



Market frictions, ambiguity and asset pricing: evidence from China

Sunil S. Poshakwale¹ · Binsheng Qian² · Anandadeep Mandal³

Received: 14 February 2025 / Accepted: 26 February 2026
© The Author(s) 2026

Abstract

We study the implications of ambiguity under arbitrage constraints and in a market dominated by retail investors to understand its impact on asset pricing. We propose a novel approach to empirically measure stock level ambiguity and analyse how ambiguity-averse investors respond to varying levels of market ambiguity. In contrast to the previous research, we find a positive ambiguity premium. We attribute this to investors' underreaction caused by the presence of significant market frictions in China. The results are robust across different factor models, alternative measure of market ambiguity, and varied portfolio formation approaches. Our findings suggest that ambiguity could be an important missing factor that could explain the much-debated high equity risk premium puzzle.

Keywords Asset pricing · Equity risk premium · Ambiguity · Market frictions · Uncertainty

JEL Classifications D53 · D81 · G11 · G12

1 Introduction

In the dynamic realm of financial markets, ambiguity and uncertainty stand as fundamental concepts shaping decision-making and risk management strategies. Despite often being conflated, they carry distinct implications for estimating expected stock returns. Ambiguity

✉ Anandadeep Mandal
a.mandal@bham.ac.uk

Sunil S. Poshakwale
sunil.poshakwale@cranfield.ac.uk

Binsheng Qian
binsheng.qian@coventry.ac.uk

¹ School of Management, Cranfield University, Milton Keynes MK43 0AL, UK

² School of Markets and The Economy, Coventry University, London E1 7JF, UK

³ Department of Finance, University of Birmingham, Birmingham B15 2TT, UK

is the uncertainty of probabilities that make up risk. While risk relates to unknown outcomes with known probability distributions, ambiguity concerns unknown probabilities associated with these returns. As suggested by Ellsberg (1961), the assumption of single probability distribution is unrealistic since in practice, investors neither possess perfect information nor do they carry homogenous expectations. This implies that relaxing the assumption would give rise to ambiguity about the probability of the return distribution. Consequently, ambiguity should have implications for the risk-return relationship proposed in the conventional asset pricing models (Brenner and Izhakian 2018).

Ambiguity could also potentially explain larger than expected risk premium coined as ‘equity premium puzzle’ by Mehra and Prescott (1985). There have been many attempts to solve the puzzle. For example, Mankiw & Zeldes (1991) examine the differences in consumption pattern between stockholders and non-stockholders. They find that stockholders consumption correlates more strongly with stock returns than with the aggregate consumption growth, implying that the difference between these two groups could help explain the equity premium puzzle. Basak and Cuoco (1998) theoretically show that the equity premium increases when fewer investors participate in the stock market. Cao et al. (2005) and Easley and O’Hara (2009) argue that the limited investor participation could stem from their aversion to ambiguity. They postulate that investors maximize utility by considering the worst-case scenario due to uncertainty about the exact return probability distribution. Consequently, when investors’ perceptions of ambiguity are sufficiently diverse, those with higher levels of ambiguity aversion tend to opt out of the stock market, leading to restricted market participation. Building on the work by Cao et al. (2005), Easley and O’Hara (2009), and Grossman (1976), Ui (2011) proposes a generalised equilibrium model to explain how ambiguity affects equity premium when there is limited participation of informed investors. He argues that as informed investors exit the market due to high ambiguity, the decline in private information they convey to the market leads to higher conditional variance and hence the demand for higher equity risk premium.

In this paper, we aim to contribute towards solving the equity premium paradox by empirically examining whether ambiguity can explain high premium. Contrary to evidence presented in the previous studies, we find a positive ambiguity premium in China over the period from 2005 to 2023. We attribute the positive premium to investors’ underreaction. We argue that unlike developed markets, Chinese market faces significant market frictions in the form of restrictions on arbitrage that limits the participation of informed investors. Thus, when devoid of informed investors, the market tends to underreact giving rise to a positive ambiguity premium. The empirical evidence presented in the paper is consistent with the theoretical predictions proposed by Ui (2011). The evidence also offers a possible explanation for the equity premium puzzle. Both Chen and Epstein (2002) and Cao et al. (2005) observe that the equity premium is made up of the risk premium and the ambiguity premium. While the risk premium is based on the standard expected utility models, ambiguity premium arises from investors’ aversion to ambiguity. Our evidence supports this conjecture and implies that higher than expected equity premium could be driven by the positive ambiguity premium.

We utilize intraday stock index returns data to measure market ambiguity and demonstrate that it significantly influences expected stock returns in China. To quantify a firm’s exposure to ambiguity, we employ an ambiguity sensitivity metric, defined by the Spearman rank correlation between daily stock returns and changes in market ambiguity.

A long-short portfolio that is long on stocks with high ambiguity sensitivity and short on those with low sensitivity generates an annual return exceeding 5%. This return cannot be explained by either the Fama-French (FF) models or China-specific models proposed by Liu et al. (2019).¹ Further, we explore the relationship between arbitrage constraints and the sensitivity to ambiguity. We find that the ambiguity premium is notably significant for stocks that face greater arbitrage constraints. Our results remain robust when we measure ambiguity premium by employing index futures, alternative portfolio formations, and asset pricing models.

Our study contributes significantly to the literature on ambiguity's role in asset pricing in several ways. First, we introduce a novel approach to empirically measure stock-level ambiguity sensitivity by utilizing the "inside uncertainty" model operationalized by Izhakian (2012, 2020). Second, to our knowledge, this study is the first to provide evidence of how arbitrage constraints affect pricing of ambiguity. The evidence implies that the negative ambiguity premium reported in previous studies could be attributed to absence of market frictions. Finally, our results imply that aversion to ambiguity could be a missing factor in solving the equity premium puzzle.

The rest of the paper is organized as follows. Section 2 discusses the relevant literature. Section 3 describes the data, variables, and the methodology used in the paper. Section 4 presents the empirical findings and Sect. 5 concludes the paper.

2 Related literature

Although the extant literature postulates that higher compensation demanded by ambiguity averse investors could be an important driver of the overall risk premium (Hansen 2014), quantifying ambiguity is an arduous task. Most previous studies have used theoretical models in defining ambiguity (Epstein & Wang, 1994; Garlappi et al. 2007; Gilboa & Schmeidler, 1989; Hansen & Sargent, 2022; Ju & Miao, 2012) while empirical evidence on both measurement and the influence of ambiguity is relatively sparse (Andreou et al. 2014; Bollerslev et al. 2009; Brenner & Izhakian, 2018).

One approach explored in the literature involves using analysts' earnings forecasts as a measure of stock-level ambiguity. Diether et al. (2002) employ this proxy and find that stocks characterized by greater variance in analysts' earnings predictions tend to yield lower future returns. However, Doukas et al. (2006) argue that the dispersion in analyst's forecasts reflects divergence of opinions which show a positive correlation with stock returns. Another avenue of research focuses on using dispersion in macroeconomic variables as an indicator of ambiguity. Lee et al. (2019), for instance, use cross-sectional dispersion in real-time forecasts of real GDP growth to measure ambiguity and observe that stocks with high ambiguity beta tend to yield lower future returns compared to those with low ambiguity beta. They attribute this phenomenon to an increase in the marginal utility of consumption when there is high level of ambiguity.

Nevertheless, neither the dispersion in analysts' earnings forecasts nor variations in macro variables directly capture the uncertainty experienced by market participants. Analysts and economic forecasters do not engage directly in stock trading, which means their perception

¹ Liu et al. (2019) construct China-specific factor models and show that their models outperform traditional Fama-French models in explaining widely reported Chinese market anomalies.

of uncertainty may diverge from that of traders. Hansen (2014) distinguishes between “outside uncertainty”, which econometricians face, and “inside uncertainty”, which agents experience. Under the “outside uncertainty” model, investors have knowledge of the probability distribution of outcomes and select asset pricing models based on rational expectations. In contrast, under the “inside uncertainty”, investors confront ambiguity about the correct asset pricing model, leading to decisions that may deviate from those under rational expectations.

Izhakian (2012 & 2020) proposes a direct measure of ambiguity that effectively captures “inside uncertainty” by calculating the expected variance of return probability distributions. Brenner and Izhakian (2018) extend this measure to estimate investors’ aversion to ambiguity and demonstrate that the positive ambiguity premium increases with the expected probability of favorable returns, underscoring the time-varying nature of the ambiguity premium. In another study using data from the German market, Kostopoulos et al. (2022) apply the “inside uncertainty” ambiguity metric and find that heightened market ambiguity prompts individual investors to reduce their risk-taking. Karahan (2025) finds that ambiguity exerts a stable and significant positive effect on gold’s convenience yield, in contrast to standard risk and alternative uncertainty measures that display weaker or inconsistent patterns. Together, these findings suggest that ambiguity could be crucial yet an overlooked risk factor in asset pricing framework.

Another important limitation in the extant literature is that most studies on market ambiguity use data from developed markets. These markets have better investor protection regulations and are dominated by institutional investors. In this paper we use emerging stock market settings in China to investigate whether and how ambiguity is priced in presence of significant market frictions and different investor dynamics. In contrast to the US markets, the emerging Chinese stock markets have a significantly higher proportion of retail investors.² While greater participation of retail investors may improve stock market liquidity and depth, it also increases volatility. Gurrola-Perez et al. (2022) show that retail investors place different values on losses and gains of the same magnitude and react differently to new information. Chinese investors also face significant short selling restrictions.

Several studies emphasise the need for addressing ambiguity in emerging market settings since the standard asset pricing models do not do a very good job of predicting stock returns in these markets. For example, Bekaert et al. (1998) show presence of non-normality in emerging market stock returns and how the distributional properties of return series change over time. Further, emerging market economies now have a larger share in the global economic growth. China is the second biggest economy in the world. Thus, an evidence based on Chinese data would contribute towards the furthering our understanding of the role of ambiguity in asset pricing.

In the existing literature, there remains a notable scarcity of empirical findings concerning the influence of ambiguity on asset pricing within emerging markets. Sahin and Danisoglu (2022) contribute to this topic by documenting a negative ambiguity premium in the Turkish emerging market. However, in contrast to Bekaert et al. (2022), Sahin and Danisoglu (2022) do not incorporate aggregate risk aversion when calculating ambiguity beta. This could be a possible reason for a negative ambiguity premium they report, as risk-averse investors typically seek safer assets to mitigate risks during economic downturns.

² Wang et al. (2022) report that, as of 2016 on the Shanghai Stock Exchange, retail investors hold 99.9% of the total number of active accounts and contribute 85.6% to daily trading volume.

The methodology we propose is superior to the one used by Sahin and Danisoglu (2022) in several respects. Firstly, their estimation of ambiguity betas relies on monthly returns. As demonstrated by Becker et al. (2021), beta estimates derived from high-frequency returns offer greater precision compared to those based on lower-frequency (e.g., monthly) data. To ensure accuracy of our ambiguity estimates, we use intraday 1-minute returns from the Shanghai Stock Exchange Composite Index (SSEC).

Secondly, Sahin and Danisoglu (2022) base their market ambiguity estimates using data from the BIST30 stock index that comprises only top 30 stocks. Thus, their measure of market ambiguity may not be representative since the most commonly followed benchmark index in Turkey is the BIST100 index which encompassing a broader spectrum of stocks. In contrast, we include all stocks traded on the Shanghai Stock Exchange to ensure a comprehensive coverage of the Chinese market.

Lastly, Sahin and Danisoglu (2022) assume a constant variance of market returns over a 48-month period which may have produced biased beta estimates. Cenesizoglu (2022) shows that the variance of market returns exhibits temporal variation across business cycles, typically increasing during economic recessions. To ensure accuracy of our ambiguity measure, we implement a one-month estimation window that enables us to capture the dynamic changes in market variance over time.

We chose to focus on the Chinese stock markets for several compelling reasons. Firstly, unlike more mature markets such as the US, China imposes significant regulations on short selling.³ This regulatory environment restricts the efficiency of stock pricing when short selling is constrained, diminishing the role of trading activities in facilitating accurate price discovery (Marsh and Payne 2012). Consequently, short selling may significantly impact market ambiguity.

Secondly, the Chinese emerging market is quite different from the US market since it is made up of a high proportion of retail investors who tend to gamble more in stock trading, thus causing greater market volatility (Chen et al. 2025; Kumar 2009). Zhu, Zhang, and Yang (2021) find that the speculative trading practices cause mispricing and unusual volatility in the Chinese A-share market. These investors also exhibit higher levels of ambiguity aversion⁴ and tend to be much more sensitive to market movements.

Thirdly, Economic Policy Uncertainty (EPU) in China tends to be elevated compared to other global markets.⁵ The heightened uncertainty arises from frequent policy changes that significantly impact asset prices (Qian et al. 2025). For instance, in 2021, to promote equality in education, the Chinese government banned the private tuition providers that led to significant decline in market values of listed companies providing private education services.⁶

Finally, China ranks as the world's second-largest market with a substantial share of the global investment landscape and is a major destination for international investors (Carpen-

³ More than 50% of listed stocks faced a short sale ban at the end of 2022 despite regulatory reform. (see https://www.securitiesfinancetimes.com/securitieslendingnews/industryarticle.php?article_id=225912&navigationaction=industrynews).

⁴ Rieger et al. (2015) presents a large-scale international survey on risk preferences in 53 countries. They report that the degree of ambiguity aversion for China is 0.67 and it is 0.42 for the U.S.

⁵ According to [policyuncertainty.com](https://www.policyuncertainty.com), the average EPU value for China (the US) is 225.64 (129.50) for the period from January 1995 to December 2022.

⁶ 'China's education crackdown 'only scratched the surface' of what's to come, former ministry spokesman says', South China Morning Post, 6th August 2021, <https://www.scmp.com/economy/china-economy/article/3143974/chinas-education-crackdown-only-scratched-surface-whats-come>.

ter et al. 2021; Lundblad et al. 2025). Thus, gaining robust insights into the fundamental drivers of stock returns in China is important for international investors seeking to diversify their portfolios by investing in Chinese stocks.

3 Data and methodology

3.1 Data sources

We obtained intra-day trading data from January 2005 to December 2023 for the Shanghai Stock Exchange Composite (SSEC) Index from the TDX terminal, provided by Shenzhen Fortune Trend Technology.⁷ The SSEC index serves as China's primary benchmark index and has the longest history among major indices in the country. Stock price and financial data are sourced from Wind Information Inc. (WIND) and the China Stock Market & Accounting Research Database (CSMAR), both recognized as leading financial databases for China.

To ensure the robustness, we refine our initial sample. First, we exclude firms that were listed for less than one year as well as stocks listed on the Beijing Stock Exchange.⁸ Additionally, we remove stocks with incomplete data. After the screenings, our final sample comprises 548,963 stock-month observations for 4,927 unique firms. To reduce the influence of potential outliers, we winsorize the data at the 1st and 99th percentiles.

3.2 Measure of market-level ambiguity

We follow Izhakian (2012 & 2020) who defines ambiguity as:

$$\mathcal{U}^2[r] = \int E[\phi(r)] \text{Var}[\phi(r)] dr \quad (1)$$

where r represents the return, $\phi(r)$ is the marginal probability, $E[\phi(r)]$ denotes the expectation of probability, and $\text{Var}[\phi(r)]$ denotes the variance of marginal probability. Unlike traditional risk measures that focus on return volatility, ambiguity captures the volatility of probabilities associated with potential outcomes (Rothschild and Stiglitz 1970). Therefore, the measure $\mathcal{U}^2[r]$ encapsulates the variability in all moments of the outcome distribution, independent of investor risk preferences or attitudes towards ambiguity (Brenner and Izhakian 2018).

We adopt the approach outlined by Ben-Rephael and Izhakian (2020) to estimate daily market ambiguity. This involves constructing histograms of intraday equity returns observed within 15-minute intervals throughout the trading day. Each histogram represents a prior distribution P within the set of possible distributions, $\mathcal{P}$. Given the four-hour trading window in the A-share markets, up to 16 histograms are generated daily. These histograms discretize

⁷ Shenzhen Fortune Trend Technology is a leading fintech company in China. It provides advanced trading software, market data services, and comprehensive financial analysis tools tailored for institutional investors, securities firms, and individual traders.

⁸ Our main analysis retains all stocks, including those with special treatment (ST or *ST). However, we exclude these and shell stocks in the robustness check.

return distributions into n bins of equal size, $B_\ell = (r_{\ell-1}, r_\ell]$, where the frequency of returns in each bin determines the probability associated with that range.

Following Ben-Rephael and Izhakian (2020), to mitigate the impact of bin size on the ambiguity, we apply a variant of Sheppard's correction and scale the probability-weighted average variance of probabilities to the bin size by $\frac{1}{\sqrt{w(1-w)}}$, where $w = |r_{\ell-1} - r_\ell|$. Consequently, Model (1) is rewritten as follows:

$$\mathcal{U}^2 = \frac{1}{\sqrt{w(1-w)}} \sum_{l=1}^n E[P(B_l)] \text{Var}[P(B_l)] \quad (2)$$

For bin formation, we divide the range of normalized returns into 1,002 intervals. We create a grid of 1,000 bins, ranging from -100% to $+100\%$, each with a width of 0.2% , along with the left and right tails defined as $(-\infty, -100\%]$ and $[+100\%, +\infty)$, respectively. We compute the mean and the variance of probabilities for each bin, assigning equal likelihood to each distribution (i.e., all histograms are equally likely). Some bins may not be populated with return realizations. In such cases, we assume a normal return distribution and use its moments to extrapolate return probabilities. Specifically, $P(B_\ell) = \Phi(r_\ell; \mu, \sigma) - \Phi(r_{\ell-1}; \mu, \sigma)$, where $\Phi(\cdot)$ denotes the cumulative normal probability distribution characterized by its mean μ and variance σ^2 .

The computed mean and variance of probabilities across all bins enable the daily estimation of ambiguity ($\mathcal{U}^2$) as follows:

$$\mathcal{U}^2 = \frac{1}{\sqrt{w(1-w)}} \left\{ \begin{aligned} &E[\Phi(r_0; \mu, \sigma)] \text{Var}[\Phi(r_0; \mu, \sigma)] \\ &+ \sum_{i=1}^{1000} E[\Phi(r_i; \mu, \sigma) - \Phi(r_{i-1}; \mu, \sigma)] \text{Var}[\Phi(r_i; \mu, \sigma) - \Phi(r_{i-1}; \mu, \sigma)] \\ &+ E[1 - \Phi(r_{1000}; \mu, \sigma)] \text{Var}[1 - \Phi(r_{1000}; \mu, \sigma)] \end{aligned} \right\} \quad (3)$$

Figure 1 illustrates the daily values of the Shanghai Stock Exchange Composite (SSEC) index alongside market ambiguity from January 2005 to December 2023.⁹ The figure highlights instances where changes in market ambiguity diverge from movements in the SSEC index, suggesting that ambiguity fluctuates independently of price volatility. Notably, ambiguity levels from 2016 to 2023 are markedly higher compared to those observed from 2005 to 2015, reflecting increased uncertainty possibly driven by geopolitical tensions in recent years.

3.3 Stock-level ambiguity sensitivity

We use a non-parametric correlation test to examine if the daily stock returns and changes in market ambiguity move in tandem. We estimate monthly Ambiguity Sensitivity (AMB^p) for each stock as the Spearman rank correlation coefficient between the daily returns of a stock and the daily changes in market ambiguity within the same month.

Market ambiguity reflects uncertainty in interpreting new public information, influencing investor behavior. A positive (negative) AMB^p indicates that a stock's returns tend to increase (decrease) when market ambiguity is elevated, suggesting that the stock is more

⁹ Extreme returns ($\pm 5\%$ log returns over one minute) and days with market-wide trading suspensions (January 4 and 7, 2016) are excluded to enhance data reliability. Furthermore, to prevent distortions caused by overnight price changes, overnight returns data are not used for ambiguity estimation.

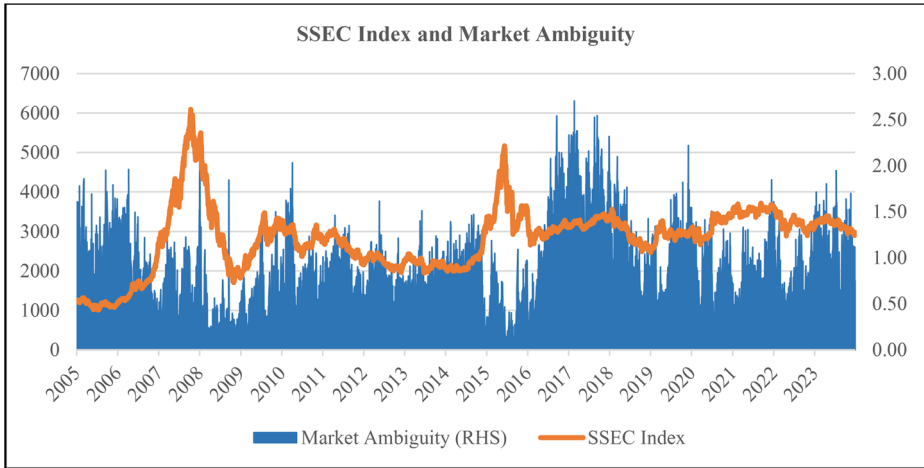


Fig. 1 Shanghai Stock Exchange Composite (SSEC) Index and Market Ambiguity. Following the methodology of Ben-Rephael and Izhakian (2020), we calculate the daily market ambiguity using the intraday returns of the Shanghai Stock Exchange Composite Index. The sample period is January 2005 – December 2023

sensitive to periods of heightened uncertainty. We interpret stocks with a positive AMB^p as potentially benefiting from investor reactions to new information under ambiguity, which may reflect optimism or favorable reinterpretation of uncertainty, while a negative AMB^p may indicate adverse reactions, possibly due to pessimism or risk aversion in ambiguous conditions (Ellsberg 1961; Epstein and Schneider 2008). When the absolute value of AMB^p is high, the likelihood of mispricing increases, as ambiguity-averse investors are less likely to participate during periods of high volatility, consistent with prior studies (Breuer et al. 2016; Kostopoulos et al., 2022; Meyer and Uhr, 2024; Ui 2011). Conversely, a low absolute AMB^p suggests reduced sensitivity to ambiguity, lowering the risk of mispricing. Thus, a significantly positive premium for ambiguity sensitivity, observed for a hedge portfolio that is long on high AMB^p stocks and short on low AMB^p stocks, implies that ambiguity-averse investors underreact to new information.

3.4 Estimating excess returns

For estimating the portfolio excess returns, we use different specifications of the Fama and French (1993 & 2015) models including a six-factor model incorporating Carhart's (1997) momentum factor.

$$\mathbf{FF3} : EXR_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \epsilon_{i,t} \quad (4)$$

$$\mathbf{FF4} : EXR_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{UMD} UMD_t + \epsilon_{i,t} \quad (5)$$

$$\mathbf{FF5} : EXR_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \epsilon_{i,t} \quad (6)$$

$$\mathbf{FF6} : EXR_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \beta_{i,t}^{UMD} UMD_t + \epsilon_{i,t} \quad (7)$$

In order to capture the stock-level variation, we estimate the cross-sectional relation between AMB^p and expected returns using Fama & MacBeth (1973) regressions. We focus on the average values of the slope coefficients from the regression predicting one-month-ahead stock returns based on AMB^p both with and without control variables:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} AMB_{i,t}^p + \lambda_{2,t} X_{i,t} + \epsilon_{i,t} \quad (8)$$

where $R_{i,t+1}$ is the realized excess return, $AMB_{i,t}^p$ is the ambiguity sensitivity of stock i in month t and $X_{i,t}$ is a collection of stock-specific variables observable at time t for stock i . Similar to Bali et al. (2017) and Han & Shi (2022), we include the following control variables: natural logarithm of market capitalization (SIZE), book-to-market ratio (BM), the 11-month momentum returns (MOM), the short-term return reversal (REV), profitability ratio (ROE), annual growth of book assets (GROW), leverage ratio (LEV), idiosyncratic volatility (IVOL), and annual stock turnover ratio (ASTO). Detailed definitions of variables are given in Table 13 in the Appendix.

4 Empirical analysis and results

4.1 Descriptive statistics of variables

The results of the descriptive analysis are presented in Table 1. The mean, minimum, first quartile, third quartile, and maximum values of stock-level Ambiguity Sensitivity (AMB^p) are 0.174, -0.819, 0.008, 0.352, and 0.880, respectively. This indicates that the distribution of AMB^p is highly skewed, with about a quarter of observations having negative ambiguity sensitivity values. The mean values for control variables, SIZE, BM, MOM, REV, GROW, LEV, IVOL, and ASTO are 22.18, 0.433, 0.148, 0.012, 0.218, 0.446, 0.116, and 4.461, respectively. These values closely align with those documented in prior studies (e.g. Han & Shi, 2022).

Table 2 presents the correlation matrix between AMB^p and various control variables. Results show that AMB^p has a significantly negative correlation at the 1% level with BM, REV, LEV, and IVOL. This suggests that high AMB^p stocks are not typically value stocks, and tend to exhibit short-term price declines and lower idiosyncratic risks. Conversely, AMB^p shows a significantly positive correlation at the 1% level with SIZE, MOM, and

Table 1 Descriptive statistics

Name	Obs.	Mean	SD	Min	p25	p50	p75	Max
AMB	548,963	0.174	0.243	-0.819	0.008	0.188	0.352	0.880
SIZE	548,963	22.118	1.228	17.985	21.347	22.037	22.818	26.249
BM	548,963	0.433	0.347	-0.927	0.197	0.346	0.568	2.831
MOM	548,963	0.148	0.624	-0.999	-0.205	0.002	0.300	12.095
REV	548,963	0.012	0.132	-0.781	-0.065	0.000	0.074	1.422
GROW	548,963	0.218	0.470	-0.529	0.012	0.102	0.252	4.943
LEV	548,963	0.446	0.218	0.027	0.273	0.439	0.604	0.999
IVOL	548,963	0.116	0.063	0.023	0.071	0.103	0.148	2.025
ASTO	548,963	4.461	3.300	0.110	2.041	3.581	6.017	23.267

This table reports descriptive statistics of variables. The sample period is January 2005 to December 2023

Table 2 Correlation matrix

Variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AMB	(1)	1.000								
SIZE	(2)	0.019	1.000							
BM	(3)	-0.060	0.070	1.000						
MOM	(4)	0.072	0.096	-0.272	1.000					
REV	(5)	-0.102	0.029	-0.104	0.022	1.000				
GROW	(6)	0.001	-0.029	-0.091	-0.053	-0.022	1.000			
LEV	(7)	-0.030	0.141	0.148	0.043	0.005	-0.098	1.000		
IVOL	(8)	-0.089	-0.054	-0.258	0.274	0.256	0.006	0.001	1.000	
ASTO	(9)	0.109	-0.051	-0.286	0.230	0.008	-0.015	-0.065	0.223	1.000

This table reports the Pearson correlation coefficients between variables. The sample period is January 2005 to December 2023. The bold values are significant at the 1% level

ASTO, indicating that stocks with high AMB^p are generally large-cap, experience positive momentum, and high trading volumes. While there is a positive relationship between GROW and AMB^p , the correlation coefficient is not statistically significant. The computed VIF statistics for independent variables are not greater than 1.3, suggesting that multicollinearity is not a concern for Model (8).

These correlations merit further discussion. The positive association between AMB^p and SIZE is partly mechanical, as larger firms' returns tend to align more closely with the market index, which by construction generates higher AMB^p values. Beyond this mechanical effect, however, the correlations with SIZE, MOM, and ASTO likely reflect meaningful economic mechanisms. Larger and more liquid firms attract greater investor attention and trading activity, which can amplify heterogeneity in investor beliefs and interpretations of market-wide information. Prior research suggests that high trading volume is often associated with greater disagreement among investors (Jin et al. 2025; Kandel and Pearson 1995), consistent with higher measured ambiguity.

The positive correlation between AMB^p and MOM is also in line with recent evidence from Wang et al. (2024), who argue that investors face fundamental uncertainty regarding the existence and persistence of momentum effects. When momentum is perceived to be strong, speculative demand increases; yet, because investors are uncertain about whether such patterns will continue, they form multiple priors about returns and may behave in an ambiguity-averse manner (Gilboa and Schmeidler 1989). This tension can generate divergent expectations and hesitancy in trading, resulting in greater measured ambiguity in high-momentum stocks. Overall, the evidence indicates that the ambiguity premium is economically meaningful and not subsumed by firm characteristics such as size, momentum and turnover.

4.2 Risk-adjusted returns of ambiguity sensitivity portfolios

In this section, we examine whether stocks with high AMB^p outperform those with low AMB^p . Table 3 presents the risk-adjusted returns of AMB^p quintiles using different factor models. Each month, we sort stocks into quintiles based on AMB^p , from the lowest (Q1) to the highest (Q5) ambiguity sensitivity portfolio. In the following month, we calculate the value-weighted and equally weighted average excess returns (raw returns minus risk-free

Table 3 Alphas of portfolios sorted by ambiguity sensitivity

Model	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	(Q5-Q1)
Panel A: Alphas based on equal-weighted excess returns						
FF3	-0.542*** (-5.08)	-0.074 (-1.13)	0.140** (1.98)	0.241*** (2.92)	0.162 (1.63)	0.524*** (3.08)
FF4	-0.539*** (-4.86)	-0.073 (-1.07)	0.144** (2.10)	0.243*** (3.08)	0.162 (1.63)	0.521*** (2.97)
FF5	-0.474*** (-5.02)	-0.048 (-0.81)	0.163** (2.43)	0.239*** (3.07)	0.159 (1.77)	0.453*** (2.93)
FF6	-0.477*** (-4.90)	-0.050 (-0.83)	0.159** (2.46)	0.237*** (3.16)	0.159 (1.77)	0.456*** (2.88)
Panel B: Alphas based on value-weighted excess returns						
FF3	-0.534*** (-3.13)	-0.115 (-1.17)	0.002 (0.02)	0.107 (0.83)	0.121 (0.86)	0.476* (1.71)
FF4	-0.534*** (-3.12)	-0.114 (-1.16)	0.004 (0.05)	0.106 (0.81)	0.117 (0.81)	0.471* (1.66)
FF5	-0.477*** (-2.87)	-0.086 (-0.98)	0.073 (0.68)	0.147 (1.10)	0.163 (1.19)	0.460* (1.78)
FF6	-0.477*** (-2.88)	-0.086 (-0.98)	0.071 (0.67)	0.149 (1.11)	0.167 (1.20)	0.464* (1.77)

At the end of each month, we sort stocks into quintiles in ascending of AMB⁹, where quintile 1 (5) consists of stocks with the lowest (highest) AMB⁹. We also form long-short portfolio (Q5-Q1) by being long on quintile 5 and short on quintile 1. In Panel A (B), we report the alphas (in percentage) relative to factor models (FF3, FF4, FF5, and FF6) based on average next-month equal-weighted (value-weighted) excess returns to quintile and long-short portfolios. FF3 is the alpha relative to market, size, and book-to-market factors. FF4 is the alpha relative to market, size, book-to-market and momentum factors. FF5 is the alpha relative to market, size, book-to-market, investment, and profitability factors. FF6 is the alpha relative to market, size, book-to-market, investment, profitability, and momentum factors. Newey-West adjusted t-statistics are given in parentheses. The sample period is January 2005 – December 2023. ***, **, and * indicate significance at 1%, 5%, 10%, respectively

rates). Panel A of Table 3 reports alphas for equal-weighted portfolios, while Panel B reports alphas for value-weighted portfolios.

Results demonstrate a significant underperformance of quintile 1 compared to quintile 5 across various factor models. For instance, in Panel A, the alpha of the long-short value-weighted portfolio (Q5 - Q1) is 0.524% with a t-statistic of 3.08 based on the FF3 model. This indicates that stocks with high ambiguity earn a positive premium after accounting for common risk factors. A monthly alpha of 0.524% translates to an annualized premium of 6.288%, which is economically significant.

Notably, the alphas of long-short portfolios are primarily driven by the underperformance of quintile 1 rather than the outperformance of quintile 5. Specifically, the FF3 equal-weighted alpha for quintile 1 is -0.542%, with a t-statistic of -5.08. In contrast, the alpha for quintile 5 is 0.162%, which is statistically insignificant. This pattern is consistent across various Fama-French factor models for both equally and value weighted portfolios.

4.3 Stock-level cross-sectional regressions

Nonetheless, as suggested by Bali et al. (2017), portfolio-level analysis may have drawbacks. Firstly, a considerable volume of firm-specific information in the cross-section can be

lost during the aggregation process. Secondly, in portfolio analysis, it may not be possible to control for multiple effects or factors simultaneously. Consequently, we extend our analysis by examining the cross-sectional association between AMB^p and expected returns at the individual stock level using Fama & MacBeth (1973) regressions.

Table 4 presents time-series averages of slope coefficients from Fama-MacBeth cross-sectional regressions. Column (1) establishes our baseline result: the univariate regression reveals a positive and statistically significant relationship between AMB^p and future stock returns, with an average monthly slope coefficient of 0.017 (significant at the 1% level). To assess the incremental contribution of ambiguity, Column (2) presents results from a multivariate regression that excludes AMB^p but includes control variables listed in Table 13, which yields an adjusted R^2 of 9.54%.

Column (3) adds AMB^p to the full control variable specification. The inclusion of our ambiguity measure increases the adjusted R^2 to 9.78%, representing a meaningful improvement in explanatory power. Crucially, the coefficient for AMB^p remains positive and statistically significant, confirming that ambiguity provides incremental information beyond

Table 4 Fama-Macbeth cross-sectional regressions

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.010 (1.41)	0.137*** (4.75)	0.133*** (4.63)	0.009 (1.23)	0.142*** (4.73)	0.140*** (4.65)
AMB^p	0.017*** (4.62)		0.005* (1.78)	0.016*** (4.74)		0.004* (1.68)
SIZE		-0.005*** (-3.98)	-0.005*** (-3.93)		-0.005*** (-4.17)	-0.005*** (-4.14)
BM		-0.004 (-1.22)	-0.004 (-1.19)		-0.003 (-0.96)	-0.003 (-0.95)
MOM		0.003 (1.01)	0.003 (1.04)		0.003 (0.99)	0.003 (1.02)
REV		-0.027*** (-3.67)	-0.027*** (-3.72)		-0.028*** (-4.08)	-0.028*** (-4.09)
GROW		-0.003** (-2.21)	-0.003** (-2.25)		-0.003** (-2.19)	-0.003** (-2.21)
LEV		0.001 (0.26)	0.001 (0.38)		0.002 (0.59)	0.002 (0.69)
IVOL		-0.116*** (-9.86)	-0.110*** (-9.56)		-0.117*** (-10.72)	-0.112*** (-10.41)
ASTO		-0.001*** (-4.60)	-0.001*** (-4.84)		-0.001*** (-5.11)	-0.001** (-5.35)
Ind. Eff.	N	N	N	Y	Y	Y
# of Obs.	548,963	548,963	548,963	548,963	548,963	548,963
Adj. R^2	0.59%	9.54%	9.78%	5.65%	13.00%	13.21%

This table reports time-series averages of the slope coefficients obtained from regressing next-month excess returns on AMB^p and a set of lagged predictive variables using Fama-MacBeth methodology. The control variables are natural logarithm of market capitalization (SIZE), book-to-market ratio (BM), 11-month momentum returns (MOM), short-term return reversal (REV), annual growth of book assets (GROW), leverage (LEV), idiosyncratic volatility (IVOL), and annual stock turnover (ASTO). Columns (1), (2) and (3) present results for univariate, multivariate regression without AMB^p and multivariate regression with AMB^p , respectively. Columns (4)–(6) present the same set of regression results controlling for the industry effect. Newey-West adjusted t-statistics are reported in parentheses. The sample period is January 2005 – December 2023. ***, **, and * indicate significance at 1%, 5%, 10%, respectively

established return predictors. Columns (4)–(6) repeat this analysis while controlling for industry fixed effects, using first-level industry classifications from the CSRC (2012). The pattern of results remains consistent: AMB^p maintains its positive and statistically significant relationship with future returns even after accounting for industry-level variation.

4.4 The impact of arbitrage constraints

The positive ambiguity premium identified in Sect. 4.2 suggests a new return anomaly in Chinese markets, where long-short portfolios based on ambiguity sensitivity can yield abnormal returns. This return predictability may arise from either rational risk premia or market mispricing. If market mispricing is the cause, arbitrageurs would be unable to fully exploit these opportunities due to market frictions (Shleifer and Vishny 1997). Conversely, if the return predictability results from rational risk premia, arbitrage constraints should not impact expected returns.

To understand the role of arbitrage constraints in the ambiguity premium, we assess their influence on the strength of this premium. Should these constraints weaken the premium, it would imply investor underreaction as a plausible cause of mispricing (Chu et al. 2020). Pontiff (2006) identifies two primary types of arbitrage constraints: transaction costs and holding costs.

To evaluate transaction costs, we consider the availability of short selling. Marsh and Payne (2012) argue that short-selling constraints significantly reduce the price discovery. Nagel (2005) finds that short-selling constraints can explain many cross-sectional return anomalies. Following Gu et al. (2018), we classify stocks facing arbitrage constraints as those not included in the CSI 300 index.¹⁰

For holding costs, we focus on idiosyncratic volatility. Shleifer & Vishny (1997) suggest that idiosyncratic risk poses a significant concern for arbitrageurs, as it cannot be hedged. McLean (2010) notes that reversal anomalies are prevalent primarily in stocks with high idiosyncratic risk. Accordingly, we define high idiosyncratic volatility stocks whose volatility exceeds the cross-sectional median volatility.

We divide the sample into two subsamples: one comprising stocks subject to arbitrage constraints and the other without such constraints. We then calculate the excess returns for long-short AMB^p quintiles within each subsample and report the comparative premiums in Table 5. The construction of the long-short quintile portfolios follows the same procedure described earlier in Sect. 3.2.

In Panel A, of Table 5 we report the results of the impact of short selling restrictions on the magnitude of the ambiguity premium. As can be observed, the excess returns for long-short AMB^p quintiles are significant across all factor models and for both equally and value weighted portfolios. The annualized alphas for non-CSI 300 index stocks that face substantial arbitrage restrictions range from 3.792% (0.316×12) to 6.528% (0.544×12), all of which are statistically significant. In contrast, the ambiguity premium is insignificant for stocks included in CSI 300 index, which are allowed to be short sold.

¹⁰ Prior to April 2010, strict short selling was prohibited in China due to the absence of CSI 300 index futures and margin trading (Qian and Poshakwale 2025). Despite this, the introduction of a low-cost CSI300 index ETF in 2005 enabled institutional investors to arbitrage between the ETF and individual stocks. For more details, refer to the source: <https://fund.stockstar.com/SS2005081730255417.shtml> (in Chinese).

Table 5 Alphas of long-short portfolios conditional on trading constraints

	Factor	Equal-weighted		Value-weighted	
	Model	Alpha (%)	T-statistic	Alpha (%)	T-statistic
Panel A: Presence of short selling restriction					
Non-CSI300 index constituents	FF3	0.544***	(3.75)	0.368**	(2.23)
	FF4	0.542***	(3.60)	0.365**	(2.15)
	FF5	0.455***	(3.29)	0.316*	(1.86)
	FF6	0.457***	(3.24)	0.319*	(1.84)
CSI300 index constituents	FF3	-0.213	(-0.68)	0.235	(0.53)
	FF4	-0.237	(-0.73)	0.213	(0.48)
	FF5	-0.313	(-1.00)	0.168	(0.39)
	FF6	-0.324	(-1.03)	0.156	(0.35)
Panel B: Level of idiosyncratic volatility					
High idiosyncratic volatility	FF3	0.658***	(3.10)	0.693*	(1.77)
	FF4	0.652***	(2.91)	0.685*	(1.72)
	FF5	0.581***	(3.10)	0.700*	(1.82)
	FF6	0.588***	(2.98)	0.707*	(1.81)
Low idio-syncratic volatility	FF3	0.038	(0.27)	-0.050	(-0.23)
	FF4	0.037	(0.25)	-0.050	(-0.23)
	FF5	0.015	(0.11)	-0.058	(-0.28)
	FF6	0.016	(0.12)	-0.058	(-0.28)

At the end of each month, we long stocks in the highest AMB^P quintile (quintile 5) and short stocks in the lowest AMB^P quintile (quintile 1) and compute the next month's excess return for the long-short portfolio. Panel A reports average next-month alphas relative to factor models (FF3, FF4, FF5, and FF6) based on CSI300 index membership status. The high (low) information asymmetry subsample consists of non-CSI300 (CSI300) index constituents. Panel B reports average next-month alphas relative to factor models (FF3, FF4, FF5, and FF6) based on the level of idiosyncratic volatility. The high (low) idiosyncratic volatility subsample consists of stocks with idiosyncratic volatility higher (lower) than cross-sectional median. Newey-West adjusted t-statistics are given in parentheses. The sample period is January 2005 – December 2023. ***, **, and * indicate significance at 1%, 5%, 10%, respectively

In Panel B, we show the impact of high and low idiosyncratic volatility on the ambiguity premiums. The results show that the annualized alphas for the high idiosyncratic volatility subsample of stocks range from 6.972% (0.581×12) to 8.484% (0.707×12), all of which are statistically significant. In contrast, the ambiguity premium is insignificant for the low idiosyncratic volatility stocks.

In summary, the findings suggest that the investors demand ambiguity premium for stocks which face short selling restrictions and carry high idiosyncratic volatility. The results show that market frictions play a critical role in the relationship between ambiguity in asset pricing in the Chinese emerging markets characterized by substantial arbitrage constraints and high idiosyncratic volatility.

An important question arises: why do these market frictions lead to investor underreaction rather than overreaction? The answer lies in the interaction between ambiguity aversion and the unique institutional features of the Chinese market. First, the Chinese market is dominated by retail investors who face cognitive constraints in processing complex information. Chen et al. (2022) and Shu and Tan (2022) demonstrate that limited attention among

Chinese retail investors leads to delayed price adjustment rather than immediate overreaction. Second, stringent short-selling restrictions prevent pessimistic information from being quickly incorporated into prices (Beber and Pagano 2013), resulting in gradual rather than immediate price adjustment when ambiguity increases. Third, following Ui (2011), when informed investors exit the market due to high ambiguity, the decline in private information reduces the credibility of price signals, causing the remaining uninformed investors to respond cautiously rather than aggressively. Finally, elevated idiosyncratic risk increases arbitrage costs (McLean 2010), preventing sophisticated traders from quickly correcting mispricing and allowing initial underreaction to persist. In essence, ambiguity-averse investors adopt wait-and-see strategies when probabilities are unknown, generating the positive ambiguity premium we document.

4.5 Robustness check

We validate the robustness of our findings by using stock index futures as an alternative measure of market ambiguity. We also employ different portfolio formation methods and use China-specific factor models for calculating ambiguity premium.

First, we examine whether our results remain consistent when we use Index futures instead of stock index for estimating ambiguity sensitivity (AMB^p). In contrast to the CSI 300 stock index returns, which are a value-weighted aggregate of the returns of 300 individual stocks, index futures returns indicate the market's expectations for the overall performance of CSI 300 stocks. We utilize intraday return data of the CSI 300 index futures, spanning from April 2010 to June 2022, to calculate AMB^p . We then form long-short portfolios following the same procedure as in Sect. 3.2. We find that the alphas of the long-short quintile portfolios remain statistically significant across various factor models, corroborating our earlier findings of positive ambiguity premium. The results are not reported here but are available on request.

Second, instead of dividing the sample into quintiles, we create deciles based on their AMB^p values. Panel A in Table 6 reports equal-weighted and value-weighted alphas of long-short deciles based on ambiguity sensitivity. For equal-weighted returns, alphas across factor models are positive and significant at the 1% level. In contrast, the value-weighted alphas based on ambiguity sensitivity deciles are not significant.

We investigate the reasons for the above contrasting results. Akbas et al. (2022) argue that the presence of very large firms in the portfolio can distort the value-weighted returns. For our sample, this could be particularly severe for the initial period which comprises smaller number of observations. Hence, following the approach of Akbas et al. (2022), we exclude the top 1% of stocks by firm size each month and then repeat the long-short portfolio analysis. We present results in Panel B of Table 6. Alphas for both value-weighted and equal-weighted are positive and significant at the 5% or better which confirm that our baseline results are robust.

Finally, we investigate whether the ambiguity premium for small-cap stocks is solely due to their potential as shell companies. Liu et al. (2019) note that small firms often serve as shells in reverse mergers to bypass strict IPO regulations in China. To investigate this issue, we exclude the smallest 30% of stocks from our sample as well as special treatment (ST/*ST) stocks to mitigate their influence on our baseline results.

Table 6 Alphas of deciles sorted by ambiguity sensitivity

Weighting	FF3	FF4	FF5	FF6
Panel A: Alphas of long-short deciles with full sample				
Equal-weighted	0.631*** (3.16)	0.510*** (3.06)	0.628*** (3.04)	0.477*** (2.99)
Value-weighted	0.515 (1.59)	0.631 (1.55)	0.510 (1.57)	0.628 (1.57)
Panel B: Alphas of long-short deciles with top 1% stocks excluded				
Equal-weighted	0.636*** (3.53)	0.520*** (3.40)	0.633*** (3.20)	0.459*** (3.15)
Value-weighted	0.523** (2.43)	0.636** (2.35)	0.520** (2.20)	0.633** (2.19)

At the end of each month, we sort stocks into deciles in ascending of AMB^p , where decile 1 (10) consists of stocks with the lowest (highest) AMB^p . We also form long-short portfolio by being long on decile 10 and short on decile 1. In Panel A (B), we report the alphas of long-short portfolios (in percentage) relative to factor models (FF3, FF4, FF5, and FF6) with full sample (with top 1% stocks excluded). FF3 is the alpha relative to market, size, and book-to-market factors. FF4 is the alpha relative to market, size, book-to-market and momentum factors. FF5 is the alpha relative to market, size, book-to-market, investment, and profitability factors. FF6 is the alpha relative to market, size, book-to-market, investment, profitability, and momentum factors. Newey-West adjusted t-statistics are given in parentheses. The sample period is January 2005 – December 2023. ***, **, and * indicate significance at 1%, 5%, 10%, respectively

The results reported in Panel A of Table 7 illustrate the impact of short selling constraints on the ambiguity premium, while Panel B shows the influence of idiosyncratic volatility. As can be seen from results in Panel A, the alphas for long-short portfolios with non-CSI 300 constituent stocks are positive and statistically significant. In contrast, the alphas for CSI 300 member stocks are statistically insignificant. Results in Panel B also confirm presence of a positive ambiguity premium for stocks that carry high idiosyncratic volatility. These results confirm our earlier findings and suggest that the magnitude of the ambiguity premium is influenced by the level of arbitrage constraints.

Additionally, we employ China-specific factor models which outperform the traditional Fama-French factor models in China and are able to explain most China-specific return anomalies (Liu et al. 2019). In the China-specific 3-factor model (CH3), Liu et al. (2019) use earnings-to-price ratio instead of the book-to-market ratio as the value factor in the Fama-French 3-factor model. Moreover, they enhance the CH3 model with a trading volume factor to capture investor sentiment, creating the China-specific 4-factor model (CH4).

We use CH3 and CH4 models to examine whether the ambiguity premium persists. Panels A and B of Table 8 show results for the full sample, while Panels C and D provide results for the sample excluding shell stocks. The results confirm the robustness of our earlier findings of a positive ambiguity premium in the Chinese market.

4.6 Additional analysis

4.6.1 Disentangling size effects from ambiguity premium

Larger stocks tend to have returns that are more closely aligned with the market index. As a result, the construction of AMB^p may mechanically generate higher values for larger firms and lower values for smaller firms. Consistent with this expectation, Table 2 documents a positive correlation between AMB^p and firm size (SIZE). This raises the question of

Table 7 Alphas conditional on trading constraints with shell stocks removed

	Factor	Equal-weighted		Value-weighted	
	Model	Alpha (%)	T-statistic	Alpha (%)	T-statistic
Panel A: Presence of short selling restriction					
Non-CSI300 index constituents	FF3	0.469***	(3.14)	0.335*	(1.94)
	FF4	0.467***	(3.07)	0.332*	(1.89)
	FF5	0.404***	(2.78)	0.315*	(1.76)
	FF6	0.405***	(2.77)	0.318*	(1.75)
CSI300 index constituents	FF3	-0.199	(-0.63)	0.231	(0.53)
	FF4	-0.223	(-0.69)	0.209	(0.47)
	FF5	-0.303	(-0.97)	0.167	(0.39)
	FF6	-0.314	(-0.99)	0.155	(0.36)
Panel B: Level of idiosyncratic volatility					
High idiosyncratic volatility	FF3	0.519**	(2.14)	0.729*	(1.77)
	FF4	0.513**	(2.05)	0.722*	(1.73)
	FF5	0.473**	(2.06)	0.762*	(1.85)
	FF6	0.478**	(2.04)	0.769*	(1.84)
Low idio-syncratic volatility	FF3	0.039	(0.24)	-0.063	(-0.28)
	FF4	0.037	(0.23)	-0.063	(-0.28)
	FF5	0.027	(0.18)	-0.052	(-0.24)
	FF6	0.029	(0.19)	-0.052	(-0.24)

Following Liu et al. (2019), we remove the smallest 30% of stocks as well as ST/*ST stocks to avoid their shell-value contamination. We then construct ambiguity sensitivity quintiles. At the end of each month, we long stocks in the highest AMB^p quintile (quintile 5) and short stocks in the lowest AMB^p quintile (quintile 1) and compute the next month's excess return for the long-short portfolio. Panel A reports average next-month alphas relative to factor models (FF3, FF4, FF5, and FF6) based on CSI300 index membership status. The high (low) information asymmetry subsample consists of non-CSI300 (CSI300) index constituents. Panel B reports average next-month alphas relative to factor models (FF3, FF4, FF5, and FF6) based on the level of idiosyncratic volatility. The high (low) idiosyncratic volatility subsample consists of stocks with idiosyncratic volatility higher (lower) than cross-sectional median. Newey-West adjusted t-statistics are given in parentheses. The sample period is January 2005 – December 2023. ***, **, and * indicate significance at 1%, 5%, 10%, respectively

whether our measure of ambiguity sensitivity is primarily capturing size effects rather than distinct ambiguity effects.¹¹

To address this concern, we conduct additional tests that disentangle the influence of firm size from ambiguity. Specifically, we partition the sample into three size groups based on the cross-sectional distribution of SIZE: the bottom 30% (small firms), the middle 40% (medium firms), and the top 30% (large firms). For each size group, we form long-short portfolios based on ambiguity quintiles and estimate alphas relative to standard factor models. Table 9 reports these results, with Columns 1–3 presenting equal-weighted alphas and Columns 4–6 reporting value-weighted alphas.

The equal-weighted results show that alphas are positive and statistically significant across all factor models and size groups. This evidence indicates that the ambiguity pre-

¹¹ We would like to thank the anonymous reviewer for making this valuable suggestion.

Table 8 Alphas sorted by ambiguity sensitivity with alternative factor models

Model	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	(Q5-Q1)
Panel A: Alphas based on equal-weighted excess returns for the full sample						
CH3	-0.260*** (-2.75)	0.210*** (3.98)	0.376*** (6.85)	0.499*** (6.57)	0.409*** (4.14)	0.489*** (2.87)
CH4	-0.171*** (-2.11)	0.238*** (4.41)	0.393*** (6.17)	0.495*** (5.60)	0.396*** (3.50)	0.387* (2.31)
Panel B: Alphas based on value-weighted excess returns for the full sample						
CH3	-0.536*** (-2.99)	0.033 (0.39)	0.222** (2.13)	0.342** (2.34)	0.364** (2.21)	0.720** (2.42)
CH4	-0.410** (-2.37)	0.098** (1.10)	0.249** (2.19)	0.327** (2.17)	0.296* (1.69)	0.525* (1.74)
Panel C: Alphas based on equal-weighted excess returns with shell stocks removed						
CH3	-0.215* (-1.97)	0.146** (2.40)	0.368*** (4.86)	0.459*** (5.60)	0.414*** (3.79)	0.448** (2.42)
CH4	-0.117 (-1.15)	0.184*** (3.07)	0.397*** (4.74)	0.471*** (5.04)	0.423*** (3.42)	0.360* (1.82)
Panel D: Alphas based on value-weighted excess returns with shell stocks removed						
CH3	-0.512*** (-2.65)	0.054 (0.61)	0.260** (2.21)	0.332** (2.15)	0.397** (2.30)	0.729** (2.27)
CH4	-0.398** (-2.10)	0.117 (1.27)	0.296** (2.34)	0.322** (1.99)	0.330* (1.82)	0.548* (1.67)

At the end of each month, we sort stocks into quintiles in ascending of AMB^P, where quintile 1 (5) consists of stocks with the lowest (highest) AMB^P. We also form long-short portfolio (Q5-Q1) by being long on quintile 5 and short on quintile 1. In Panel A (B), we report the alphas (in percentage) relative to China-specific factor models (CH3 and CH4) for the full sample. In Panel C (D), we report the alphas (in percentage) relative to China-specific factor models (CH3 and CH4) with shell stocks removed. CH3 model employs market, size, and earning-to-price factors. CH4 model uses market, size, earnings-to-price, and trading volume factors. Newey-West adjusted t-statistics are given in parentheses. The sample period is January 2005 – December 2023. ***, **, and * indicate significance at 1%, 5%, 10%, respectively

mium is not simply a manifestation of size effects. For value-weighted portfolios, alphas remain positive across the board, but statistical significance is confined to small and medium firms. The lack of significance for large firms is likely attributable to the disproportionate influence of a few dominant large-cap stocks, which may distort the cross-sectional relationship between ambiguity and returns in value-weighted settings.

The institutional composition of large-cap stocks in China may further explain this pattern. State-Owned Enterprises (SOEs) account for 60.52% of the large-size tercile, compared to 40.52% for medium-size and 23.95% for small-size firms. SOEs typically benefit from implicit government support, extensive regulatory oversight and analyst coverage, and more stable earnings owing to their strategic importance in key sectors (Cull et al. 2015; Wang et al. 2025). These characteristics reduce information asymmetry surrounding SOE valuations, potentially diminishing investors' sensitivity to market-wide ambiguity fluctuations and thereby attenuating the ambiguity premium in the large-cap segment. Taken together, these findings demonstrate that the ambiguity premium persists after controlling for firm size, supporting the robustness of our main conclusions.

Table 9 Alphas of bivariate portfolios sorted by AMB^p after controlling for size factor

Model	Equal-weighted excess returns			Value-weighted excess returns		
	Q1 (Low)	Q5 (High)	(Q5-Q1)	Q1 (Low)	Q5 (High)	(Q5-Q1)
Panel A: Alphas for low size group						
FF3	0.098 (0.76)	0.752*** (4.86)	0.628*** (4.17)	0.003 (0.02)	0.673*** (4.46)	0.625*** (4.17)
FF4	0.107 (0.80)	0.762*** (5.34)	0.627*** (4.11)	0.010 (0.07)	0.682*** (4.92)	0.623*** (4.11)
FF5	0.153 (1.35)	0.706*** (5.14)	0.506*** (3.29)	0.064 (0.55)	0.629*** (4.71)	0.504*** (3.34)
FF6	0.152 (1.31)	0.706*** (5.60)	0.506*** (3.27)	0.064 (0.53)	0.629*** (5.13)	0.504*** (3.32)
Panel B: Alphas for medium size group						
FF3	-0.662*** (-6.19)	0.076 (0.74)	0.690*** (4.12)	-0.665*** (-5.82)	0.058 (0.54)	0.664*** (3.91)
FF4	-0.657*** (-5.94)	0.075 (0.73)	0.688*** (4.05)	-0.662*** (-5.68)	0.057 (0.53)	0.662*** (3.84)
FF5	-0.586*** (-6.13)	0.066 (0.69)	0.628*** (4.10)	-0.596*** (-5.70)	0.052 (0.50)	0.611*** (3.76)
FF6	-0.586*** (-6.02)	0.067 (0.69)	0.628*** (4.09)	-0.596*** (-5.68)	0.052 (0.50)	0.611*** (3.75)
Panel C: Alphas for high size group						
FF3	-0.390** (-2.29)	0.043 (0.32)	0.468* (1.76)	-0.390* (-1.67)	0.209 (1.05)	0.517 (1.35)
FF4	-0.396** (-2.40)	0.032 (0.24)	0.458* (1.68)	-0.391* (-1.67)	0.198 (0.99)	0.508 (1.31)
FF5	-0.338** (-2.15)	0.105 (0.81)	0.461* (1.85)	-0.394* (-1.67)	0.266 (1.41)	0.531 (1.49)
FF6	-0.338** (-2.20)	0.106 (0.80)	0.462* (1.81)	-0.394* (-1.67)	0.267 (1.38)	0.531 (1.47)

This table presents the alphas of long-short portfolios formed using a two-way sorting approach based on risk factors and ambiguity sensitivity (AMB^p). Stocks are first sorted into terciles based on the SIZE factor and then further sorted within each tercile into quintiles based on AMB^p. Quintile 1 (Q1) contains stocks with the lowest ambiguity sensitivity, while Quintile 5 (Q5) contains those with the highest. The reported alphas represent the next-month return differences between Q5 and Q1 portfolios, calculated using both equal-weighted and value-weighted returns. Panels A, B, and C correspond to results for low, medium, and high size groups, respectively. Newey-West adjusted t-statistics are reported in the corresponding columns. The sample period spans January 2005 to December 2023. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

4.6.2 Differentiating ambiguity from uncertainty

Our baseline results show a positive ambiguity premium in China, consistent with investor aversion to unknown distributions. A potential concern, however, is that this premium may partly capture uncertainty effects – risks associated with known probabilities.¹² To disentangle these effects, we conduct bivariate portfolio analyses following Jiang et al. (2005), using four proxies for information uncertainty: firm age (AGE), annual stock turnover (ASTO), implied equity duration (DUR), and annual return volatility based on daily returns (RVOL). For each proxy, stocks are sorted into three groups using a 30:40:30 percentile break: the

¹² We gratefully acknowledge the insightful suggestions provided by the anonymous reviewer.

bottom 30% (low uncertainty), the middle 40% (medium uncertainty), and the top 30% (high uncertainty). Within each tercile, stocks are further divided into quintiles based on ambiguity sensitivity (AMB^p). This double-sorting approach allows us to estimate the ambiguity premium while holding uncertainty constant.

Table 10 presents the results. Using equal-weighted returns, the ambiguity premium remains positive and statistically significant across terciles and factor models, with monthly alphas ranging from 0.396% to 0.996%, suggesting strong economic significance. Value-weighted results display a similar pattern, except in the low AGE and low RVOL terciles, where alphas are positive but insignificant, likely reflecting trading irregularities in newly listed firms and illiquid stocks. Overall, the evidence confirms that the ambiguity premium persists after controlling for uncertainty, highlighting its distinct role in asset pricing.

4.6.3 Incremental effects of ambiguity sensitivity in return prediction

Table 4 shows that AMB^p exhibits significant explanatory power for returns in a multivariate setting. To further assess its incremental role, we estimate bivariate Fama–MacBeth regressions, reported in Table 11, where AMB^p is paired with one control variable at a time. All regressions include industry fixed effects. Across specifications, the coefficients on AMB^p remain positive and statistically significant at the 5% level or better. These results indicate that AMB^p provides incremental information beyond traditional anomaly variables, underscoring the economic relevance of ambiguity in asset pricing within China's emerging markets.

4.6.4 Short selling constraints: evidence from the MTSS program

Table 5 (Panel A) and 7 (Panel A) show that the ambiguity premium depends on short-selling constraints, proxied by CSI 300 index membership, where CSI 300 constituents are classified as unconstrained and non-CSI 300 constituents as constrained. However, this proxy may also capture large-cap attributes such as greater analyst coverage and liquidity. To address this concern, we employ a more direct measure based on the Margin Trade and Short Selling (MTSS) program introduced in 2010 (see footnote 10). For the period April 2010 to December 2023, MTSS-listed stocks are classified as unconstrained and non-MTSS stocks as constrained. We then re-estimate the long-short ambiguity-sensitivity quintile portfolios separately for MTSS and non-MTSS stocks, with results reported in Table 12. Panel A shows that equal- and value-weighted alphas for MTSS stocks are statistically insignificant across factor models, while Panel B shows that alphas for non-MTSS stocks are positive and significant. These results are consistent with Tables 5 and 7, confirming that short-selling constraints are a key driver of the ambiguity premium.

5 Conclusion

Differentiating ambiguity from uncertainty has significant implications for asset pricing. Previous research suggests that higher compensation demanded by ambiguity averse investors could be an important driver of the equity risk premium. However, most previous studies use theoretical models to identify ambiguity since quantifying it is an arduous task. The

Table 10 Alphas of bivariate portfolios sorted by AMB^p after controlling for uncertainty

Model	Equal-weighted excess returns			Value-weighted excess returns		
	Low	Median	High	Low	Median	High
Panel A: Alphas by AGE groups						
FF3	0.442** (2.42)	0.736*** (4.07)	0.874*** (4.19)	0.709 (1.58)	0.653* (1.86)	0.845** (2.38)
FF4	0.444** (2.46)	0.730*** (3.86)	0.869*** (4.08)	0.699 (1.54)	0.644* (1.82)	0.837** (2.32)
FF5	0.400** (2.40)	0.699*** (4.05)	0.794*** (4.11)	0.748* (1.69)	0.736** (2.15)	0.737** (2.13)
FF6	0.400** (2.42)	0.699*** (3.94)	0.794*** (4.03)	0.748* (1.68)	0.736** (2.13)	0.738** (2.10)
Panel B: Alphas by ASTO groups						
FF3	0.434** (1.99)	0.712*** (3.94)	0.934*** (5.07)	0.696* (1.69)	0.823*** (2.73)	1.055*** (3.73)
FF4	0.429* (1.94)	0.708*** (3.81)	0.933*** (5.05)	0.690* (1.67)	0.812*** (2.63)	1.053*** (3.71)
FF5	0.396** (1.99)	0.644*** (3.81)	0.848*** (4.93)	0.735* (1.82)	0.815*** (2.66)	1.003*** (3.55)
FF6	0.396* (1.96)	0.644*** (3.75)	0.848*** (4.96)	0.736* (1.81)	0.815*** (2.63)	1.003*** (3.55)
Panel B: Alphas by IDUR groups						
FF3	0.434** (1.99)	0.712*** (3.94)	0.934*** (5.07)	0.696* (1.69)	0.823*** (2.73)	1.055*** (3.73)
FF4	0.429* (1.94)	0.708*** (3.81)	0.933*** (5.05)	0.690* (1.67)	0.812*** (2.63)	1.053*** (3.71)
FF5	0.396** (1.99)	0.644*** (3.81)	0.848*** (4.93)	0.735* (1.82)	0.815*** (2.66)	1.003*** (3.55)
FF6	0.396* (1.96)	0.644*** (3.75)	0.848*** (4.96)	0.736* (1.81)	0.815*** (2.63)	1.003*** (3.55)
Panel C: Alphas by RVOL groups						
FF3	0.352* (1.95)	0.727*** (3.96)	0.966*** (5.10)	0.530 (1.48)	1.054*** (3.07)	1.094*** (4.71)
FF4	0.346* (1.86)	0.725*** (3.90)	0.959*** (4.87)	0.523 (1.46)	1.046*** (3.00)	1.087*** (4.56)
FF5	0.336** (2.11)	0.683*** (3.89)	0.797*** (4.69)	0.619* (1.77)	1.015*** (3.06)	0.899*** (3.76)
FF6	0.336** (2.04)	0.683*** (3.85)	0.797*** (4.61)	0.620* (1.75)	1.015*** (3.03)	0.899*** (3.75)

This table presents the alphas of long-short portfolios formed using a two-way sorting approach based on risk factors and ambiguity sensitivity (AMB^p). Stocks are first sorted into terciles based on a given uncertainty proxy (AGE, ASTO, IDUR, or RVOL), and then further sorted within each tercile into quintiles based on AMB^p. Quintile 1 (Q1) contains stocks with the lowest ambiguity sensitivity, while Quintile 5 (Q5) contains those with the highest. The reported alphas represent the next-month return differences between Q5 and Q1 portfolios, calculated using both equal-weighted and value-weighted returns. Panels A, B, and C correspond to results using AGE, ASTO, IDUR, and RVOL as the primary sorting factors, respectively. Newey-West adjusted t-statistics are reported in the corresponding columns. The sample period spans January 2005 to December 2023. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Table 11 Robustness checks for Fama-Macbeth cross-sectional regressions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.105*** (3.28)	0.008 (0.99)	0.010 (1.31)	0.009 (1.11)	0.010 (1.27)	0.009 (1.33)	0.029*** (3.58)	0.139* (1.87)
AMB ^p	0.014*** (4.56)	0.015*** (5.02)	0.016*** (5.12)	0.012*** (3.85)	0.016*** (4.82)	0.016*** (4.84)	0.006** (1.99)	0.016*** (5.07)
SIZE	-0.004*** (-3.29)							
BM		0.006 (1.59)						
MOM			-0.001 (-0.38)					
REV				-0.045*** (-6.08)				
GROW					-0.003** (-2.15)			
LEV						-0.0004 (-0.14)		
IVOL							-0.123*** (-9.99)	
ASTO								-0.001** (-4.41)
Ind. Eff.	Y	Y	Y	Y	Y	Y	Y	Y
# of Obs.	548,963	548,963	548,963	548,963	548,963	548,963	548,963	548,963
Adj. R ²	8.19%	6.92%	7.27%	7.24%	6.08%	6.27%	6.90%	6.68%

This table reports the robustness check results from Fama–MacBeth regressions of next-month excess returns on AMB^p and a set of lagged predictive variables. Columns (1)–(8) present bivariate regressions, where AMB^p is included alongside one control variable at a time. All regressions control for industry fixed effects. Newey–West adjusted t-statistics are reported in parentheses. The sample period is January 2005 – December 2023. ***, **, and * indicate significance at 1%, 5%, 10%, respectively

paper addresses this gap by proposing a direct empirical measure of ambiguity that captures ‘inside uncertainty’ using intraday returns of Chinese stock market index.

The empirical evidence presented in the paper is consistent with the theoretical predictions proposed by Ui (2011) who suggests that the absence of informed investors reduces the availability of credible signals for informed pricing of stocks. Consequently, the investors remaining in the market demand higher returns for bearing greater ambiguity risk. Consistent with Ui’s (2011) model, we find evidence of a positive ambiguity premium which can be attributed to high proportion of ambiguity averse retail investors in the Chinese emerging markets.

Further, the evidence presented in the paper shows that market frictions arising from both the restrictions on short selling and the presence of high idiosyncratic volatility contribute to the positive ambiguity premium. This suggests that the negative ambiguity premium reported in previous studies could be due to absence of market frictions. Our findings also indicate that aversion to ambiguity may be a missing factor that can potentially explain equity premium puzzle.

The empirical findings presented in the paper imply that ambiguity is an important risk factor that could explain mispricing of stocks and return anomalies. Our paper makes impor-

Table 12 Robustness check for short-selling constraints and the ambiguity premium

Model	Equal-weighted excess returns			Value-weighted excess returns		
	Q1 (Low)	Q5 (High)	(Q5-Q1)	Q1 (Low)	Q5 (High)	(Q5-Q1)
Panel A: MTSS-Included (Unconstrained) Stocks						
FF3	-0.231 (-1.67)	-0.081 (-0.51)	-0.043 (-0.19)	-0.123 (-0.70)	-0.036 (-0.20)	-0.107 (-0.36)
FF4	-0.228 (-1.56)	-0.077 (-0.50)	-0.042 (-0.19)	-0.121 (-0.67)	-0.036 (-0.20)	-0.109 (-0.36)
FF5	-0.202 (-1.29)	-0.056 (-0.37)	-0.046 (-0.21)	-0.145 (-0.84)	-0.006 (-0.04)	-0.054 (-0.19)
FF6	-0.194 (-1.19)	-0.046 (-0.31)	-0.044 (-0.20)	-0.140 (-0.80)	-0.007 (-0.04)	-0.060 (-0.21)
Panel B: MTSS-Excluded (Constrained) Stocks						
FF3	-0.436*** (-4.16)	0.113 (1.00)	0.527*** (3.57)	-0.369** (-2.39)	-0.015 (-0.10)	0.330* (1.84)
FF4	-0.434*** (-3.92)	0.115 (1.08)	0.526*** (3.02)	-0.369** (-2.40)	-0.016 (-0.11)	0.327* (1.68)
FF5	-0.420*** (-4.12)	0.101 (1.01)	0.477*** (2.64)	-0.348** (-2.24)	0.031 (0.22)	0.338* (1.93)
FF6	-0.416*** (-3.86)	0.105 (1.09)	0.477*** (2.63)	-0.348** (-2.25)	0.028 (0.20)	0.335* (1.85)

This table examines the effect of short-selling constraints on the ambiguity premium from April 2010 to December 2023, during which the regulator progressively relaxed constraints through expansions of the Margin Trade and Short Selling (MTSS) list. Each month, we form a long–short portfolio by buying stocks in the highest AMB^b quintile (Q5) and shorting those in the lowest quintile (Q1), and compute next-month excess returns. Panel A (Panel B) reports average alphas from factor models (FF3, FF4, FF5, FF6) for MTSS-included (excluded) stocks. MTSS-included stocks are classified as short-selling constrained and MTSS-excluded stocks as unconstrained. Newey–West t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

tant contributions to the literature by demonstrating the importance of market frictions in pricing of ambiguity. Future research could explore the extent of ambiguity premium across countries with heterogenous institutional and market characteristics. Such investigations may help in furthering our understanding of how various types of market frictions influence the pricing of ambiguity globally.

Appendix

Table 13 Definitions of variables

Variables	Definitions
AMB ^p	The Spearman rank correlation coefficient between daily stock returns and daily change in market ambiguity within a given month.
SIZE	Natural logarithmic of a firm's market capitalization.
BM	Book-to-market ratio.
MOM	The 11-month return momentum, skipping the most recent month.
REV	Return reversal measured as stock returns in the most recent month.
GROW	Annual growth rate of book value of total assets.
LEV	Book leverage ratio measured as total debt divided by total assets.
IVOL	Idiosyncratic risk measured as the standard deviation of residuals from the Fama-French three-factor model.
ASTO	Annual share turnover ratio.

Declarations

Conflict of interest The authors declare that they have no financial or non-financial interests that are directly or indirectly related to the work submitted for publication.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Akbas F, Boehmer E, Jiang C, Koch PD (2022) Overnight returns, daytime reversals, and future stock returns. *J Financ Econ* 145(3):850–875. <https://doi.org/10.1016/j.jfineco.2021.09.019>
- Andreu P, Kagkadis A, Maio P, Philip D (2014) Stock market ambiguity and the equity premium. SSRN Elect J, ahead of print, January 1. <https://doi.org/10.2139/ssrn.2379606>
- Bali TG, Stephen JB, Tang Y (2017) Is economic uncertainty priced in the cross-section of stock returns? *J Financ Econ* 126(3):471–489. <https://doi.org/10.1016/j.jfineco.2017.09.005>
- Basak S, Cuoco D (1998) An equilibrium model with restricted stock market participation. *Rev Financial Stud* 11(2):309–341. <https://doi.org/10.1093/rfs/11.2.309>
- Beber A, Pagano M (2013) Short-selling bans around the world: evidence from the 2007–09 crisis. *J Finance* 68(1):343–381. <https://doi.org/10.1111/j.1540-6261.2012.01802.x>
- Becker J, Hollstein F, Prokopczuk M, Sibbertsen P (2021) The memory of beta. *J Banking Finance* 124:106026. <https://doi.org/10.1016/j.jbankfin.2020.106026>
- Bekaert G, Erb CB, Harvey CR, Viskanta TE (1998) Distributional characteristics of emerging market returns and asset allocation. *J Portf Manag* 24(2):102–116. <https://doi.org/10.3905/jpm.24.2.102>

- Bekaert G, Engstrom EC, Xu NR (2022) The time variation in risk appetite and uncertainty. *Manage Sci* 68(6):3975–4004. <https://doi.org/10.1287/mnsc.2021.4068>
- Ben-Rephael A, Izhakian Y (2020) Should i stay or should i go? Trading behavior under ambiguity. SSRN Elect J ahead of print. <https://doi.org/10.2139/ssrn.3628757>
- Bollerslev T, Tauchen G, Zhou H (2009) Expected stock returns and variance risk premia. *Rev Financial Stud* 22(11):4463–4492. <https://doi.org/10.1093/rfs/hhp008> Business Source Complete
- Brenner M, Izhakian Y (2018) Asset pricing and ambiguity: empirical evidence. *J Financ Econ* 130(3):503–531. <https://doi.org/10.1016/j.jfineco.2018.07.007>
- Breuer W, Rieger MO, Can Soypak K (2016) Corporate cash holdings and ambiguity aversion. *Rev Finance* May 20:r fw025. <https://doi.org/10.1093/rof/rfw025>
- Cao H, Henry T, Wang, Harold H, Zhang (2005) Model uncertainty, limited market participation, and asset prices. *Rev Financial Stud* 18(4):1219–1251. <https://doi.org/10.1093/rfs/hhi034>
- Carhart MM (1997) On persistence in mutual fund performance. *J Finance* 52(1):57–82. <https://doi.org/10.2307/2329556>
- Carpenter JN, Lu F, Robert F, Whitelaw (2021) The real value of China's stock market. *J Financ Econ* 139(3):679–696. <https://doi.org/10.1016/j.jfineco.2020.08.012>
- Cenesizoglu T (2022) Return decomposition over the business cycle. *J Banking Finance* 143:106592. <https://doi.org/10.1016/j.jbankfin.2022.106592>
- Chen Z, Epstein L (2002) Ambiguity, risk, and asset returns in continuous time. *Econometrica* 70(4):1403–1443. <https://doi.org/10.1111/1468-0262.00337>
- Chen X, Diao X, Wu C (2022) Heterogeneous investor attention and post earnings announcement drift: evidence from China. *Econ Model* 110:105796. <https://doi.org/10.1016/j.econmod.2022.105796>
- Chen J, Haboub A, Khan A, Mahmud S (2025) Investor clientele and intraday patterns in the cross section of stock returns. *Rev Quant Financ Acc* 64(2):757–797. <https://doi.org/10.1007/s11156-024-01319-8>
- Chu Y, Hirshleifer D, Ma L (2020) The causal effect of limits to arbitrage on asset pricing anomalies. *J Finance* 75(5):2631–2672. <https://doi.org/10.1111/jofi.12947>
- CSRC (2012) Guidelines for the industry classification of listed companies (2012 Revision). China Securities Regulatory Commission. http://www.csrc.gov.cn/pub/zjhpublic/G00306201/201211/t20121116_216990.htm
- Cull R, Li W, Sun B, Xu LC (2015) Government connections and financial constraints: evidence from a large representative sample of Chinese firms. *J Corp Finance* 32(June):271–294. <https://doi.org/10.1016/j.jcorpfin.2014.10.012>
- Diether KB, Christopher J, Malloy, Scherbina A (2002) Differences of opinion and the cross section of stock returns. *J Finance* 57(5):2113–2141. <https://doi.org/10.1111/0022-1082.00490> JSTOR
- Doukas JA Chansog (Francis) K, Christos P (2006) Divergence of opinion and equity returns. *J Financial Quant Anal* 41(3): 573–606. JSTOR
- Easley D, O'Hara M (2009) Ambiguity and nonparticipation: the role of regulation. *Rev Financial Stud* 22(5):1817–1843. <https://doi.org/10.1093/rfs/hhn100> Business Source Complete
- Ellsberg D (1961) Risk, ambiguity, and the savage axioms. *Quart J Econ* 75(4):643–669. <https://doi.org/10.2307/1884324> Business Source Complete
- Epstein LG, Wang T (1994) Intertemporal asset pricing under knightian uncertainty. *Econometrica* 62(2):283–322. <https://doi.org/10.2307/2951614> Business Source Complete
- Epstein LG, Schneider M (2008) Ambiguity, information quality, and asset pricing. *J Finance* 63(1):197–228. <https://doi.org/10.1111/j.1540-6261.2008.01314.x>
- Fama EF, MacBeth JD (1973) Risk, return, and equilibrium: empirical tests. *J Polit Econ* 81(3):607. <https://doi.org/10.1086/260061>
- Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. *J Financ Econ* 33(1):3–56. [https://doi.org/10.1016/0304-405X\(93\)90023-5](https://doi.org/10.1016/0304-405X(93)90023-5)
- Fama EF, French KR (2015) A five-factor asset pricing model. *J Financ Econ* 116(1):1–22. <https://doi.org/10.1016/j.jfineco.2014.10.010> Business Source Complete
- Garlappi L, Uppal R, Wang T (2007) Portfolio selection with parameter and model uncertainty: a multi-prior approach. *Rev Financial Stud* 20(1):41–81. <https://doi.org/10.1093/rfs/hhl003> Business Source Complete
- Gilboa I, Schmeidler D (1989) Maximin expected utility with non-unique prior. *J Math Econ* 18(2):141–153. [https://doi.org/10.1016/0304-4068\(89\)90018-9](https://doi.org/10.1016/0304-4068(89)90018-9) Business Source Complete
- Grossman S (1976) On the efficiency of competitive stock markets where trades have diverse information. *J Finance* 31(2):573–585. <https://doi.org/10.1111/j.1540-6261.1976.tb01907.x>
- Gu M, Kang W, Xu B (2018) Limits of arbitrage and idiosyncratic volatility: evidence from China stock market. *J Banking Finance* 86:240–258. <https://doi.org/10.1016/j.jbankfin.2015.08.016>

- Gurrola-Perez P, Kaitao L, Bill S (2022) Retail trading: an analysis of global trends and drivers. Unpublished working paper. World Federation of Exchanges. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4562259
- Han C, Shi Y (2022) Chinese stock anomalies and investor sentiment. *Pac-Basin Financ J* 73:101739. <https://doi.org/10.1016/j.pacfin.2022.101739>
- Hansen LP (2014) Nobel lecture: uncertainty outside and inside economic models. *J Polit Econ* 122(5):945–987. <https://doi.org/10.1086/678456> Business Source Complete
- Hansen LP, Sargent TJ (2022) Structured ambiguity and model misspecification. *J Econ Theory* 199:105165. <https://doi.org/10.1016/j.jet.2020.105165> Business Source Complete
- Izhakian Y (2012) Shadow probability theory and ambiguity measurement. *SSRN Elect J* ahead of print. <https://doi.org/10.2139/ssrn.1938628>
- Izhakian Y (2020) A theoretical foundation of ambiguity measurement. *J Econ Theory* 187:105001. <https://doi.org/10.1016/j.jet.2020.105001>
- Jiang G, Lee CMC, Zhang Y (2005) Information uncertainty and expected returns. *Rev Acc Stud* 10(2/3):185–221. <https://doi.org/10.1007/s11142-005-1528-2>
- Jin J, Zhang Q, Wang X (2025) Decoding high-volume stock momentum: disagreement or disposition? *J Behav Finance* January 6:1–31. <https://doi.org/10.1080/15427560.2024.2441703>
- Ju N, Miao J (2012) Ambiguity, learning, and asset returns. *Econometrica* 80(2):559–591. <https://doi.org/10.3982/ECTA7618>
- Kandel E, Pearson ND (1995) Differential interpretation of public signals and trade in speculative markets. *J Polit Econ* 103(4):831. <https://doi.org/10.1086/262005> Business Source Complete
- Karahan CC (2025) Knight in shining armor: ambiguity and gold prices. *Econ Lett* 248:112218. <https://doi.org/10.1016/j.econlet.2025.112218>
- Kostopoulos D, Meyer S, Uhr C (2022) Ambiguity about volatility and investor behavior. *J Financ Econ* 145(1):277–296. <https://doi.org/10.1016/j.jfineco.2021.07.004>
- Kumar A (2009) Who gambles in the stock market? *J Finance* 64(4):1889–1933. <https://doi.org/10.1111/j.1540-6261.2009.01483.x>
- Lee D-H, Min B-K, Kim TS (2019) Dispersion of beliefs, ambiguity, and the cross-section of stock returns. *J Empir Finance* 50:43–56. <https://doi.org/10.1016/j.jempfin.2019.01.001>
- Liu J, Stambaugh RF, Yuan Y (2019) Size and value in China. *J Financ Econ* 134(1):48–69. <https://doi.org/10.1016/j.jfineco.2019.03.008>
- Lundblad CT, Shi D, Zhang X, Zhang Z (2025) Foreign capital in the Chinese Stock market: a firm-level study. *J Financial Quant Anal* September 2:1–42. <https://doi.org/10.1017/S0022109025102081>
- Mankiw NG, Zeldes SP (1991) The consumption of stockholders and nonstockholders. *J Financ Econ* 29(1):97–112. [https://doi.org/10.1016/0304-405x\(91\)90015-c](https://doi.org/10.1016/0304-405x(91)90015-c)
- Marsh IW, Payne R (2012) Banning short sales and market quality: The UK's experience. *J Banking Finance* 36(7):1975–1986. <https://doi.org/10.1016/j.jbankfin.2012.03.005>
- McLean RD (2010) Idiosyncratic risk, long-term reversal, and momentum. *J Financial Quant Anal* 45(4):883–906. <https://doi.org/10.1017/S0022109010000311>
- Mehra R, Prescott EC (1985) The equity premium. *J Monet Econ* 15(2):145–161. [https://doi.org/10.1016/0304-3932\(85\)90061-3](https://doi.org/10.1016/0304-3932(85)90061-3) Business Source Complete
- Meyer S, Uhr C (2024) Ambiguity and private investors' behavior after forced fund liquidations. *J Financ Econ* 156:103849. <https://doi.org/10.1016/j.jfineco.2024.103849>
- Nagel S (2005) Short sales, institutional investors and the cross-section of stock returns. *J Financ Econ* 78(2):277–309. <https://doi.org/10.1016/j.jfineco.2004.08.008>
- Pontiff J (2006) Costly arbitrage and the myth of idiosyncratic risk. *J Account Econ* 42(1–2):35–52. <https://doi.org/10.1016/j.jacceco.2006.04.002>
- Qian B, Poshakwale S (2025) Economic policy uncertainty and stock returns in China: the role of regulatory short-selling constraints. *J Emerg Market Finance* December 14:09726527251392742. <https://doi.org/10.1177/09726527251392742>
- Qian B, Tan Y, Power G (2025) and Anandadeep Mandal. Economic policy uncertainty, information production, and transparency. *International Review of Financial Analysis*, March, 104203. <https://doi.org/10.1016/j.irfa.2025.104203>
- Rieger M, Oliver MW, Hens T (2015) Risk preferences around the world. *Manage Sci* 61(3):637–648. <https://doi.org/10.1287/mnsc.2013.1869> Business Source Complete
- Rothschild M, Stiglitz JE (1970) Increasing risk: I. A definition. *J Econ Theory* 2(3):225–243 [https://doi.org/10.1016/0022-0531\(70\)90038-4](https://doi.org/10.1016/0022-0531(70)90038-4)
- Sahin BC, Danisoglu S (2022) Ambiguity and asset pricing: an empirical investigation for an emerging market. *Int Rev Financial Anal* 84:102338. <https://doi.org/10.1016/j.irfa.2022.102338>

- Shleifer A, Vishny RW (1997) The limits of arbitrage. *J Finance* 52(1):35–55. <https://doi.org/10.1111/j.1540-6261.1997.tb03807.x>
- Shu H, Tan W (2022) Investor limited attention, opinion divergence, and post-earnings-announcement drift: evidence from China. *Emerg Markets Finance Trade* 58(14):3985–4000. <https://doi.org/10.1080/1540496X.2022.2079975>
- Ui T (2011) The ambiguity premium vs. the risk premium under limited market participation. *Rev Finance* 15(2):245–275. <https://doi.org/10.1093/rof/rfq012>
- Wang X, Kim MH, Suardi S (2022) Herding and China's market-wide circuit breaker. *J Banking Finance* 141:106533. <https://doi.org/10.1016/j.jbankfin.2022.106533>
- Wang L, Yang S, Zhao S (2024) The momentum ambiguity and investor trading behavior. *Econ Lett* 235:111533. <https://doi.org/10.1016/j.econlet.2024.111533>
- Wang J, Wang L, Hongrui F, Zhang J (2025) Politically connected CEOs and liquidity risk: some chinese evidence. *Rev Quant Financ Acc* 64(4):1671–1718. <https://doi.org/10.1007/s11156-024-01344-7>
- Zhu Hong-bing, Zhang B, Li-hua Y (2021) The gambling preference and stock price: evidence from China's stock market. *Emerg Markets Rev* 49:100803. <https://doi.org/10.1016/j.ememar.2021.100803>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.



DSPACE

<https://dspace.org/>

Market frictions, ambiguity and asset pricing: evidence from China

Poshakwale, Sunil S.; Qian, Binsheng; Mandal, Anandadeep

2026-12-31

Springer

<https://doi.org/10.1007/s11156-026-01508-7>

Poshakwale SS, Qian B, Mandal A. (2026) Market frictions, ambiguity and asset pricing: evidence from China. Review of Quantitative Finance and Accounting, Available online 28 March 2026