SMB	SMB factor of the Fama-French(1993) three-factor model
HML	HML factor of the Fama-French(1993) three-factor model
Momt	Stock price momentum using prior 20 days returns (including day t).

Table 4. Pairwise correlation of riskiness measurements

	Beta	Beta_MKT	Beta_SMB	Beta_HML	AS_nig	CumAS_nig	AS_normal	Beta_PA	Beta_RA	Momt
Beta	1.0000									
Beta_MKT	0.7790***	1.0000								
Beta_SMB	0.0250***	0.3015***	1.0000							
Beta_HML	0.3017***	-0.2190***	0.7986***	1.0000						
AS_nig	-0.0011**	-0.0020**	-0.0024**	-0.0005**	1.0000					
CumAS_nig	0.0042***	0.0031***	-0.0002**	0.0042***	0.8032***	1.0000				
AS_normal	-0.0006	0.0000	-0.0000	0.0004	0.6014***	0.0697***	1.0000			
Beta_PA	0.6873***	0.0025***	0.0062***	0.0096***	0.0006	-0.0001	-0.0001	1.0000		
Beta_RA	0.2741***	0.0009*	0.0003	0.0042**	0.0003	-0.0051*	0.0000	0.7639***	1.0000	
Momt	0.0759**	0.0051***	0.0021***	-0.0019*	0.0110*	-0.0159*	0.0001	0.0158**	0.0174***	1.0000

Source: CSMAR; daily data from 1st May 2005 to 31st December 2016; Pearson correlations of the CAPM beta, betas of the Fama-Frech three-factor model, Cumulative Aumann-Serrano Index(nig) and Aumann-Serrano Index (normal and nig), beta after potential growth adjustment, risk adjustment, both potential growth adjustment and risk adjustment and stock price momentum. See Table 3 for variable definitions. ***, **, * denotes significance at 1%, 5% and 10% respectively.

Table 4 summarizes pairwise correlations, and it shows: correlations between different risk measurements (CumAS_nig, AS_nig, Beta, Beta_MKT, Beta_SMB, Beta_HML) are statistically significant, but the AS_normal index only has a significant correlation with the AS_nig index and CumAS_nig. This may imply either the AS_normal is less informative compared with the AS_nig or it is wrong. Literature confirms the latter, which is consistent with a well-established recognition that daily return series in the stock market deviates away from Gaussian but converge to a normal inverse Gaussian (NIG) distribution[9]. It is also clear from Table 4 that

8 In the Chinese stock market, a reversal effect prevails rather than the momentum, and that momentum strategies are profitable only at short time horizons (within 4-week holding periods). For a survey in this field, please see Pan and Xu (2011). It is possible that this is caused by an overreaction of market participants (Gang, Qian and Xu, 2018).

9 For the NIG distribution and its application, please see Andersson (2001), Bollerslev et al. (2009), Eriksson et al.

correlations between the CumAS_nig and beta, MKT, HML are significant (6th. row in Table 4, and at 5% significance level) and positive. But if we replace the CumAS_nig with AS_nig, the above correlations become significantly negative. After adjusting the "growth" and "risk", correlations between the AS index (also CumAS_nig) and the Beta_PA, Beta_RA respectively become insignificant (8th and 9th column in Table 4), which suggests that the AS index contains information on the potential growth of a company. Recall now that a firm's growth potential is related to the idiosyncratic risk and the AS index contains comprehensive information on the risk associated with the firm compared with traditional measures.

5. Empirical evidence from Chinese A-share stock market

In this section, we estimate how the AS index correlates with stock returns and, most importantly, evaluate whether it could be a better factor to determine the risk-return relationship. We build the riskiness index by calculating the change in the cumulative AS index. This measurement reflects the innovation of market perception of riskiness towards a specific asset. Henceforth, when we refer to the AS index, we mean the change in the cumulative AS index. After obtaining values of the riskiness for each cross-sectional panel, we implement the Fama-Macbeth (1973) approach to run cross-sectional regressions and thereby calculate the corresponding t-values. We also test the correlation between the AS index and stock price momentum and compare their explanatory power on stock returns.

5.1 Panel analysis

We estimate seven models based on our data panels and results of each model are exhibited as rows in Table 5. Columns in Table 5 contain estimated coefficients (betas) that correspond to different factors of the regressions. Beta, as shown in column 3 is the premium for the individual stock as per market excess return. Therefore, Model 1 with a zero intercept stands for a classic CAPM model. The estimated coefficients of Model 1 include a significantly positive intercept (alpha) with a value of 0.2275 (significant at a level of 1%), which suggests after adjusting for the systematic risk, there still exist abnormal returns for individual stocks. Hence, a significant alpha indicates either the CAPM model is mis-specified or beta itself is an incompetent measure of risk. Augmented and generalized models and explanations as such are well-documented. Therefore, from the results in Model 1, it is consistent with the literature that stock market violates the CAPM model because it does not fully explain individual stock returns. In Chinese case, one proven explanation is irrationality happens more often since the number of individual investors dominates the number of institutional investors. This phenomenon is corroborated by many studies focusing on Chinese A-share market. For instance, Wu and Xu (2004) point out that the return of Chinese market is determined by risk factors and some significant irrational events which often cause simultaneity in price movements. Another result from Model 1 is that the estimated beta is negative, which implies that the beta of each stock may even hardly explain its return.

(2009), Zakamouline and Koekebakker (2009), Homm and Pigorsch (2012).

As mentioned before, violation of the CAPM revealed by Model 1 may imply beta is an imprecise measure of risk. We then use the risk-adjusted beta to replace the CAPM-beta and get results as shown by Model 2 in Table 5. Estimates of Model 2 show this model hardly captures any systematic risk and has a highly significant abnormal return. Model 3 uses the growth-adjusted beta to replace beta in the CAPM. In contrast to the results by Da et al. (2012) for the US market, Model 3 does not perform well in the Chinese market either. Model 4 shows the performance of a standard Fama-French three-factor model. All three factors are insignificant at 5% significant level but the constant term is highly significant. Therefore, the performance of the Fama-French three-factor model explains little. To sum up, none of the above model does a good job to explain Chinese A-share market.

As we discussed in Section 3, betas and the adjusted betas fail to satisfy the duality axiom proposed by Aumann and Serrano (2008) and may omit valuable information regarding risk premium of higher orders. Hence, we re-construct Model 5 in Table 5 by simply using the AS index as a substitute for the beta in the classic CAPM (hereafter, Model 5 is defined as the "AS-CAPM"). Surprisingly, the estimated coefficient of the AS-index in the AS-CAPM is highly significant. It suggests that, in general, individual stock's return volatility, after adjusted for higher-order risks, tends to negatively correlate to the stock return. By employing our definition of the riskiness as shown above (the change in the cumulative AS index, or the innovation of perceived risk of a given asset), the negative beta is interpreted as a current decrease in the innovation of the riskiness implying a higher expected return in the future.

To further explore the explanatory power of the AS index, we add it to the adjusted CAPM of Da *et al*. (2012) and to the Fama-French three-factor model. When both the growth-adjusted beta and the AS index are used to explain the growth-adjusted stock return, none of them are statistically significant. However, the AS index alone is a significant explanatory variable for the growth-adjusted stock return. This result is reported as Model 6 in Table 5. Model 7 is a four-factor model which includes the Fama-French three factors and the AS index. Not only the AS index has significant explanatory power in this model, including the AS index also strengthens the explanatory power of the Fama-French factors.

Ang *et al*. (2006, 2009) find that idiosyncratic risk as measured by the idiosyncratic volatility is negatively associated with individual stock returns. Chen and Petkova (2012) further show that average stock variance is an omitted risk factor in the traditional factor models. The factor loading of the omitted risk factor is negative. Because the idiosyncratic risk positively correlates to the average stock variance, it negatively correlates to the stock return. Our result is consistent with these findings. However, our results as presented are more general because our AS index is a composite index of the idiosyncratic risk. Specifically, our function consists of not only the second-order risk but also risk of higher-orders. Barberis and Huang (2008) raise a theory which indicates positively skewed stocks are overpriced and have lower average returns. Our results indirectly confirm that higher-order conditional moments help explain the stock returns in cross section. The focus of this paper is not to go that far to reconstruct a theory on asset pricing, but our results do re-confirm that idiosyncratic risk affects asset prices. The explanatory power of our AS index towards the stock return is much higher compared with the CAPM and the Fama-French three-factor model.

Table 5. Panel Regression Results of the Asset Pricing Models

Model	Constant	Beta	Beta_RA	Beta_PA	Beta_MKT	Beta_SMB	Beta_HML	AS
1	0.2275*** (4.43)	-0.0743 (-1.64)						
2	0.1236*** (3.00)		0.0083 (1.28)					
3	-0.0079 (-0.08)			-0.0185 (-0.43)				
4	0.2359*** (4.67)				-0.0972* (-1.99)	0.0075 (0.62)	-0.0104 (-0.56)	
5	0.1365*** (3.30)							**-0.0210*** (-7.94)**
6	0.3926*** (-9.27)		-					**-0.0013*** (-1.94)
7	0.1204*** (3.03)				0.0041 (0.47)	0.0132*** (2.62)	-0.0067** (-1.98)	**-0.1331*** (-14.20)**

Source: CSMAR; daily data from 1st May 2005 to 31st December 2016; Dependent variable is the daily stock return. The stock return is adjusted using equation (5) in Model 2-3 and 6. Independent variables consist of CAPM beta, betas of the Fama-French three-factor model, risk-adjusted betas, potential growth-adjusted beta, and the Aumann-Serrano risk index. The coefficient is the mean value of all the cross-sectional regression; and the t-value is calculated using Fama-Macbeth (1973) approach. ***, ** and * denotes the significance level at 1%, 5% and 10% respectively.

In summary, results from Table 5 shows that using the AS index as a proxy for the risk factor outperforms the CAPM model, Fama-French three-factor model and the option-adjusted CAPM models. We now examine possible reasons and try to present explanations.

Our model, as in Model 5 in Table 5, can be explicitly expressed as follows:

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \sum_{k=1}^{n} Risk_{k,t} \cdot Premium_{k,t} + \tilde{\varepsilon}_{i,t} \tag{6}$$

The estimated coefficient before the AS index in Model 5 of Table 5 can be seen as the risk premium associated to the risk measured by the AS index (hereafter, the "AS premium"). We firstly examine the relationship between the market return and the AS premium. Table 6 presents two estimations of for the AS premium. There is no significant relationship between the market return and the AS premium, and the fittings are trivial. This indicates the explanatory power of the market excess return on the compensation for higher-order risk captured by the AS index is very limited. This may explain why the performance of the risk-adjusted beta model is dominated by the AS-CAPM. A possible extension using the Fama-French three factors (Model 2 in Table 6) shows similar features. Therefore, results in Table 6 suggest that the AS premium is somewhat beyond the scope of the traditional factor models.

Table 6. Regressions of the Premium of the Aumann-Serrano Index

Model	Constant	Market Return (MKT)	SMB	HML	R^2
1	-0.0027*** (-4.24)	-0.0002 (-0.66)			0.0004
2	-0.0048*** (-7.28)	0.0001 (0.96)	0.0004 (0.89)	-0.0002 (-0.31)	0.0003

Source: CSMAR; daily data from 1st May 2005 to 31st December 2016; The dependent variable is the risk premium for the AS index, i.e. the coefficient of the AS index for each cross-section; the independent variables are the market return and Fama-French three factors (MKT, SMB, HML). We apply the time-series regression and all series are stationary. The value in the parentheses is the t-value for each regressor. ***, ** and * denotes the significance level at 1%, 5% and 10% respectively.

5.2 The AS index and momentum

The last row in Table 4 summarizes the correlations between betas, the AS index, and the momentum of stock prices. Traditionally, the momentum is usually seen as a phenomenon of collective irrationality which may be related to investor over-reactions. However, if the momentum factor can be partly explained by some risk measurement, then the excess risk compensation under rationality still holds even for an evident behavior of momentum. That says even if momentum strategy generates an excess profit margin that could not be explained by classic factor modeling, it is possible that this abnormal return may not be a bonus to superior trading strategy. Instead, one part of the momentum profit merely means traders take on skew and/or tail risks which are impossible to diversify. Therefore, momentum is some yield on the higher-order risks, but not gift money to show off. Hence, it is important to investigate whether the AS index correlates with the momentum of stock prices.

Three models are considered: the CAPM augmented by the momentum factor; the AS-CAPM augmented by the momentum factor; a model with the momentum as the single factor. Results are shown in Table 7. Results of all three models show that momentum plays a very important (and robust) role to explain daily stock returns. Estimates of the coefficients before the momentum factor are both highly significant and consistent in all three models.

Table 7. Regressions with the Momentum Factor

Model	Constant	Beta	AS Index	Momt	R^2
1	0.0213 (0.56)	-0.0210 (-0.93)		0.0467*** (33.38)	0.1245
2	0.0024 (0.06)		-0.0220*** (-8.74)	0.0429*** (31.86)	0.0592
3	-0.0287 (-0.69)			0.0503*** (36.69)	0.0802

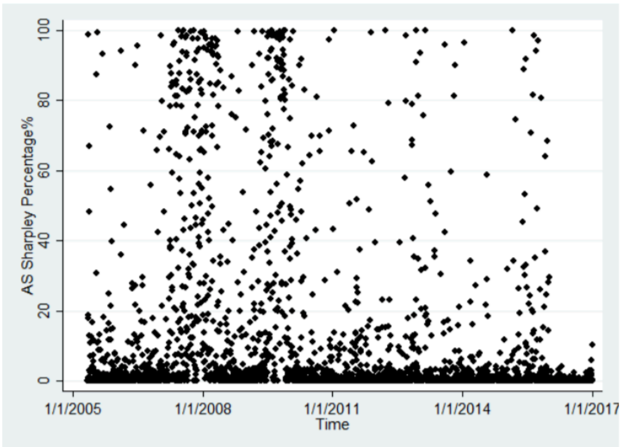
Source: CSMAR; daily data from 1st May 2005 to 31st December 2016; Dependent variable is daily return of stocks, independent variables consists of CAPM beta, Aumann-Serrano risk index and the stock price momentum term. The coefficient is the mean value of all the cross-sectional regressions; and the t-value is calculated using Fama-Macbeth (1973) approach. ***, ** and * denotes the significance level at 1%, 5% and 10% respectively.

Model 1 of Table 7 shows the momentum factor improves the performance of a classic CAPM. Model 2 includes both the AS index and the momentum factor as independent variables. The estimated coefficient of the AS index, in this case, is both consistent in value (with Model 5 in Table 5) and significant at 1% level.

We use the Shapley variance decomposition to compare the explanatory power of the AS index and the momentum factor after orthogonalizing these two variables to the daily returns. Figure 2 and 3 present the results of the Shapley variance decomposition. In Figure 2, the x-axis represents the time line, and the y-axis represent the Shapley value, which stands for the explanatory power of the AS index (or residual of the AS index after the first-stage regression). Each spot in the figure represents the Shapley value of the AS index at each period. Figure 3 gives the corresponding quantile percentage of the AS index. Most of the observed values in Figure 2 are concentrated at the bottom, which suggests that momentum explains more variations of daily stock returns in most of the days. Figure 3 further confirms this intuition. However, there is still a substantial number of dates on which the Sharpley percentage of the AS index is high. This means that the explanatory power of the AS index is also non-negligible. Interestingly, the dates on which the AS index has a high explanatory power tends to cluster around 2009 and 2015, which suggests that the AS index and momentum factor could have comparative advantages in different market regimes.

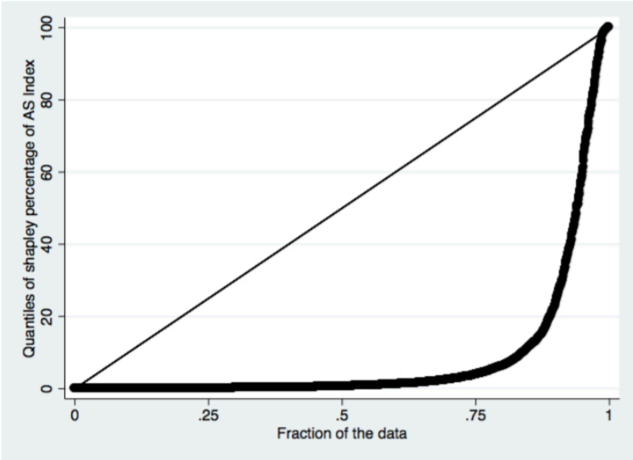
To further investigate this phenomenon, we classify the days on which the AS index outperforms the stock price momentum in explaining the equity premium and vice versa into two groups, and using the mean, variance, skewness and kurtosis of the prior 20 days HS index return on a rolling basis to quantify different market regimes in different days. Group 1 consists of the days on which the AS index significantly outperforms stock price momentum and Group 2 consists of the days on which stock price momentum significantly outperforms the AS index. We use two quantitative criteria for the classification. Criterion 1 is based on the absolute value of the Shapley percentage. Those days with higher than 90 Shapley percentage of the AS index go to Group 1 while those days with less than 10 Shapley percentage go to Group 2. Criterion 2 is based on percentiles of the sample. The top 10% Shapley percentage of AS index goes to Group 1 while the bottom 10% go to Group 2. In Table 8, we present the ANOVA analysis of the inter-group difference.

Figure 2. Shapley Percentage of the AS Index Term



Notes: The y-axis is the Shapley percentage of AS index; the x-axis is the date.

Figure 3. Quantile Percentage of the AS Index Term



Notes: The y-axis is the quantiles of Shapley percentage of the AS index; the x-axis is the fraction of the data

Table 8. ANOVA analysis

	Mean Value		ANOVA F-Value	P-Value
	Group 1	Group 2		
Criterion 1				
Mean	0.0759	0.7448	145.47	0.0000
Variance	12.1813	6.8913	559.16	0.0000
Skewness	1.6375	0.8436	507.2	0.0000
Kurtosis	31.8789	8.1471	272.50	0.0000
Criterion 2				
Mean	0.1206	0.4681	868.98	0.0000
Variance	19.5554	7.3506	781.32	0.0000
Skewness	2.6633	1.1037	19.11	0.0000
Kurtosis	77.7593	14.8949	164.09	0.0000

Source: CSMAR; daily data from 1st May 2005 to 31st December 2016; Criterion 1:The days with higher than 90 Shapley percentage of AS index go to group 1, while those days with less than 10 Shapley percentage go to group 2. Criterion 2 : The top 10% Shapley percentage of AS index go to group 1, while the bottom 10% go to group 2. F-value and P-value are calculated by ANOVA. The mean, variance, skewness and kurtosis data is the correspondent statistics of prior 20 days market return.

From Table 8, we notice that there are significant differences in return distributions between the days on which the AS index performs better and the days on which stock price momentum performs better. From the ANOVA analysis, we discovered that there are significant differences in the variance, skewness and kurtosis of the return distribution between the two groups no matter which criterion is applied to group the dates. These results further confirm that the AS index and stock price momentum has their comparative advantages in explaining the equity premium in different market regimes. The AS index outperforms momentum in volatile market conditions, where big market swings, or even, market crash, tend to happen. But the momentum factor dominates AS index when the market is relatively calm and shows some deterministic trending over time. Therefore, those two factors are complementary in a good stock pricing model for Chinese A-share stock market.

6. Conclusion

This paper focuses on the performance of alternative riskiness measurement in stock pricings in Chinese stock market. Our paper shows that the CAPM and Fama-French three-factor models with their corresponding risk-measurement cannot explain the equity premium. A replication of Da et al. (2012) adjusted-CAPM does not work either in China. We show that our AS-CAPM model explains the daily return better. The AS index not only satisfies Aumann's two axioms but also absorbed the higher-order risk of individual assets under extreme market regimes. Moreover, the market return and the three factors in the Fama-French model has a limited explanatory power of the risk premium for the AS index. This study also shows that the AS index and the momentum factor are complementary: the AS index explained more in the volatile market while the momentum factor performs better when the market is relatively calm. Hence, the change of risk perception as reflected by our cumulative AS index is one important and robust factor for asset pricing in China. Compared with the momentum factor, it performs as a dominating risk measurement under extreme market circumstances.

References

Ahn, J. and Cogman, D. (2007), "A quiet resolution in Chinese capital market", The McKinsey Quarterly.

Ai H. and Kiku D., (2013), "Growth to value: Option exercise and the cross section of equity returns", Journal of Financial Economics, 107(2), 325-349.

Ai H., Croce M. M. and Li K. (2013), "Toward a quantitative general equilibrium asset pricing model with intangible capital", Review of Financial Studies, 26(2), 491-530.

Ang A., Hodrick R. J., Xing Y. and Zhang X., (2006), "The cross-section of volatility and expected returns", The Journal of Finance, 61(1), 259-299.

Ang A., Hodrick R. J., Xing Y. and Zhang X., (2009), "High idiosyncratic volatility and low returns: International and further US evidence", Journal of Financial Economics, 91, 1-23.

Aumann R. J. and Serrano R., (2008), "An economic index of riskiness", Journal of Political Economy, 116(5), 810-836.

Banz R. W., (1981), "The relationship between return and market value of common stocks", Journal of Financial Economics, 9(1), 3-18.

Bao Y., (2009), "Estimation risk-adjusted Sharpe ratio and fund performance ranking under a general return distribution", Journal of Financial Econometrics, 7(2), 152-173.

Barberis N., Greenwood R., Jin L. and Shleifer A., (2015), "X-CAPM: An extrapolative capital asset pricing model", Journal of Financial Economics, 115(1), 1-24.

Barberis N., Huang M., (2008), "Stocks as lotteries: the implications of probability weighting for security prices", American Economic Review, 98(5), 2066-2100.

Basu S., (1983), "The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence", Journal of Financial Economics, 12(1), 129-156.

Bekaert G., Hodrick R. J. and Zhang X., (2012), "Aggregate idiosyncratic volatility", Journal of Financial and Quantitative Analysis, 47(06), 1155-1185.

Bollerslev T., Engle R. F. and Wooldridge J. M., (1988), "A capital asset pricing model with time-varying covariances", The Journal of Political Economy, 116-131.

Bondt W. F. and Thaler R., (1985), "Does the stock market overreact?", The Journal of Finance, 40(3), 793-805.

Brockett P. L. and Kahane Y., (1992), "Risk, return, skewness and preference",

Management Science, 38(6), 851-866.
Carhart M. M., (1997), "On persistence in mutual fund performance", The Journal of Finance, 52(1), 57-82.
Cao C., Simin T. and Zhao J., (2008), "Can growth options explain the trend in idiosyncratic risk?", Review of Financial Studies, 21(6), 2599-2633.
Chen Z., Petkova R., (2012), "Does individual volatility proxies for risk exposure", Review of Financial Studies, 25(9), 2725-2787.
Cont R., (2001), "Empirical properties of asset returns: stylized facts and statistical issues", Quantitative Finance, 1(2), 223.
Cooper M. J., Gulen H. and Schill M. J., (2008), "Asset growth and the cross‐section of stock returns", The Journal of Finance, 63(4), 1609-1651.
Da Z., Guo R. J. and Jagannathan R., (2012), "CAPM for estimating the cost of equity capital: Interpreting the empirical evidence", Journal of Financial Economics, 103(1), 204-220.
Dennis S. A., Simlai P. and Smith W. S. (2011), "Modified Beta and Cross-Sectional Stock Returns", Midwest Finance Association 2012 Annual Meetings Paper.
Dybvig P. H. and Ingersoll Jr J. E., (1982), "Mean-variance theory in complete markets", Journal of Business, 233-251.
Fama E. F., (1968), "Risk, return and equilibrium: some clarifying comments", The Journal of Finance, 23(1), 29-40.
Fama E. F. and French K. R., (2015), "A five-factor asset pricing model", Journal of Financial Economics, 116(1), 1-22.
Fama E. F. and French K. R., (1993), "Common risk factors in the returns on stocks and bonds", Journal of Financial Economics, 33(1), 3-56.
Fama E. F. and French K. R., (2012), "Size, value, and momentum in international stock returns", Journal of Financial Economics, 105(3), 457-472.
Farinelli S., Ferreira M., Rossello D., Thoeny M., and Tibiletti L., (2008), "Beyond Sharpe ratio: Optimal asset allocation using different performance ratios", Journal of Banking & Finance, 32(10), 2057-2063.
Fernandez P., (2009), "Betas used by Professors: a survey with 2,500 answers", IESE Business School, SSRN, 1-12.
Frencha C. W., (2003), "The Treynor capital asset pricing model", Journal of Investment Management, 1(2), 60-72.
Gang J., Qian Z. and Xu T., (2018), "The Momentum and overreaction: evidence from the Chinese A-share stock market", Working paper.
Goyal A., (2012), "Empirical cross-sectional asset pricing: a survey", Financial Markets and Portfolio Management, 26(1), 3-38.
Graham J. R. and Harvey C. R., (2001), "The theory and practice of corporate finance: Evidence from the field", Journal of Financial Economics, 60(2), 187-243.
Gregory A., Tharyan R. and Christidis A., (2013), "Constructing and testing alternative versions of the Fama–French and Carhart models in the UK", Journal of Business Finance & Accounting, 40(1-2), 172-214.
Griffin J. M., (2002), "Are the Fama and French factors global or country specific?", Review of Financial Studies, 15(3), 783-803.
Grullon G., Lyandres E. and Zhdanov A., (2012), "Real options, volatility, and stock returns", The Journal of Finance, 67(4), 1499-1537.
Homm U., and Pigorsch C., (2012), "Beyond the Sharpe ratio: An application of the Aumann–Serrano index to performance measurement", Journal of Banking & Finance, 36(8), 2274-2284.
Homm U. and Pigorsch C., (2010), "The Aumann-Serrano index of riskiness for

normal inverse Gaussian distributed gambles", University of Bonn (mimeo).
Hung C. D., Chen Q. and Fang V., (2015), "Non-tradable share reform, liquidity, and stock returns in China", International Review of Finance, 15(1), 27-54.
Jegadeesh N. and Titman S., (1993), "Returns to buying winners and selling losers: Implications for stock market efficiency", The Journal of Finance, 48(1), 65-91.
Jensen M. C., Black F. and Scholes M. S., (1972), "The capital asset pricing model: Some empirical tests", Studies in the Theory of Capital Markets, Praeger Publishers Inc.
Jiang, B., Laurenceson, J. and Tang, K. (2008), "Share reform and performance of Chinese listed companies", China Economic Review, 19, 489–501.
Li M., (2014), "On Aumann and Serrano's economic index of risk", Economic Theory, 55(2), 415-437.
Lintner J., (1965), "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets", The Review of Economics and Statistics, 13-37.
Liu W., (2006), "A liquidity-augmented capital asset pricing model", Journal of Financial Economics, 82(3), 631-671.
Merton R. C., (1973), "An intertemporal capital asset pricing model", Econometrica, 867-887.
Pan L. and Xu J., (2011), "The price continuation and reversal in China's A-share stock market", Journal of Financial Research, 149-166.
Reinganum M. R., (1981), "A new empirical perspective on the CAPM", Journal of Financial and Quantitative Analysis, 16(04), 439-462.
Schlueter T. and Sievers S., (2014), "Determinants of market beta: the impacts of firm-specific accounting figures and market conditions", Review of Quantitative Finance and Accounting, 42(3), 535-570.
Schulze K., (2014), "Existence and computation of the Aumann–Serrano index of riskiness and its extension", Journal of Mathematical Economics, 50, 219-224.
Schulze K., (2015), "General dual measures of riskiness", Theory and Decision, 78(2), 289-304.
Sentana E. and Wadhwani S., (1992), "Feedback traders and stock return autocorrelations: evidence from a century of daily data", The Economic Journal, 415-425.
Sharpe W. F., (1964), "Capital asset prices: A theory of market equilibrium under conditions of risk", The Journal of Finance, 19(3), 425-442.
Sharpe W. F., (1966), "Mutual fund performance", Journal of Business, 119-138.
Sharpe W. F., (1994), "The sharpe ratio", The Journal of Portfolio Management, 21(1), 49-58.
Shiller R. J., (1980), "Do stock prices move too much to be justified by subsequent changes in dividends?"
Stambaugh, R. F., Yu, J., & Yuan, Y., (2012). The short of it: Investor sentiment and anomalies. Journal of Financial Economics, 104(2), 288-302.
Treynor J. L., (1961), "Market value, time, and risk", Unpublished manuscript, 95-209.
Treynor J. L. (1961), "Toward a theory of market value of risky assets"
Welch I., (2008), "The consensus estimate for the equity premium by academic financial economists in December 2007", Available at SSRN: http://ssrn.com/abstract=1084918.
Wu S. and Xu N. (2004), "A Comparative Study on the Rational Asset Pricing Model and Irrational Asset Pricing Model: Evidence from Stock Market in China",

Economic Research Journal, 6, 105-116.