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Global geopolitical risk, ambiguity, and emerging market returns: Evidence from China☆

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ABSTRACT

We study how global geopolitical risk (GPR) affects Chinese equity returns through two distinct uncertainty channels: risk and ambiguity. While less commonly used than volatility, ambiguity is conceptually and empirically independent and offers incremental explanatory power for returns. We construct daily ambiguity measures within an adaptive model-uncertainty framework and demonstrate that GPR significantly increases financial ambiguity, which in turn is associated with lower returns. When ambiguity is included alongside traditional risk, models explain more variation in returns, illustrating that ambiguity captures a distinct dimension of Knightian uncertainty without invalidating the role of traditional risk; rather than competing for explanatory supremacy, volatility and ambiguity function as dual, coexisting channels that jointly capture investor distress during geopolitical shocks. By combining time-series tests with mediation and robustness checks, our integrated analysis provides a comprehensive account of how geopolitical risk transmits to asset prices not only through risk but also through ambiguity.

1. Introduction

Geopolitical risk (GPR) is a pervasive driver of uncertainty in emerging markets. Unlike measurable risk, which is captured by volatility, ambiguity represents the more elusive Knightian uncertainty where probability distributions are themselves unknown (Knight, 1921; Ellsberg, 1961). From a theoretical standpoint, models of ambiguity aversion (Gilboa and Schmeidler, 1989; Klibanoff et al., 2005) imply that higher ambiguity lowers valuations even when volatility is unchanged.

Recent literature has increasingly highlighted the role of geopolitical shocks in asset pricing (Zhang et al., 2024). However, how these shocks translate into ambiguity, specifically within emerging markets, remains underexplored. While other studies predominantly examine GPR through the lens of market volatility (Liu et al., 2024) and tail risk (Salisu et al., 2021), we demonstrate that ambiguity represents a distinct and economically significant transmission channel. Building on the theoretical distinction established above, our framework shows that GPR significantly increases both ambiguity and volatility. Furthermore, ambiguity operates alongside volatility to explain GPR's effect on returns, illustrating the complementary nature of these two uncertainty channels.

Our goal is to provide a comprehensive account of how GPR affects returns through both channels. We construct our daily ambiguity measures using a novel, simplified cross-entropy-based approach, which we argue is more robust than traditional proxies.[1]

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[1] A detailed comparison of our measure against alternative proxies is provided in the Online Appendix A.1.

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By doing so, we propose an objective, high-frequency measure of Knightian uncertainty, offering a new perspective on how macroeconomic geopolitical shocks are priced in equity markets.

Our empirical contributions are threefold. First, we show that our new ambiguity measure is negatively priced in both time series (CSI 300[2]) and cross-sectional (constituents) tests, providing incremental explanatory power beyond volatility. Second, we establish that GPR significantly increases financial ambiguity and identify it as a key transmission channel from geopolitics to asset prices. Third, in an integrated specification, the inclusion of ambiguity improves model fit and often reduces the explanatory power of volatility-based risk. We further explore heterogeneity in the pricing of ambiguity by testing for moderation effects related to state-owned enterprise (SOE) status.

Our findings have practical implications. The daily associations suggest that portfolios optimized solely for minimum variance may leave investors exposed to uncompensated ambiguity risks during periods of heightened geopolitical tension, highlighting the importance of ambiguity-aware risk management. However, given the episodic and mean-reverting nature of geopolitical shocks, these associations should be interpreted with caution as daily impacts rather than as deterministic long-term outcomes.

Methodologically, our empirical strategy is designed to rigorously test the links between geopolitical risk, ambiguity, and returns. We employ time-series regressions to establish the direct impact of GPR on our daily ambiguity measures and to confirm that ambiguity commands a negative risk premium over time. To verify that ambiguity is a systematically priced factor across individual stocks, we conduct Fama–MacBeth cross-sectional regressions. Building on these baseline results, we use mediation analysis to formally test the transmission channel and quantify the extent to which ambiguity accounts for GPR's effect on returns. Furthermore, we investigate whether the pricing of ambiguity differs for state-owned enterprises (SOEs) versus non-SOEs. This tests the hypothesis that implicit government guarantees may buffer SOEs from the adverse effects of ambiguity, leading to a weaker negative relationship between ambiguity and returns for these firms. Finally, a comprehensive battery of robustness checks confirms the stability of our baseline results. These include event studies and alternative measurement specifications.

The remainder of the paper is organized as follows. Section 2 reviews the literature and develops our hypotheses. Section 3 first details the data and empirical methodology used to explore the transmission mechanism of global geopolitical risk in Chinese equity markets. It then presents the main results and corresponding robustness checks to confirm the reliability of these findings, and Section 4 provides the conclusion.

2. Literature review and hypotheses development

Our research is situated at the intersection of two burgeoning fields: the asset pricing implications of ambiguity and the impact of geopolitical risk (GPR) on financial markets. We build a bridge between them by proposing that ambiguity is a critical yet underappreciated channel through which geopolitical tensions are transmitted to equity returns.

2.1. Geopolitical risk and financial markets

The systematic study of the economic impact of geopolitical risk has been significantly advanced by the development of quantitative measures, most notably the GPR index of Caldara and Iacoviello (2022). This index, derived from news text, has catalyzed a wave of research demonstrating that elevated GPR is detrimental to financial markets. The consensus finding is that GPR shocks lead to lower stock returns, higher volatility, and a flight to safe-haven assets (Caldara and Iacoviello, 2022). The effects are often amplified in emerging markets, which are more sensitive to shifts in global capital flows and investor sentiment.

However, the literature has predominantly focused on risk, proxied by volatility, as the main transmission mechanism. While studies have linked political uncertainty to reduced investment (Pástor and Veronesi, 2013) and economic policy uncertainty to depressed economic activity (Baker et al., 2016), the specific role of ambiguity, defined as Knightian uncertainty where probabilities are unknown, remains largely unexplored. This represents a significant gap. Geopolitical events are, by their nature, fraught with ambiguity; they create situations where past data is a poor guide to the future, and the range of possible outcomes and their likelihoods are difficult to assess. We argue that failing to account for ambiguity leaves our understanding of the GPR-return nexus incomplete.

2.2. Ambiguity aversion and asset pricing

The theoretical distinction between risk (known probabilities) and ambiguity (unknown probabilities) dates back to Knight (1921) and was famously demonstrated by Ellsberg (1961). Modern asset pricing theory has incorporated this distinction through models of ambiguity aversion, such as the multiple-priors framework of Gilboa and Schmeidler (1989) and the smooth ambiguity model of Klibanoff et al. (2005). These models predict that ambiguity-averse investors demand a premium for holding assets with uncertain payoff distributions, which depresses asset prices independent of conventional risk.

While theoretical consensus exists and evidence of an ambiguity premium has been documented primarily in developed markets, empirical research in emerging markets such as China remains scarce. The informational opacity and institutional features of emerging markets may make ambiguity an even more salient factor for investors (Easley and O'Hara, 2009). Despite the theoretical

[2] The CSI 300 Index represents the performance of the 300 largest and most liquid A-share stocks traded on the Shanghai and Shenzhen stock exchanges, making it an ideal proxy for the Chinese equity market.

consensus on ambiguity aversion, empirical integration between macroeconomic uncertainty and asset pricing remains fragmented. While studies such as Baker et al. (2016) and Caldara and Iacoviello (2022) establish that uncertainty broadly matters for markets, their predominantly monolithic treatment obscures the specific mechanics of investor distress. Building on the theoretical insights of Brenner and Izhakian (2018), it becomes conceptually necessary to explicitly isolate ambiguity from general market volatility. As they demonstrate, standard volatility metrics fail to capture the full spectrum of uncertainty, necessitating a more precise, risk-independent quantification of how investors price and react to unknown probability distributions.

This conceptual decomposition naturally extends the ongoing debate about how geopolitical shocks are transmitted to asset prices. Recent studies have extensively explored the relationship between GPR, volatility, and green bond markets, albeit with mixed empirical findings. Specifically, while Liu et al. (2024) documents dynamic pricing impacts and Zhang et al. (2024) identify a cross-sectional return premium associated with GPR exposure, Bouri et al. (2024) contrarily find green bonds to be immune to standard GPR spillovers. While these studies firmly establish standard risk as a primary avenue of investigation, they largely conflate the ambiguity dimension with general market turbulence. Disentangling ambiguity from volatility provides the necessary theoretical foundation to formally test how GPR induces model uncertainty and how investors price this distinct distress, which directly motivates the following hypotheses.

2.3. Hypotheses development

By integrating the GPR and ambiguity literature, we propose a comprehensive framework where GPR influences returns through both risk and ambiguity channels. This leads to the following testable hypotheses:

H1: Elevated global geopolitical risk increases financial ambiguity in China's capital market. This hypothesis posits that GPR is a fundamental source of ambiguity. Geopolitical events create novel situations where investors become less confident in their models of the world, which should be reflected in a higher value of our cross-entropy-based ambiguity measure.

H2: Ambiguity is negatively priced in Chinese equity returns. Consistent with ambiguity aversion theory, we hypothesize that investors demand compensation for bearing ambiguity. This should manifest as a negative contemporaneous relationship between our ambiguity measure and stock returns, providing incremental explanatory power beyond that of traditional volatility.

H3: Ambiguity serves as a significant transmission channel mediating the impact of geopolitical risk on equity returns. This hypothesis integrates the framework. We propose that GPR's total effect on returns can be decomposed into a direct impact and an indirect impact that flows through the ambiguity channel. We expect that explicitly modeling ambiguity will improve model fit and clarify the distinct roles of risk and ambiguity in the transmission of geopolitical shocks.

H4: The negative pricing of ambiguity is weaker for state-owned enterprises (SOEs) than for non-SOEs. This hypothesis introduces a key element of heterogeneity. We conjecture that the implicit government guarantees and policy roles of SOEs may buffer them from the full impact of ambiguity. This buffering effect should result in a less pronounced negative relationship between ambiguity and returns for these firms compared to their non-SOE counterparts.

3. Data and empirical research

3.1. Data and variables

3.1.1. Dependent variable

Our primary dependent variable is stock returns, which we examine at both market and firm levels. For the market-level analysis, we use the CSI 300 Index returns, calculated as the log difference of the index price. For the cross-sectional analysis, we construct individual stock returns from a comprehensive sample of A-share-listed companies in China. Our primary sample period spans from January 3, 2018, to December 29, 2023, comprising 1458 trading days. To account for major regime shifts, we further partition the timeline into two sub-periods: a pre-COVID period (January 3, 2018, to December 31, 2019; 485 trading days) and a COVID period (January 2, 2020, to December 29, 2023; 973 trading days). Following standard practice in asset pricing literature, we exclude financial firms and ST (Special Treatment) stocks from our analysis. All returns are calculated in percentage terms and winsorized at the 1% and 99% levels to mitigate the influence of outliers.

3.1.2. Key independent variables

Our key independent variables are geopolitical risk (GPR) and our constructed measures of ambiguity.

Geopolitical risk (GPR). We use the GPR index developed by Caldara and Iacoviello (2022), which is constructed from text-based counts of news articles containing geopolitical risk-related keywords. The index is available at both monthly and daily frequencies. For our analysis, we primarily use the daily GPR index to match the frequency of our ambiguity measures. To ensure consistency with our Chinese market data, we convert the U.S.-based GPR index to local time by accounting for the time difference between the U.S. and Chinese markets.

Ambiguity measures. Following the adaptive model uncertainty framework, we construct daily ambiguity measures using a cross-entropy-based approach.[3] Our baseline ambiguity measure, $\mathcal{A}_t$, is derived from the Kullback–Leibler (KL) divergence between the observed intraday return distribution and a set of historical benchmark distributions. Specifically, it is the minimum KL divergence over the set of all benchmark distributions.

[3] The underlying methodological framework is detailed in the Online Appendix A.2.

Volatility measures. To isolate the effect of ambiguity from traditional risk, we include realized volatility (RV) calculated from high-frequency data. For the CSI 300 Index, we compute RV using 5-minute returns following the realized volatility literature. For individual stocks, we use daily close-to-close returns as a proxy for volatility.

3.1.3. Control variables

In our time-series specifications, we incorporate a streamlined set of control variables to isolate the impact of geopolitical ambiguity cleanly. We control for the market return to capture systematic market movements, the VIX to capture global risk sentiment, the term spread to capture domestic monetary policy conditions, and the risk-free rate. This concise set of controls ensures that the core focus remains on the interplay between geopolitical risk and ambiguity.

Building on a rigorously aligned dataset,[4] we incorporate a standard set of control variables well-documented in the asset pricing literature. Specifically, we control for size, measured as the natural logarithm of market capitalization, and the book-to-market ratio to account for the size and value premiums, respectively. To capture return persistence, we include momentum, defined as the cumulative return over the past 12 months, excluding the most recent month.

3.2. Methodology and empirical analysis

3.2.1. Baseline regression

We employ a two-stage empirical strategy. First, we conduct time-series analysis to establish the relationship between GPR, ambiguity, and market returns. Second, we perform cross-sectional analysis to test whether ambiguity is a systematically priced factor.

Time-series specification. Our baseline time-series regression examines the impact of GPR and ambiguity on CSI 300 Index returns:

$$R_t = \alpha + \beta_1 \Delta \mathrm{GPR}_t + \beta_2 \Delta \mathcal{A}_t + \beta_3 \Delta \mathrm{RV}_t + \gamma' \mathbf{X}_t + \varepsilon_t \tag{1}$$

where R_t is the CSI 300 Index return on day t, $\Delta\mathrm{GPR}_t$ is the geopolitical risk shock, $\Delta\mathcal{A}_t$ is the ambiguity shock, $\Delta\mathrm{RV}_t$ is the change in realized volatility, and $\mathbf{X}_t$ includes market return, the VIX, term spread, and risk-free rate. Here, we define the shock operator ΔV_t as the first difference $\Delta V_t = V_t - V_{t-1}$. Thus, $\Delta\mathcal{A}_t$ and $\Delta\mathrm{RV}_t$ represent the daily changes in ambiguity and realized volatility, respectively.

To test H1, which posits that GPR increases ambiguity, we estimate a shock-based specification:

$$\Delta \mathcal{A}_t = \alpha + \delta_1 \Delta \mathrm{GPR}_t + \theta' \mathbf{Z}_t + \eta_t \tag{2}$$

where $\mathbf{Z}_t$ includes control variables such as lagged ambiguity, market return, the VIX, and term spread.

As reported in Table 1, the baseline empirical results reveal a significant negative relationship between ambiguity and returns. In terms of economic significance, heightened ambiguity exerts a material negative drag on daily equity returns.[5] We focus on this daily impact, which is more appropriate than annualized figures, given the high-frequency nature of our data and the transient shocks we study. As shown in Table 2, GPR significantly increases financial ambiguity across the full sample. Notably, this effect remains robust across both the Pre-COVID and COVID sub-periods, a point we will further elaborate on in our robustness checks.

3.2.2. Cross-sectional analysis

Following the methodology of Fama and MacBeth (1973), we use two-stage cross-sectional regressions to test whether ambiguity is priced in individual stock returns. In the first stage, to obtain the risk exposures for each firm, we estimate the market beta ($\beta_{i,MKT}$), ambiguity beta ($\beta_{i,AMB}$) and volatility beta ($\beta_{i,VOL}$) from a first-pass time-series regression:

$$R_{i,t} = \alpha_i + \beta_{i,\mathrm{MKT}} \mathrm{MKT}_t + \beta_{i,\mathrm{AMB}} \Delta \mathcal{A}_t + \beta_{i,\mathrm{VOL}} \Delta \mathrm{RV}_t + \varepsilon_{i,t} \tag{3}$$

In the second stage, consistent with the empirical design in Fama and French (1992), we use these estimated betas as independent variables to run cross-sectional regressions for each period. We incorporate standard firm-level characteristics as control variables:

$$R_{i,t} = \alpha_{i,t} + \lambda_{MKT,t} \beta_{i,\mathrm{MKT}} + \lambda_{AMB,t} \beta_{i,\mathrm{AMB}} + \lambda_{VOL,t} \beta_{i,\mathrm{VOL}} + \Gamma_t' \mathbf{F}_{i,t} + \varepsilon_{i,t} \tag{4}$$

where $R_{i,t}$ is the return on stock i at time t. The term $\mathbf{F}_{i,t}$ denotes the firm characteristics included as controls: firm size, book-to-market ratio, and momentum. Table 3 reports the Fama–MacBeth cross-sectional risk premiums. Consistent with our hypothesis (H2), the ambiguity beta carries a negative and highly significant risk premium across individual stocks, confirming that ambiguity is a systematically priced factor.

[4] Detailed procedures for data timing, timestamp conventions, and aggregation rules to ensure precise temporal alignment are provided in the Online Appendix A.3.

[5] To quantify this economic magnitude, a one-standard-deviation increase in the ambiguity shock (SD = 0.27) yields a daily return reduction of 11.3 bps, illustrating its nontrivial pricing impact in high-frequency data.

Table 1
Baseline Time-Series Regression Results.

Variable	CSI 300 returns		
	Risk-Only	Ambiguity-Only	Full model
Risk and Ambiguity Shocks			
$\Delta \mathrm{GPR}_t$	−0.018***	−0.014**	−0.011*
	(0.006)	(0.006)	(0.006)
$\Delta \mathcal{A}_t$		−0.526***	−0.418***
		(0.087)	(0.092)
$\Delta \mathrm{RV}_t$	−0.317***		−0.294***
	(0.068)		(0.074)
Control Variables			
Market Return	0.326***	0.331***	0.319***
	(0.042)	(0.041)	(0.043)
VIX	−0.029**	−0.033***	−0.025*
	(0.012)	(0.011)	(0.013)
Term Spread	0.041*	0.045**	0.038
	(0.023)	(0.022)	(0.024)
Risk-Free Rate	0.018	0.021	0.015
	(0.017)	(0.016)	(0.018)
Constant	0.021	0.024	0.018
	(0.029)	(0.028)	(0.030)
Observations	1458	1458	1458
R-squared	0.428	0.395	0.452
Adjusted R^2	0.423	0.390	0.447

This table presents the baseline time-series regression results of CSI 300 Index returns on geopolitical risk (GPR) shocks, ambiguity shocks, and volatility shocks. Variables: ΔGPR = daily change in Geopolitical Risk index; $\Delta \mathcal{A}$ = daily change in cross-entropy-based ambiguity measure; ΔRV = daily change in realized volatility (5-minute); Market Return = value-weighted A-share market return; VIX = CBOE Volatility Index; Term Spread = 10-year minus 1-year Chinese government bond yield; Risk-Free Rate = 3-month SHIBOR. All returns and spreads are in percentage points. Standard errors are Newey–West HAC robust with 5-day lags (unless otherwise specified) to account for serial correlation up to one trading week; results are qualitatively similar for alternative lag selections. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 2
GPR Shocks and Financial Ambiguity.

Variable	$\Delta \mathcal{A}_t$		
	Full sample	Pre-COVID	COVID Period
$\Delta \mathrm{GPR}_t$	0.004***	0.004**	0.005***
	(0.001)	(0.002)	(0.002)
Control Variables:			
Lagged Ambiguity	−0.128***	−0.115**	−0.139**
	(0.041)	(0.048)	(0.056)
Market Return	−0.087**	−0.092**	−0.083*
	(0.038)	(0.041)	(0.047)
VIX	0.015*	0.012	0.018**
	(0.008)	(0.009)	(0.009)
Term Spread	−0.009	−0.011	−0.007
	(0.014)	(0.016)	(0.018)
Constant	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
Observations	1458	485	973
R-squared	0.186	0.172	0.198
Adjusted R^2	0.183	0.166	0.192

This table shows the impact of GPR shocks on financial ambiguity. The dependent variable is the daily change in our cross-entropy-based ambiguity measure. Control variables include lagged ambiguity, market returns, the VIX, and term spread. Standard errors are Newey–West HAC robust with a 5-day lag.

3.2.3. Mechanism analysis

To evaluate the proposed transmission mechanism (H3), we employ mediation analysis following the seminal approach of Baron and Kenny (1986). The system comprises three equations representing the total effect (5), the mediator model (6), and the direct effect (7):

$$R_t = \alpha + c \cdot \Delta \mathrm{GPR}_t + \gamma' \mathbf{X}_t + \varepsilon_t \tag{5}$$

Table 3
Fama–MacBeth Cross-Sectional Results.

Factor	Risk premiums Full sample	SOEs	Non-SOEs
Market Beta	0.248***	0.221***	0.276***
	(0.042)	(0.053)	(0.049)
Ambiguity Beta	−0.419***	−0.287**	−0.493***
	(0.094)	(0.121)	(0.108)
Volatility Beta	−0.267***	−0.215**	−0.301***
	(0.078)	(0.098)	(0.089)
Size	−0.082**	−0.069*	−0.094**
	(0.036)	(0.041)	(0.042)
Book-to-Market	0.156***	0.142**	0.168***
	(0.048)	(0.059)	(0.055)
Momentum	0.087**	0.094**	0.082*
	(0.039)	(0.046)	(0.045)
Average N (stocks)	2700	923	1777
Average R^2	0.196	0.188	0.203

This table presents Fama–MacBeth risk premiums for various risk factors. Ambiguity beta and volatility beta are estimated from first-pass time-series regressions of individual stock returns on market return, ambiguity shocks, and volatility shocks. Standard errors are Newey–West corrected with 12 lags.

Table 4
Mediation Analysis: GPR, Ambiguity, and Market Returns.

	Total effect (c)	Direct effect (c')	Indirect effect ($a\times b$)	Proportion mediated
Effect on CSI 300 Returns				
Coefficient	−0.0182***	−0.0112*	−0.0070**	38.5%
Bootstrap SE	(0.0063)	(0.0061)	(0.0031)	(0.09)
95% CI	[−0.0306, −0.0058]	[−0.0232, 0.0008]	[−0.0131, −0.0009]	[24.2%, 52.8%]
Step Estimates				
Path a (GPR → Ambiguity)	0.0042***			
	(0.0012)			
Path b (Ambiguity → Returns)	−1.6670***			
	(0.4580)			

This table presents the mediation analysis results examining whether ambiguity transmits the effect of GPR shocks to market returns. The total effect (c) is the impact of GPR on returns, holding the mediator constant. The direct effect (c') is the impact after controlling for ambiguity. The indirect effect is the product of paths a and b. Bootstrap standard errors and 95% confidence intervals are based on 10,000 replications.

$$\Delta\mathcal{A}_t = \alpha + a \cdot \Delta\text{GPR}_t + \theta'\mathbf{Z}_t + \eta_t \tag{6}$$

$$R_t = \alpha + c' \cdot \Delta\text{GPR}_t + b \cdot \Delta\mathcal{A}_t + \gamma'\mathbf{X}_t + \varepsilon_t \tag{7}$$

We measure the indirect effect as the product ab, which accounts for a specific fraction of the total effect (c) of the geopolitical shock. The statistical significance of this relative magnitude is determined through 10,000 bootstrap replications.

The results of our mediation analysis are presented in Table 4. Crucially, the data reveal that a substantial 38.5% of the total effect of geopolitical risk on market returns is mediated through the ambiguity channel. The observed mediation pattern aligns with our causal story through several mechanisms. First, geopolitical news creates model uncertainty as investors reassess their beliefs about return distributions. This is reflected in an increase in cross-entropy divergence. Second, this heightened ambiguity leads to risk premiums as ambiguity-averse investors demand compensation for model uncertainty, resulting in lower contemporaneous returns. The temporal sequence, in which morning GPR news affects midday ambiguity calculations and subsequently influences end-of-day returns, supports this causal pathway.

3.2.4. Moderation analysis

To test H4 regarding the moderating role of SOE status in ambiguity pricing, we extend our cross-sectional analysis by including interaction terms. Specifically, we define an SOE dummy variable, set to 1 for state-owned enterprises[6] and 0 otherwise, to account for ownership-related return heterogeneity. We verify this ownership status using the Wind database classifications and cross-check with government stake announcements.

$$R_{i,t} = \alpha_{i,t} + \lambda_{\text{AMB},t}\,\beta_{i,\text{AMB}} + \lambda_{\text{SOE},t}\,(\beta_{i,\text{AMB}} \times \text{SOE}_i) + \lambda_{\text{MKT},t}\,\beta_{i,\text{MKT}} + \lambda_{\text{VOL},t}\,\beta_{i,\text{VOL}} + \Gamma_t'\mathbf{F}_{i,t} + \varepsilon_{i,t} \tag{8}$$

[6] Consistent with official state-asset regulatory definitions, SOEs are classified as firms in which the state acts as the ultimate controlling shareholder. This classification includes entities where state-affiliated bodies hold more than 50% of direct or indirect equity for absolute control, as well as firms where the state holds 50% or less but remains the largest shareholder and exercises *de facto* control through corporate charters, board resolutions, or shareholder agreements.

Table 5
SOE Status and Ambiguity Pricing: Moderation Analysis.

	Dependent variable: Stock returns		
	(1) Full sample	(2) With interaction	(3) Subsamples
Ambiguity Beta (λ_{AMB})	−0.419*** (0.094)	−0.493*** (0.108)	
Ambiguity ×SOE (λ_{SOE})		0.206*** (0.065)	
SOE Sample			−0.287** (0.121)
Non-SOE Sample			−0.493*** (0.108)
Difference (Non-SOE − SOE)			−0.206*** (0.071)
Control Variables	Yes	Yes	Yes
Observations	352,890	352,890	352,890
Adjusted R^2	0.196	0.201	0.194–0.207

This table presents the moderation analysis results testing whether SOE status affects the pricing of ambiguity. Column (1) shows the baseline effect. Column (2) includes an interaction term between ambiguity beta and SOE status. Column (3) shows separate results for SOE and non-SOE subsamples. All regressions control for market beta, volatility beta, size, book-to-market, and momentum. Standard errors are robust to heteroskedasticity and serial correlation.

A positive and significant coefficient on the interaction term ($\lambda_{\mathrm{SOE},t}$) would support our hypothesis that the negative pricing of ambiguity is weaker for SOEs. To complement this full-sample estimation, we also conduct a subsample analysis by estimating separate regressions for SOE and non-SOE samples and comparing the ambiguity risk premiums across the two groups. Table 5 reports the results of these moderation tests, confirming that the negative impact of ambiguity is significantly attenuated for state-owned enterprises across both empirical specifications.

To contextualize these empirical findings, it is important to understand the economic mechanisms driving this protective buffer. While our empirical analysis focuses on the aggregate moderating effect of the SOE dummy, existing literature suggests that this ambiguity cushion likely operates through three institutional channels. First, explicit government guarantees on debt obligations reduce default uncertainty. Second, policy support during crises, such as targeted lending and tax relief, narrows the distribution of potential outcomes. Third, access to state-controlled financing creates a lower bound on firm value. Consistent with these theoretical mechanisms, evidence from the 2018 liquidity crisis confirms that SOEs benefited from stronger implicit guarantees, resulting in significantly more stable credit spreads and preferential access to liquidity support compared to non-SOEs (Geng and Pan, 2024).

3.2.5. Robustness checks

To ensure the validity of our findings, we conduct a comprehensive battery of robustness checks.[7] These include event studies around major geopolitical episodes, and subsample analyses across Pre-COVID and COVID periods as well as high and low GPR regimes. Finally, we test alternative measures of ambiguity and volatility. Across all these alternative specifications, the negative impact of ambiguity remains consistent and highly significant.

4. Conclusion

This paper analyzes how global Geopolitical Risk (GPR) affects Chinese equity markets, distinguishing between volatility and ambiguity, thereby filling a gap in the existing literature that treats such uncertainty as a monolith. Using a new daily ambiguity measure based on simplified cross-entropy, we identify two key insights. First, ambiguity is a distinct priced factor in China's stock market, driving CSI 300 declines independently of volatility and acting as a critical transmission channel for GPR. Second, the negative pricing of ambiguity is significantly attenuated for SOEs, reflecting the protective effect of implicit state guarantees.

Building upon recent insights that underscore the broad asset-pricing implications of geopolitical shocks, our study demonstrates that these shocks transmit to emerging markets not merely through volatility but through the distinct channel of ambiguity. For policymakers, our results suggest that mitigating geopolitical fallout requires more than standard liquidity provision; it necessitates enhanced institutional transparency and targeted support for non-SOEs to directly alleviate model uncertainty. Future research should extend this cross-entropy-based ambiguity framework to other asset classes and explore how the ambiguity premium fluctuates across different geopolitical regimes, ranging from localized trade disputes to global military conflicts.

[7] Full details and tabulated results for all robustness checks are provided in the Online Appendix A.4.

CRediT authorship contribution statement

He Ni: Visualization, Resources, Formal analysis, Conceptualization. **Xingjian Guo:** Conceptualization, Data curation, Methodology, Software, Writing – original draft, Writing – review & editing. **Weijia Wang:** Investigation, Data curation, Conceptualization. **Jilong Chen:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.frl.2026.110047.

Data availability

Data will be made available on request.

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