American Journal of Applied Mathematics
2022; 10(4): 118-124
http://www.sciencepublishinggroup.com/j/ajam
doi: 10.11648/j.ajam.20221004.11
ISSN: 2330-0043 (Print); ISSN: 2330-006X (Online)

Ambiguity—Risk—Return: Evidence from the Stock Market in China

Yingxiu Zhao[1], Baojuan Shi[1], Fang Song[2, *], Lin Zhou[2]

[1]School of Economics, North China University of Science and Technology, Tangshan, China
[2]School of Economics and Management, Qinghai Minzu University, Xining, China

Email address:
fangsong@tju.edu.cn (Fang Song)
[*]Corresponding author

To cite this article:
Yingxiu Zhao, Baojuan Shi, Fang Song, Lin Zhou. Ambiguity—Risk—Return: Evidence from the Stock Market in China. *American Journal of Applied Mathematics*. Vol. 10, No. 4, 2022, pp. 118-124. doi: 10.11648/j.ajam.20221004.11

Received: May 25, 2022; **Accepted**: June 27, 2022; **Published**: July 5, 2022

Abstract: In the past decades, ambiguity in the stock market has been widely studied theoretically and experimentally. Most existing studies focus on foreign financial markets, such as American stock market. However, there are essential differences between Chinese stock market and others stock market, such as its participants and trading mechanisms. Therefore, it is necessary to study the relation of ambiguity, risk and expected return in China's stock market. This study analyzes CSI 300 index data for January 2006 to February 2020 to investigate the relationships between ambiguity, risk, and expected returns in China's stock market. We apply empirical methods to measure the degree of ambiguity and assess attitudes toward ambiguity from the China's market data, the results indicate that: (1) the degree of ambiguity increases with the expected return; (2) when risk and ambiguity are introduced simultaneously, the expected return of China's stock market is significant negative; and (3) in addition, we also prove that the investors' level of aversion to or preference for ambiguity, which depends on the expected probability of favorable returns. In sum, our results not only clarify ambiguity and risk regarding expected returns but also provide the theoretical and practical implications for the problem of asset prices in China's stock market.

Keywords: Ambiguity, Ambiguity Version, Return, Risk

1. Introduction

In this study, we investigate relationships between ambiguity, risk, and expected returns in China's stock market. Previous studies on the American stock market introduce ambiguity into their pricing models and suggest that ambiguity is significant factors of expected return [1-3]. China's stock market, a major financial market, has features distinct from those of the American market, including limits daily trading fluctuations, more retail investors, and so on. As there is currently no study on the relationships between ambiguity, risk, and expected return in China's stock market, this study aims to address this gap in the literature.

In stock markets, risk always represent the future returns, which are realized with known probabilities, while, ambiguity means that the probabilities associated with these realizations are not known or not uniquely assigned [3]. In this study, we focus the relationships between ambiguity, risk, and expected return in China's stock market over time. Based on the model of Menachem and Yehuda [3], we measure ambiguity by using the actual data from the listed companies in China. We find that ambiguity improves the expected return, and, furthermore, investors' propensities for ambiguity are asymmetric.

This study makes several contributions. First, prior research on ambiguity mainly emphasizes the attitude toward ambiguity, with only a few studies focusing on the actual measurement of ambiguity. Our study supplements the empirical research to date with an examination of China's stock market. Second, we study the relationship between ambiguity and predicted return in China's stock market, and find that ambiguity has a considerable impact on the price change in China's stock market as it improves the expected return. Moreover, risk fluctuation has an important negative impact on expected returns when we consider ambiguity. Thus, ambiguity is a crucial index of the stock market. Third, investors have asymmetric propensities for ambiguity; investors prefer ambiguity when they have high expected probability of gains and are averse to ambiguity when they have a high expected probability of losses. Thus, although there are more retail investors in China's stock market, investors in both Chinese and American stock markets show similar behaviors in their ambiguity preferences.

2. Literature Review

As a missing factor in asset pricing models, ambiguity affects not only asset prices but also the relationship between risk and return. Some scholars made helpful attempts to examine ambiguity, Epstein and Schneider calibrate a model to real data [4], while, the others [5, 6] explore proxies for ambiguity by analyzing the disagreement among analysts [5, 6]. The entropy of inflation, the Volatility Index (VIX), and the prices of put options written on the S & P 500 Index are used to estimate ambiguity [1, 7, 8].

Studies on individual behavior indicate that investors are averse to ambiguity when facing high probability gains; while they tend to accept ambiguity when facing high probability losses. Mele and Sangiorgi pointed out that, in an ambiguous market, the acquisition of useful information is more valuable for investment. Investors can avoid losses by purchasing other people's information sources [9]. Other studies demonstrate that asset pricing generates an uncertainty premium to compensate for the possible losses caused by the unknown [10, 11]. Mohammad and Liu report that ambiguity aversion injects the agent's endogenous pessimism into its business cycle model, which can explain the mystery of equity premium [12]. Wakker et al. suggest that individuals have a disposition to embrace ambiguity in their analysis of health insurance information [13]. Moreover, other scholars imply that individuals show ambiguity-loving behavior when facing a relatively high probability of loss, and ambiguity aversion when facing a relatively high probability of gain [14-16]. Our findings are in line with those of prior research. Furthermore, we help clarify particular functional form of attitudes toward ambiguity by investigating aggregate preferences considering ambiguity.

3. Hypotheses and the Ambiguity Premium

3.1. Hypotheses

Wakker et al. find that reducing ambiguity decreases the value of uncertain options [13]. Ui shows that higher stock returns will lead to lower equity premiums without ambiguity or private signal [2]. Driouchi et al. imply that ambiguous options ease the lead-lag relationship between volatility and realized volatility [1].

H1: The higher the ambiguity, the higher the expected return.

As early as Merton, numerous studies discuss the fundamental (linear) relationship between the risk and return of the market portfolio [17]. However, these studies report conflicting positive [18-21] or negative relationships [22, 23].

H2: When considering ambiguity, risk fluctuation has a significant negative impact on expected return.

Maffioletti and Michele report that individuals tend to seeking ambiguity in their trading behavior by assuming [24]. Other studies of individual behavior indicate that investors show ambiguity-loving behavior when facing a relatively high probability of loss and ambiguity aversion when facing a relatively high probability of gain [14-16]. Menachem and Yehuda state that investors typically exhibit ambiguity aversion when expecting favorable returns [3].

H3: Investors typically prefer ambiguity when expecting unfavorable returns. The degree of aversion to ambiguity decreases with the increase in the expected return probability.

3.2. The Ambiguity Premium

We use the theoretical framework of expected utility with uncertain probabilities (EUUP), which is put forward by Menachem and Yehuda to model two-layer uncertainty [3]. In the first stage, investors form their perceived probability of all events related to their decision-making, which implies an uncertain probability; in the second stage, they estimate the expected value of each alternative, which means uncertain results.

Using the second-order probability measure ϑ, we define the expected marginal probability and cumulative probability of the uncertain return r a:

$$E\big(\varphi(r)\big) = \int \varphi(r) d\vartheta \tag{1}$$

$$E\big(P(r)\big) = \int P(r) d\vartheta \tag{2}$$

The variance of marginal probability is defined as

$$Var[\varphi(r)] = \int (\varphi(r) - E[\varphi(r)])^2 d\vartheta \tag{3}$$

We obtain the expected return and return variance as

$$\mathrm{E}[r] = \int E[\varphi(r)] r dr \tag{4}$$

$$Var[r] = \int E[\varphi(r)](r - \mathrm{E}[r])^2 dr \tag{5}$$

where $\varphi(r)$ is the marginal probability associated with the cumulative probability. Ambiguity preference is defined as a strictly increasing continuous quadratic differentiable function in probability: $\Upsilon: [0,1] \rightarrow \mathbb{R}$. Under the EUUP framework, we can approximate the expected utility of investment opportunities as:

$$W(1+r) \approx \int_{r \le r_f}^{A} U(1+r) E[\varphi(r)] \left(1 - \frac{\Upsilon''\big(1-E(P(r))\big)}{\Upsilon'(1-E[P(r)])} Var[\varphi(r)]\right) dr + \int_{r \ge r_f}^{A} U(1+r) E[\varphi(r)] \left(1 + \frac{\Upsilon''\big(1-E(P(r))\big)}{\Upsilon'(1-E[P(r)])} Var[\varphi(r)]\right) dr \tag{6}$$

where $P(r)$ is the cumulative probability of the return being lower than r, with r_f being the reference point.

Using equation (6), we have

$$\mho^2[r] = \int E[\varphi(r)] Var[\varphi(r)] dr \tag{7}$$

where we can use $\mho^2$, as a measure of ambiguity, to verify the theoretical and experimental evidence based on human decision-making. In particular, the return distribution of each trading day is differing, so we assume that the return of the market portfolio is normally distributed. Therefore, the measure of ambiguity is

$$\mho^2[r] = \int E[\phi(r;\mu;\sigma)]Var[\phi(r;\mu;\sigma)]dr \quad (8)$$

where $\phi(\cdot)$ is a normal probability density function, μ is the mean, and σ^2 is variance.

4. Data and Parameter Estimation

4.1. Data

We used the data for the CSI 300 index covering the period between January 2006 and February 2020 for this study. We take the prices of the shares every five minutes from 9:30 a.m. to 11:30 a.m. and 1:00 p.m. to 3:00 p.m., which includes 48 prices for each day. We obtain daily and monthly reports, and one-month Treasury bonds from the CSMAR database.

4.2. Parameter Estimation

Then we estimate risk and ambiguity as follows:

First, the time series value of monthly risk is estimated by the variance of daily returns. In Figure 1, we depict the time series of the volatility of shares from 2006 to 2020.

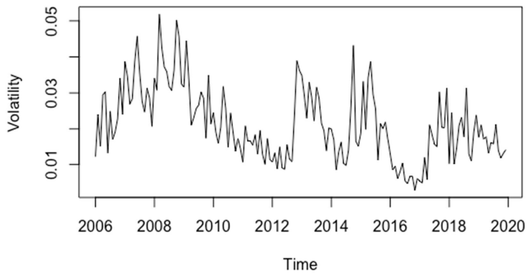
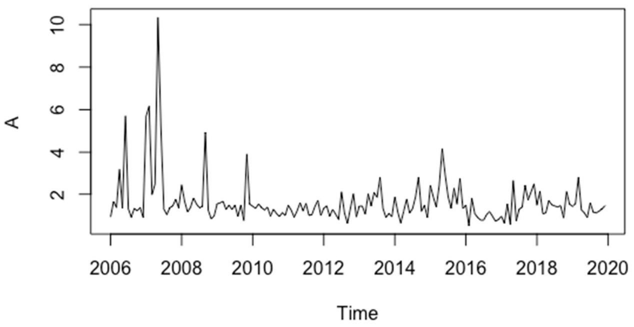


Figure 1. *Time series of stocks fluctuation.*

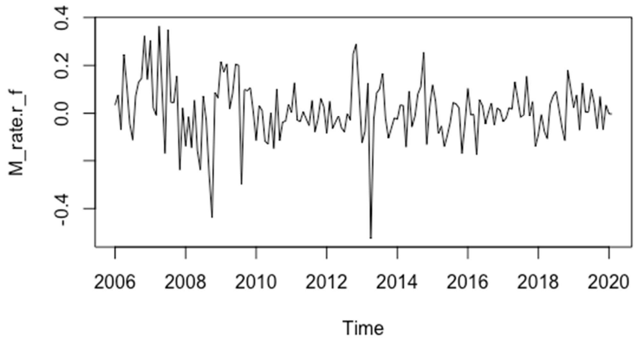
The second step is to estimate the time series value of ambiguity. We compute returns using five-minute intervals, making 48 observations for each day. Subsequently, we can analyze the normalized daily mean and variance of return, which we denote as μ and σ^2, respectively. The cumulative probability of favorable returns for each day is calculated, which is marked as $P(r \geq r_f) = 1 - \phi(r_f;\mu;\sigma)$. The expectation of favorable returns is determined by the daily ratio of the sample average to the standard deviation $\frac{\mu}{\sigma}$. In addition, we calculate the monthly degree of ambiguity using equation (8). We represent each daily return distribution as a histogram, and divide the range of daily returns, from −4% to +4%, into 20 intervals (bins), where the width of each interval is 0.4%. We compute the probability of the return being in each bin and the probability of the return being below −4% and above +4%. Then, we compute the mean and variance of the probabilities for each of the 42 bins. Finally, the degree of ambiguity of each month is estimated as follows:

$$\mho^2[r] = \frac{1}{w(1-w)} \times \left(E[\phi(r_0;\mu,\sigma)]Var[\phi(r_0;\mu,\sigma)] + \sum_{i=1}^{20} E[\phi(r_i;\mu,\sigma) - \phi(r_{i-1};\mu,\sigma)]\,Var[\phi(r_i;\mu,\sigma) - \phi(r_{i-1};\mu,\sigma)] + E[1 - \phi(r_{20};\mu,\sigma)]Var[1 - \phi(r_{20};\mu,\sigma)]\right) \quad (9)$$

where $r_0 = -0.06, w = r_i - r_{i-1}$, $\frac{1}{w(1-w)}$ scales the weighted-average volatilities of the probabilities of the bin size according to Menachem and Yehuda [3]. As with the expected probabilities, we compute the variance of probabilities assuming that the daily ratios $\frac{\mu}{\sigma}$ are student's-t distributed [3]. We depict the time series of the changes in ambiguity and returns in China's stock market from 2006 to 2020 in Figure 2, the figure shows that a relatively high average ambiguity is accompanied by a relatively high excess return from 2006 to 2008.



a Time series of stocks ambiguity



b Time series of stock excess return

Figure 2. *Time series of ambiguity and excess return in Chinese stock market.*

Note. The estimated expected values are for the period between January 2006 and February 2020 in China's stock market.

4.3. Descriptive Statistics

Panel A of Table 1 provides the descriptive statistics of intraday returns. We calculate the probability of favorable returns P as $\frac{\mu}{\sigma}$ $(-0.476 < \frac{\mu}{\sigma} < 0.576)$, which has a mean of -0.002. Panel B of Table 1 provides the descriptive statistics of the variables. The dependent variable is the monthly return of the CSI 300 index r, minus the risk-free return r_f, which represents the return of the market portfolio. From 2006 to 2020, the average monthly rate of return is 1.3%, and the average monthly risk-free interest rate is 0.3%. The average value of the monthly excess return is 1%. The distribution of monthly excess return is negative skewed, and the positive excess kurtosis is 2.530, indicating that the return has a tail. The risk is the standard deviation of monthly return, the average risk is 2.1%, and the monthly average risk is 0.4%. The ambiguity degree ranges from 0.392 to 7.896, with an average of 1.259. Panel C of Table 1 provides the correlation between the main variables. The average probability of a favorable rate of return is positively correlated with the excess rate of return, and the relationship between excess return and volatility is positively correlated and not significant. However, we see no correlation between risk and ambiguity, which provides independent evidence for their impact on excess return.

Table 1. *Summary statistics.*

	N	Mean	M	Min	Max	Std.dev	Ske	Kur
Panel A Daily descriptive statistic								
μ	3367	-0.000	0.000	-0.003	0.003	0.001	-0.147	3.630
σ	3367	0.004	0.003	0	0.022	0.002	2.077	7.547
μ/σ	3367	-0.003	-0.001	-0.587	0.403	0.128	-0.216	-0.022
P	3367	0.534	0.721	0	1	0.461	-0.142	-1.867
P	3367	0.460	0.265	0	1	0.461	0.156	-1.866
Panel B Monthly descriptive statistic								
r_f	168	0.003	0.003	0.001	0.005	0.001	-0.049	-0.920
r	168	0.013	-0.007	-0.400	0.837	0.147	1.351	6.072
Δ	168	0.010	-0.008	-0.403	0.834	0.147	1.359	6.117
v	168	0.024	0.021	0.006	0.063	0.012	0.965	0.431
ϑ	168	0.004	0.004	0	0.026	0.005	1.549	2.894
$\bar{P}$	168	0.538	0.525	0.284	1	0.115	0.480	0.806
Pd		0.464	0.454	0.177	1	0.130	0.384	0.949
$\mho$	168	1.575	1.441	0	8.610	0.950	3.503	19.186
Panel Cross-correlations								
	Δ	v	ϑ	$\bar{P}$	$\mho$			
Δ	1							
v	0.10	1						
	(0.22)							
ϑ	0.39	0.55	1					
	(0.00)	(0.00)						
$\bar{P}$	0.57	0.14	0.36	1				
	(0.00)	(0.07)	(0.00)					
P	0.56	0.37	0.44					
	(0.00)	(0.00)	(0.00)					
$\mho$	0.03	0.50	0.27	0.00	1			
	(0.69)	(0.00)	(0.00)	(0.98)				

5. Empirical Methods and Results

5.1. Empirical Methodology

We test our hypotheses by estimating the expected values of volatility (v), average absolute deviation between the rate of return and expected rate of return (θ), probability of favorable return (P), and degree of ambiguity ($\mho$). The results of the stability test and noise test indicate that the autoregressive moving average (ARMA) model is appropriate for evaluating these values. We predict volatility by using the ARMA (5,5) model, which is reliable according to the minimum corrected Akaike information criterion (AICC).

$$\widehat{v_t} = \alpha_0 + \epsilon_t + \sum_{i=1}^{5}\beta_i v_{t-i} + \sum_{i=1}^{5}\tau_i\epsilon_{t-i} \quad (10)$$

We calculate the expected volatility as:

$$v_{t+1}^E = \mathbb{E}_t[v_{t+1}] = \widehat{v_t} + \mathbb{V}ar[\mu_t] \quad (11)$$

where $Var[\mu_t]$ is the minimum prediction variance of the error term. For every month t, we use the data from the 15 preceding months, i.e., that is, from month $t-15$ to month $t-1$. The coefficients that attain the minimal AICC (i.e., the highest-quality model) are then used to evaluate the expected volatility. Similarly, we estimate the expected absolute deviation ϑ using its monthly realized value. We estimate the expected ambiguity value through the time series model ARMA (5,9)

$$\widehat{\mho_t} = \alpha_0 + \epsilon_t + \sum_{i=1}^{p=5}\beta_i\mho_{t-i} + \sum_{i=1}^{q=9}\tau_i\epsilon_{t-i} \quad (12)$$

The expected ambiguity is calculated as

$$(\mho_{t+1}^2)^E = \mathrm{E}_t[\mho_{t+1}^2] = \widehat{\mho_t} + \mathrm{V}ar[\mu_t] \quad (13)$$

Then, we estimate the expected probability of unfavorable return, $\widehat{\ln Q_t}$ is

$$\ln Q_t = \alpha_0 + \epsilon_t + \sum_{i=1}^{p=5}\beta_i lnQ_{t-i} + \sum_{i=1}^{q=9}\tau_i\epsilon_{t-i} \quad (14)$$

where $Q_t = \frac{\overline{P_t}}{1-\overline{P_t}}$. We obtain the expectation of favorable return probability

$$P_{t+1}^E = \frac{\exp(lnQ_t + \frac{1}{2}Var[\mu_t])}{1+\exp(lnQ_t + \frac{1}{2}Var[\mu_t])} \quad (15)$$

In the Panel A of Table 2, we present the descriptive statistics for the expected volatility, expected absolute deviation, expected probability, and expected ambiguity according to the equations (10)-(14). Comparing, Table 2 with

Table 1 offers several findings. First, dispersion of the expected value is less than that of the actual value, which illustrates that the expected values have a smoother curve. Second, the values are below the realized value, which are the difference between the minimum and maximum values, variance, skewness, and kurtosis of the estimated expected value. Panel B of Table 2 provides the correlation between the expected values.

Table 2. *Expected value summary statistics.*

	N	Mean	M	Min	Max	Std.dev	Ske	Kur
Panel A Descriptive statistic of forecasted variables								
v	153	0.019	0.019	0.013	0.019	0.001	-5.242	29.374
ϑ	153	0.005	0.005	0.004	0.006	0.000	-2.155	20.624
$\bar{P}$	153	0.537	0.538	0.483	0.579	0.013	-0.502	4.058
Pd		0.463	0.464	0.414	0.502	0.009	-1.573	12.790
$\mho$	153	1.564	1.565	1.304	1.749	0.039	-1.332	20.207
Panel B Cross-correlations								
	v	ϑ	$\bar{P}$	Pd	$\mho$			
v	1							
ϑ	0.61	1						
	(0.00)							
$\bar{P}$	0.38	0.23	1					
	(0.00)	(0.00)						
Pd	0.14	0.06		1				
	(0.09)	(0.43)						
$\mho$	0.35	0.15	-0.13	-0.07	1			
	(0.00)	(0.07)	(0.45)	(1)				

Furthermore, we obtain the range of expected probabilities by winsorizing the very few outlier values, (0.38,0.44]. We also divide this range into ten equal intervals (bins) of 0.01 each and apply the following empirical model as following:

$$r_{t+1} - r_{f,t+1} = \beta + \xi v_t + \lambda(\mho_t \times \vartheta_t) + \sum_{i=1}^{5} \lambda_i \left(D_{i,t} \times P_i^E \times \vartheta_t \times \mho_t\right) + \epsilon_t \quad (16)$$

where if the expected probability of favorable return in month t falls into the i-th interval, then the dummy variable $D_{i,t}$ is 1, otherwise, it is 0. P_i^E is the midpoint of the probability of interval i. We should note that the attitude towards ambiguity can change with the probability of expected favorable returns.

5.2. Regression Results

We examine the hypotheses in Table 3 using ordinary least squares (OLS) regressions. The dependent variable is the monthly excess return of the CSI 300 index. We use Newey-West estimations to address the potential autocorrelation and heteroscedasticity in the error term. Panel A of Table 3 reports the coefficients of the regressions that test the model in equation (15). In the first regression, we examine the risk-return relation excluding ambiguity. The expected volatility as an explanatory variable is negatively and insignificantly correlated with excess return. In the second regression, we find a positive but insignificant relationship between ambiguity and excess returns, which implies that we cannot reject hypothesis 1. The third regression does not consider the impact of risk. The results show that the ambiguity coefficients are significant at the 10% level except λ_5. In the fourth regression, the risk factor and expected volatility are taken as main explanatory variables. We find that the expected volatility coefficient is negative and significant at the 5% level. Therefore, hypothesis 2 is confirmed; that is, when ambiguity is considered alongside risk, the relationship of risk and the equity premium is a negative.

Table 3. *Main regression results by using OLS.*

	β	ξ	ω	λ	λ_1	λ_2	λ_3	λ_4	λ_5	N	R^2	$A.R^2$
Panel A The results of regression												
1	0.388***	-0.057								153	0.006	-0.001
	(6.82)	(-0.29)										
2	0.244***		0.166							153	0.014	0.007
	(3.83)		(1.46)									
3	0.507			0.595**	-0.666	0.206	0.293	0.002	0.110	153	0.045	0.005
	(1.47)			(1.98)	(-0.24)	(0.5)	(1.19)	(0.01)	(0.54)			
4	0.512	-0.007**		0.596***	-0.776	0.199**	0.294	0.004	0.116	153	0.045	-0.002
	(1.43)	(-2.06)		(2.97)	(-0.24)	(2.46)	(1.19)	(0.02)	(0.51)			
Panel B Coefficients of ambiguity attitude												
P^E					0.405	0.420	0.435	0.450	0.465			
					0.420	0.435	0.450	0.465	0.480			
3				0.595	-0.071	0.801	0.888	0.597	0.705			
4				0.596	-0.180	0795	0.890	0.600	0.712			

Note. The estimated expected values are for the period between January 2006 and February 2020 in China's stock market. Panel A reports the results of OLS regression by equation (15). Panel B is the coefficients of ambiguity attitudes.

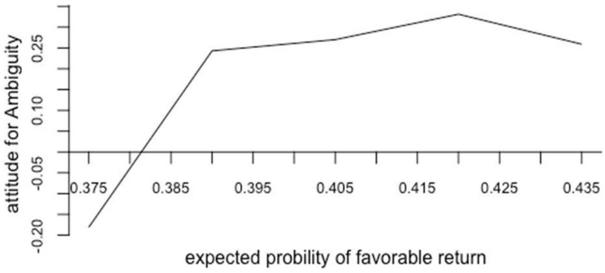


Figure 3. *Ambiguity attitudes.*

Note. The figure depicts ambiguity attitudes contingent upon the expected probability of favorable returns. The x-axis shows the expected probability of favorable returns. The y-axis shows the coefficient of the ambiguity attitude. The estimated expected values are for the period between January 2006 and February 2020 in China's stock market.

The attitudes toward ambiguity are estimated in Panel B of Table 3, which also shows the level of aversion to ambiguity, depending on the expected probability of favorable returns, calculated for each probability bin i by $\eta(P_i^E) = \hat{\eta} + \hat{\eta_i}$. Figure 3 depicts the probability correlation coefficient of ambiguity attitudes in the fourth regression. λ_1 is connected with probabilities of favorable returns (gains) in the range $[0.38, 0.39]$ and λ_2 with probabilities in the range $[0.39, 0.40]$. Figure 3 shows that the degree of preference for ambiguity decreases as probability of favorable expectation increases, and the relationship of the degree of aversion to ambiguity with the probability of favorable expectation is positive, consistent with hypothesis 3 [14-16].

Furthermore, we repeat our tests using weighted least squares (WLS). The results in Table 4 imply that the impact of expected volatility is negative, the influence of expected ambiguity on probability intervals is significant (except λ_4), and the effect of expected ambiguity is consistent with the result of the OLS regressions. These results support hypotheses 1-4.

Table 4. *Main regression results by using WLS.*

	β	ξ	Ω	λ	λ_1	λ_2	λ_3	λ_4	λ_5	N	R^2	$A.R^2$
Panel A The results of regression												
1	0.600***	-0.014								153	0.000	-0.006
	(3.89)	(-0.24)										
2	0.570		0.098							153	0.005	-0.002
	(0.48)		(0.87)									
3	0.525			0.832**	-0.553	0.335**	-0.369	0.012	0.106	153	0.035	-0.005
	(1.400)			(2.41)	(-1.61)	(2.05)	(-1.15)	(0.43)	(0.87)			
4	0.517	-0.012**		0.605***	-0.665	-0.198	0.298	0.007	0.119	153	0.100	0.035
	(1.38)	(-2.11)		(2.93)	(-0.23)	(-1.45)	(1.13)	(1.04)	(1.49)			
Panel B Coefficients of ambiguity attitude												
P^E					0.405	0.420	0.435	0.450	0.465			
					0.420	0.435	0.450	0.465	0.480			
3				0.832	0.279	1.167	0.463	0.844	0.938			
4				0.605	-0.060	0.407	0.904	0.612	0.724			

Note. The estimated expected values are for the period between January 2006 and February 2020 from China's stock market. Panel A reports the results of WLS regression by equation (15). Panel B is the coefficients of ambiguity attitudes.

6. Conclusion

In this study, we consider ambiguity in the traditional risk-return relationship in the Chinese stock market using the EUUP theoretical framework of Menachem and Yehuda [3]. We estimate the expected volatility, expected ambiguity, expected probability of unfavorable return, and absolute deviation of the average return from the expected return. By using the regressions of OLS and WOLS regressions, we find a positive relationship between the degree of ambiguity and expected return; when we introduce risk and ambiguity simultaneously, the expected return of China's stock market is negative. In addition, we prove that the investors' level of aversion to or preference for ambiguity depends on the expected probability of favorable returns in China's stock market.

Funding

This work is supported by the National Natural Science Foundation of China (72072054), and the Talents Project of Qinghai Minzu University in 2021, China, (2021XJG01).

Conflicts of Interest

All the authors do not have any possible conflicts of interest.

Acknowledgements

This work was funded by the National Natural Science Foundation of China (72072054), and the Talents Project of Qinghai Minzu University in 2021, China (2021XJG01).

References

[1] Driouchi T., Trigeorgis L., So R. H. Option Implied Ambiguity and Its Information Content: Evidence from the Subprime Crisis [J]. Annals of Operations Research, 2018: 262–491.

[2] Ui T. The Ambiguity Premium vs. the Risk Premium under Limited Market Participation [J]. Review of Finance, 2011, 15: 245–275.

[3] Menachem B., Yehuda I. Asset Pricing and Ambiguity: Empirical Evidence [J]. Journal of Financial Economics, 2018, 130: 1-48.

[4] Epstein L. G., Schneider, M. Ambiguity, Information Quality, and Asset Pricing [J]. Journal of Finance, 2008, 63: 197–228.

[5] Anderson E. W., Ghysels E., Juergens J. L. The Impact of Risk and Uncertainty on Expected Returns [J]. Journal of Financial Economics, 2009, 94: 233–263.

[6] Antoniou C., Harris, R. D., Zhang, R. Ambiguity Aversion and Stock Market Participation: An Empirical Analysis [J]. Journal of Banking & Finance, 2015, 58: 57–70.

[7] Ulrich M. Inflation Ambiguity and the Term Structure of US Government Bonds [J]. Journal of Monetary Economics, 2013, 60: 295–309.

[8] Williams C. D. Asymmetric Responses to Earnings News: A Case for Ambiguity [J]. Accounting Review, 2015, 90: 785–817.

[9] Mele A., Sangiorgi F. Ambiguity, Information Acquisition and Price Swings in Asset Markets [J]. Review of Economic Studies, 2015, 82 (4): 1533-1567.

[10] Scot C. Living with Ambiguity: Prices and Survival When Investors Have Heterogeneous Preferences for Ambiguity [J]. Economic Theory, 2008, 36 (1): 81-108.

[11] Tan R. Q., Manahov V., Thijsen J. The Effect of Ambiguity on the UK Stock Market: Evidence from a New Empirical Approach [J]. Investment Management and Financial Innovations, 2017, 14 (4): 133-147.

[12] Mohammad R. J., Liu H. Ambiguity Aversion and Asset Prices in Production Economies [J]. Review of Financial Studies, 2014, 27 (10): 3060-3097.

[13] Wakker P. P., Timmermans D. R. M., Machielse I. The Effects of Statistical Information on Risk and Ambiguity Attitudes, and on Rational Insurance Decisions [J]. Management Science, 2007, 53: 1770–1784.

[14] Mangelsdorff L., Weber, M. Testing Choquet Expected Utility [J]. Journal of Economic Behavior and Organization, 1994, 25: 437–457.

[15] Abdellaoui M., Vossmann F., Weber M. Choice-based Elicitation and Decomposition of Decision Weights for Gains and Losses under Uncertainty [J]. Management Science, 2005, 51: 1384–1399.

[16] Du N., Budescu D. V. The Effects of Imprecise Probabilities and Outcomes in Evaluating Investment Options [J]. Management Science, 2005, 51: 1791–1803.

[17] Merton R. C. On Estimating the Expected Return on the Market: An Exploratory Investigation [J]. Journal of Financial Economics, 1980, 8: 323–361.

[18] French K. R., Schwert G. W., Stambaugh, R. F. Expected stock returns and volatility [J]. Journal of Financial Economics, 1987, 19: 3–29.

[19] Campbell J. Y., Hentschel L. No news is good news: An asymmetric model of changing volatility in stock returns [J]. Journal of Financial Economics, 1992, 31: 281–318.

[20] Guo H., Whitelaw R. F. Uncovering the Risk-return Relation in the Stock Market [J]. Journal of Finance, 2006, 61: 1433–1463.

[21] Pastor L., Sinha M., Swaminathan B. Estimating the Intertemporal Risk–return Tradeoff Using the Implied Cost of Capital [J]. Journal of Finance, 2008, 63: 2859–2897.

[22] Nelson D. B. Conditional Heteroskedasticity in Asset Returns: A New Approach [J]. Econometrica, 1991, 59: 347–70.

[23] Harvey C. R. The Specification of Conditional Expectations [J]. Journal of Empirical Finance, 2001, 8: 573–637.

[24] Maffioletti A., Santoni M. Do Trade Union Leaders Violate Subjective Expected Utility? Some Insights from Experimental Data [J]. Theory and Decision, 2005, 59: 207–253.