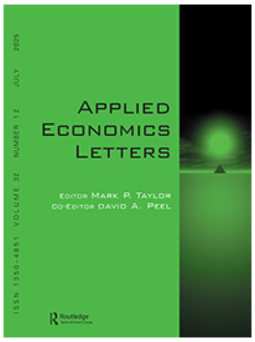

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Geopolitical risk and U.S. stock market volatility: evidence from the U.S.–China Tension Index

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Geopolitical risk and U.S. stock market volatility: evidence from the U.S.–China Tension Index

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ABSTRACT

As the two most influential economies in the world, the U.S. and China have had a profound impact on global capital flows, supply chain stability, and market expectations. Against this backdrop, this study employs the GJR-GARCH-MIDAS model to systematically examine the impact of the U.S.-China Tension Index (UCT) on the daily price volatility of the S&P 500 Index (SPX) and the Nasdaq Composite Index (IXIC). Empirical results show that both markets exhibit significant volatility clustering and asymmetric volatility characteristics, validating the structural features of financial market volatility. More importantly, the positive and negative changes in the UCT have directional effects on long-term price volatility, with increases significantly amplifying long-term volatility and decreases having a mitigating effect. Additionally, out-of-sample forecasting results indicate that the GJR-GARCH-MIDAS model, which incorporates dual asymmetric characteristics, outperforms other models in forecasting performance. Further robustness tests also confirm that models incorporating bidirectional asymmetric shocks exhibit superior forecasting accuracy.

KEYWORDS

U.S.-China tensions; GJR-GARCH-MIDAS; price volatility; asymmetric volatility

JEL CLASSIFICATION

C22; C58; F51; G15; G17

I. Introduction

In recent years, the escalating tensions between the U.S. and China have emerged as a defining feature of the global geopolitical landscape. Trade frictions (Bianconi, Esposito, and Sammon 2021; Yilmazkuday 2025a), technological competition (K. H. Zhang 2024), and the evolution of strategic military postures (Glaser 2015) have continued to exacerbate uncertainty in international financial markets. Given the systemic importance of both countries in the global economic system, fluctuations in their bilateral relations are likely to have far-reaching implications for global economic operations and financial stability.[1]

This study aims to investigate whether the escalation of geopolitical tensions between the U.S. and China has a measurable impact on U.S. stock market volatility. Although previous studies have generally found that geopolitical risks tend to increase market volatility and raise risk premiums (Bloom 2009), systematic empirical tests of the specific impact of bilateral tensions between China and the U.S. remain lacking. The existing literature primarily relies on macroeconomic indicators, such as the Geopolitical Risk Index (GPR) (Caldara and Iacoviello 2022; Yilmazkuday, 2025b) or the Economic Policy Uncertainty Index (EPU) (D. Li, Zhang, and Li 2023)[2] . While these indicators reflect overall risk levels, they struggle to capture the unique characteristics and directional effects of U.S.-China bilateral political conflicts. As competition between the two countries intensifies in key areas such as trade, technology, and capital flows (Egger and Zhu 2020), there is an urgent need to develop more targeted and explanatory measurement tools.

To address this research gap, this paper introduces the U.S.–China Tension Index (UCT) recently proposed by Rogers, Sun, and Sun (2024). The index is based on the Economic Policy Uncertainty (EPU) framework developed by Baker, Bloom, and Davis (2016).[3] It uses text analysis methods to measure the proportion of articles that simultaneously mention both the

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[1]A detailed overview of U.S.–China relations and geopolitical tensions is provided in *Appendix A*, available in the online supplementary material.
[2]A comprehensive literature review is provided in *Appendix B*, available in the online supplementary material.
[3]Data sources and descriptive statistics are provided in *Appendix D*, available in the online supplementary material.

Supplemental data for this article can be accessed online at https://doi.org/10.1080/13504851.2025.2534501

U.S. and China, focus on controversial bilateral issues, and contain keywords such as 'tension'. Compared with traditional GPR and EPU indices, the UCT offers a more bilateral-specific and targeted approach to measuring geopolitical risk.

To assess the specific impact of U.S.-China tensions on U.S. stock market volatility, this paper uses the GJR-GARCH-MIDAS model. This model not only captures the asymmetric effects of volatility but also allows for the organic combination of high-frequency financial market data (daily) and low-frequency macro political information (monthly), thereby decomposing market volatility into short-term dynamics and long-term trends driven by geopolitical shocks. The empirical analysis focuses on the S&P 500 Index (SPX) and the Nasdaq Composite Index (IXIC), which represent the broad-based and technology-intensive sectors of the U.S. stock market, respectively.

The main contributions of this paper are as follows: Firstly, as the first study to systematically examine the impact of UCT on U.S. stock market volatility, this study provides new empirical evidence for the quantitative assessment of bilateral geopolitical risk. Secondly, this study finds that U.S.-China tensions have a directional asymmetric effect on market volatility, which is an increase in UCT significantly exacerbates long-term volatility, but a decrease has a mitigating effect. This result echoes the theoretical view in behavioural finance that investors are more sensitive to negative information. Thirdly, through out-of-sample forecasting tests, the results indicate that the extended bidirectional asymmetric GJR-GARCH-MIDAS model outperforms other model settings in terms of forecasting accuracy, further validating its practical application value in risk management and policy-making.

II. Methodology

This study builds upon the GARCH-MIDAS model proposed by Engle, Ghysels, and Sohn (2013). It incorporates Conrad and Kleen (2020) modelling suggestions to construct the GJR-GARCH-MIDAS model, aiming to characterize the dynamic impact of U.S.-China geopolitical risks on stock market volatility. This model not only integrates mixed-frequency data by incorporating high-frequency daily returns and low-frequency geopolitical indicators into a unified analytical framework, but also effectively captures the asymmetry in volatility prevalent in financial markets, thereby identifying the directional effects of geopolitical shocks. The model is specified as follows[4]

First, based on the GARCH-MIDAS framework, the daily return equation is set as follows:

$$r_{i,t} = \mu + \sqrt{\tau_t * g_{i,t}}\varepsilon_{i,t} \ \forall i = 1, \ldots, N_t \quad (1)$$

Among them, the short-term volatility component $g_{i,t}$ is modelled using the GJR-GARCH(1,1) form to capture the asymmetry of volatility:

$$g_{i,t} = \left(1 - \alpha - \frac{\gamma}{2} - \beta\right) + \left(\alpha + \gamma * I_{\{\varepsilon_{i-1,t} < 0\}}\right)\frac{\varepsilon^2_{i-1,t}}{\tau_t} + \beta g_{i-1,t} \quad (2)$$

The long-term wave component τ_t is modelled using the following logarithmic form:

$$ln\tau_t = m + \theta_{RV}\sum_{k=1}^{K}\varphi_k(w_1, w_2)RV_{t-k} \quad (3)$$

Among them, $\varphi_k(w_2)$ is the Beta weighting function, and after setting $w_1 = 1$, it can be simplified as follows:

$$\varphi_k(w_1, w_2) = \frac{\left(\frac{k}{K}\right)^{w_1-1}\left(1 - \frac{k}{K}\right)^{w_2-1}}{\sum_{j=1}^{K}\left(\frac{j}{K}\right)^{w_1-1}\left(1 - \frac{j}{K}\right)^{w_2-1}} \quad (4)$$

The above formulas (1) to (4) constitute the single-factor GJR-GARCH-MIDAS model, denoted as Model 1.

Based on Model 1, to examine the long-term impact of geopolitical factors, after controlling for historical volatility (RV), the rate of change of the UCT geopolitical index is further introduced to expand the long-term volatility term to:

$$n\tau_t = m + \theta_{RV}\sum_{k=1}^{K}\varphi_k\left(w_{1,RV}, w_{2,RV}\right)RV_{t-k} + \theta_{UCT}\sum_{k=1}^{K}\varphi_k\left(w_{1,UCT}, w_{2,UCT}\right)UCT_{t-k} \quad (5)$$

[4]Detailed model specification is provided in *Appendix C*, available in the online supplementary material.

Combining Equations (1), (2), (5), and (4) yields the two-factor GJR-GARCH-MIDAS model, hereinafter referred to as Model 2.

Furthermore, based on the research by S. Li, Chen, and Chen (2025), the impact of UCT on long-term volatility is decomposed into positive shocks ($UCT^{+}_{\boldsymbol{t-k}} = \sum_{j=1}^{N} UCT_{t-k} I_{\{UCT_{t-k}>0\}}$) and negative shocks ($UCT^{-}_{\boldsymbol{t-k}} = \sum_{j=1}^{N'} UCT_{t-k} I_{\{UCT_{t-k}<0\}}$), to identify the heterogeneous effects of geopolitical risks in different directions on market volatility.

Accordingly, the long-term volatility term is further expanded to:

$$\begin{aligned} ln\tau_t = m &+ \theta_{RV} \sum_{k=1}^{K} \varphi_k(w_{1,RV}, w_{2,RV}) RV_{t-k} \\ &+ \theta^{+}_{UCT} \sum_{k=1}^{K} \varphi_k\left(w^{+}_{1,UCT}, w^{+}_{2,UCT}\right) UCT^{+}_{t-k} \\ &+ \theta^{-}_{UCT} \sum_{k=1}^{K} \varphi_k\left(w^{-}_{1,UCT}, w^{-}_{2,UCT}\right) UCT^{-}_{t-k} \end{aligned} \tag{6}$$

Finally, the two-factor asymmetric GJR-GARCH-MIDAS model is constructed by combining Equations (1), (2), (6), and (4), and is denoted as Model 3.

III. Empirical results

In-sample estimation results analysis

Table 1 reports the estimated parameters of all in-sample models. First, regarding the parameters that capture short-term volatility dynamics, the results satisfy the conditions $\alpha > 0; \beta \geq 0$, and $\alpha + \beta + \frac{\gamma}{2} < 1$, indicating significant volatility clustering in the SPX and IXIC markets.

Second, concerning the γ parameter that tests for asymmetric market effects, all estimates are significantly positive, further supporting the widely established conclusion that stock markets exhibit asymmetric volatility responses.

The analysis then examines the impact of exogenous variables on long-term market volatility, with a focus on the coefficient θ. Empirical results show

Table 1. In-sample estimation results for the model.

	SPX			IXIC		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
μ	0.029***	0.029***	0.030***	0.050***	0.050***	0.048***
	(0.010)	(0.010)	(0.010)	(0.013)	(0.013)	(0.013)
α	2E−06	2E−06	2E−06	0.002	0.002	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
β	0.846***	0.846***	0.837***	0.841***	0.842***	0.831***
	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.012)
γ	0.224***	0.224***	0.223***	0.198***	0.198***	0.206***
	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.014)
m	−0.334***	−0.338***	−1.364***	−0.168**	−0.165**	−1.430***
	(0.074)	(0.075)	(0.138)	(0.061)	(0.063)	(0.128)
θ_{RV}	0.017***	0.014***	0.011***	0.013***	0.013***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
θ_{UCT}		0.013			−0.006	
		(0.030)			(0.013)	
θ_{UCT^+}			0.003**			0.005***
			(0.002)			(0.002)
θ_{UCT^-}			−0.004**			−0.005***
			(0.001)			(0.001)
$w_{2,RV}$	6.167***	6.119***	7.500***	5.837***	5.831***	1.000***
	(0.775)	(0.808)	(0.156)	(0.664)	(0.709)	(0.223)
$w_{2,UCT}$		1.000			10.074	
		(0.342)			(23.296)	
w_{2,UCT^+}			1.000***			1.000***
			(0.333)			(0.223)
w_{2,UCT^-}			1.316***			1.146***
			(0.390)			(0.256)
LLH	−9696.886	−9696.826	−9677.922	−11487.658	−11487.113	−11454.887
BIC	19455.815	19473.420	19453.339	23037.358	23053.994	23007.269

This table reports the parameter estimates of all the factor models. LLH is the log-likelihood function and BIC indicates the Bayesian information criterion. The numbers in parentheses are the standard errors. ***, **, and * denote respectively the significance levels at 1%, 5%, and 10%.

Table 2. MCS test results.

1000 days	MSE T_R	MSE T_{max}	MAE T_R	MAE T_{max}	R^2LOG T_R	R^2LOG T_{max}
SPX						
Model 1	**0.312**	**0.225**	**0.253**	**0.239**	**0.121**	**0.363**
Model 2	**0.312**	**0.265**	**0.294**	**0.294**	**0.695**	**0.695**
Model 3	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
IXIC						
Model 1	**0.415**	**0.212**	**0.290**	**0.129**	**0.426**	**0.214**
Model 2	**0.415**	**0.225**	**0.290**	**0.126**	**0.426**	**0.295**
Model 3	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

The numbers in the table are p-values. Numbers greater than 0.10 are in bold and underlined, indicating that the corresponding model performs significantly better in the model set. The time horizon is 1000 days.

that increases in realized volatility significantly raise long-term volatility. However, after controlling for the effect of realized volatility, the overall impact of the UCT on long-term volatility is statistically insignificant.

When the UCT is further decomposed into positive changes (UCT^+) and negative changes (UCT^-), the results reveal directional heterogeneity in their effects on long-term volatility: the estimated coefficient θ_{UCT^+} is significantly positive, indicating that rising UCT amplifies long-term market volatility; in contrast, θ_{UCT^-} is significantly negative, suggesting that declining UCT contributes to a dampening effect on long-term volatility.

This asymmetry can be attributed to the market's nonlinear response to uncertainty. When uncertainty rises, investors demand higher risk premiums, leading to asset repricing and heightened volatility (Pástor and Veronesi 2013). Conversely, market adjustments tend to be slower when uncertainty declines due to 'risk memory' and behavioural inertia (Bloom 2009). Moreover, behavioural finance theory suggests that investors respond more strongly to negative information, intensifying volatility increases (Kumar and Lee 2006).

Out-of-sample forecast analysis

The out-of-sample predictive ability of volatility models cannot be ignored. Therefore, to systematically evaluate the out-of-sample forecasting performance of multiple models, the MCS test method proposed by Hansen, Lunde, and Nason (2011) has been widely applied. This method is based on a prediction loss function and, under a specified confidence level ($p = 0.1$), progressively excludes statistically inferior models to construct a confidence set containing models with 'no significant inferiority', thereby enhancing the robustness and reliability of model evaluation. Table 2 presents the MCS test results with a 1,000-day out-of-sample interval. It can be observed that the extended double asymmetric model 3 performs best in both markets. This demonstrates the superior out-of-sample forecasting capability of the extended model.

IV. Robustness checks

Given that out-of-sample prediction performance may be highly sensitive to the setting of the prediction interval, it is necessary to redefine the out-of-sample interval and conduct a re-evaluation to ensure the robustness of the assessment results. Based on this consideration, this study adjusted the out-of-sample forecast interval to 500 days and re-examined the model's out-of-sample forecasting ability. As shown in Table 3, consistent with the results obtained when the forecast interval was set to 1,000 days, Model 3 demonstrated excellent forecasting ability in out-of-sample forecasting. This finding reinforces the validity and necessity of our model.

Table 3. MCS test results.

500 days	MSE T_R	MSE T_{max}	MAE T_R	MAE T_{max}	R^2LOG T_R	R^2LOG T_{max}
SPX						
Model 1	**0.486**	**0.240**	0.055	0.027	0.000	0.000
Model 2	**0.654**	**0.654**	0.055	0.051	0.001	0.001
Model 3	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
IXIC						
Model 1	**0.199**	**0.403**	0.001	0.000	0.000	0.000
Model 2	**0.895**	**0.865**	0.001	0.000	0.000	0.000
Model 3	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

The numbers in the table are p-values. Numbers greater than 0.10 are in bold and underlined, indicating that the corresponding model performs significantly better in the model set. The time horizon is 500 days.

V. Conclusions and implements

Conclusions

This study employs the GJR-GARCH-MIDAS model to investigate the impact of the UCT on the prices of two representative U.S. stock indices. The results show that both the SPX and IXIC markets exhibit significant volatility clustering and symmetric volatility characteristics. In terms of long-term volatility, the realized volatility significantly enhances the market's long-term volatility level. Additionally, changes in the UCT have a directional impact on long-term volatility; an increase in the UCT significantly amplifies long-term volatility. In contrast, a decrease has a mitigating effect. This reveals that the market has an asymmetric response mechanism to uncertain information. Finally, MCS tests indicate that the extended double-asymmetric model demonstrates optimal predictive performance in both the SPX and IXIC markets. Further robustness tests also validate this conclusion.

Discussion

The asymmetric impact of UCT directional changes on long-term stock market volatility highlights a pronounced structural response bias in financial markets when confronted with geopolitical risks. From an economic standpoint, this asymmetry reflects both behavioural heterogeneity and rational constraints in the transmission of risk information. Specifically, an increase in UCT typically signals heightened future uncertainty, prompting a rise in risk premiums, greater demand for liquidity, and the repricing of assets (Y. Zhang et al. 2023). This process often triggers herd-like risk-averse behaviour, amplifying price volatility and undermining market stability (He 2023).

Conversely, although a decline in UCT is theoretically expected to stabilize markets, its volatility-mitigating effects tend to materialize with a lag. This delay can be attributed to bounded rationality Yao and Li (2013) and information rigidity (Coibion and Gorodnichenko 2015) – core concepts in behavioural economics. Investors generally react more promptly and strongly to negative information, while exhibiting inertia or hesitation in response to positive signals, consistent with well-documented phenomena such as loss aversion (Kahneman and Tversky 1979) and the phenomenon of sticky expectations. Moreover, the process of restoring confidence, recalibrating risk perceptions, and rebalancing portfolios during periods of easing geopolitical tension requires time, contributing to persistent volatility and delayed information absorption (Ormos and Timotity 2016).

This asymmetrical response mechanism not only corroborates behavioural finance theories of risk perception bias but also aligns with the 'time-asymmetric risk premium' hypothesis in modern financial economics. Together, these insights deepen our understanding of how geopolitical shocks influence financial market dynamics through the channels of expectation formation, risk pricing, and asset allocation, offering both theoretical contributions and practical implications for market participants and policymakers.

Implications

These findings provide valuable insights for both investment strategy and the design of regulatory policy. For investors, heightened geopolitical tensions – reflected in rising UCT – necessitate greater flexibility in asset allocation and the dynamic management of tail risks, particularly during periods of elevated uncertainty. While easing tensions may temporarily suppress volatility, the risk of 'false stability' calls for caution. Overly optimistic expectations during such periods can lead to misallocation of assets and the emergence of new market risks. From a regulatory perspective, it is crucial to enhance the capacity to detect and respond to the transmission of geopolitical shocks. In the face of rising UCT, regulators should proactively deploy macroprudential tools – such as countercyclical capital buffers, leverage constraints, and stress testing – to curb the build-up of systemic risks. Moreover, the development of cross-market risk monitoring and coordination mechanisms is essential for achieving timely, information-driven, and integrated financial oversight. Finally, addressing behavioural biases in market sentiment formation is vital. Strengthening information disclosure and investor education can help mitigate overreactions to negative shocks, thereby reducing excessive volatility and limiting its spillover effects on the real economy.

Shortcomings and perspectives

This study has certain limitations. Because the UCT used in this study is constructed based on mainstream U.S. media texts, there may be narrative bias and a lack of cross-cultural objectivity. This single perspective may lead to bias in characterizing market volatility reactions. Future research may consider constructing a parallel index based on Chinese media to reveal the heterogeneity of market reactions from different cognitive perspectives, thereby enhancing the robustness and explanatory power of the conclusions.

Author contributions

CRediT: **Shun Li:** Data curation, Methodology, Writing – original draft; **Yang Liu:** Data curation, Validation, Writing – review & editing.

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Availability of data and materials

The data presented in this study are available on request from the corresponding author.

References

Baker, S. R., N. Bloom, and S. J. Davis. 2016. "Measuring Economic Policy Uncertainty*." *The Quarterly Journal of Economics* 131 (4): 1593–1636. https://doi.org/10.1093/qje/qjw024.

Bianconi, M., F. Esposito, and M. Sammon. 2021. "Trade Policy Uncertainty and Stock Returns." *Journal of International Money and Finance* 119:102492. https://doi.org/10.1016/j.jimonfin.2021.102492.

Bloom, N. 2009. "The Impact of Uncertainty Shocks." *Econometrica* 77 (3): 623–685. https://doi.org/10.3982/ECTA6248.

Caldara, D., and M. Iacoviello. 2022. "Measuring Geopolitical Risk." *American Economic Review* 112 (4): 1194–1225. https://doi.org/10.1257/aer.20191823.

Coibion, O., and Y. Gorodnichenko. 2015. "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts." *American Economic Review* 105 (8): 2644–2678. https://doi.org/10.1257/aer.20110306.

Conrad, C., and O. Kleen. 2020. "Two are Better Than One: Volatility Forecasting Using Multiplicative Component garch-Midas Models." *Journal of Applied Econometrics* 35 (1): 19–45. https://doi.org/10.1002/jae.2742.

Egger, P. H., and J. Zhu. 2020. "The U.S.–Chinese Trade War: An Event Study of Stock-Market Responses." *Economic Policy* 35 (103): 519–559. https://doi.org/10.1093/epolic/eiaa016.

Engle, R. F., E. Ghysels, and B. Sohn. 2013. "Stock Market Volatility and Macroeconomic Fundamentals." *The Review of Economics and Statistics* 95 (3): 776–797. https://doi.org/10.1162/REST_a_00300.

Glaser, C. L. 2015. "A U.S.-China Grand Bargain? The Hard Choice Between Military Competition and Accommodation." *International Security* 39 (4): 49–90. https://doi.org/10.1162/ISEC_a_00199.

Hansen, P. R., A. Lunde, and J. M. Nason. 2011. "The Model Confidence Set." *Econometrica* 79 (2): 453–497. http://www.jstor.org/stable/41057463.

He, Z. 2023. "Geopolitical Risks and Investor Sentiment: Causality and TVP-VAR Analysis." *The North American Journal of Economics and Finance* 67:101947. https://doi.org/10.1016/j.najef.2023.101947.

Kahneman, D., and A. Tversky. 1979. "Prospect Theory: An Analysis of Decision Under Risk." *Econometrica* 47 (2): 263–291. https://doi.org/10.2307/1914185.

Kumar, A., and C. M. C. Lee. 2006. "Retail Investor Sentiment and Return Comovements." *The Journal of Finance* 61 (5): 2451–2486. https://doi.org/10.1111/j.1540-6261.2006.01063.x.

Li, D., L. Zhang, and L. Li. 2023. "Forecasting Stock Volatility with Economic Policy Uncertainty: A Smooth Transition Garch-Midas Model." *International Review of Financial Analysis* 88:102708. https://doi.org/10.1016/j.irfa.2023.102708.

Li, S., H. Chen, and G. Chen. 2025. "The U.S.-China Tension and Fossil Fuel Energy Price Volatility Relationship." *Finance Research Letters* 74:106707. https://doi.org/10.1016/j.frl.2024.106707.

Ormos, M., and D. Timotity. 2016. "Unravelling the Asymmetric Volatility Puzzle: A Novel Explanation of Volatility Through Anchoring." *Economic Systems* 40 (3): 345–354. https://doi.org/10.1016/j.ecosys.2015.09.008.

Pástor, Ľ., and P. Veronesi. 2013. “Political Uncertainty and Risk Premia.” *Journal of Financial Economics* 110 (3): 520–545. https://doi.org/10.1016/j.jfineco.2013.08.007.

Rogers, J. H., B. Sun, and T. Sun. 2024. “U.S.-China Tension.” *Available at SSRN 4815838*. https://doi.org/10.2139/ssrn.4815838.

Yao, J., and D. Li. 2013. “Bounded Rationality as a Source of Loss Aversion and Optimism: A Study of Psychological Adaptation Under Incomplete Information.” *Journal of Economic Dynamics and Control* 37 (1): 18–31. https://doi.org/10.1016/j.jedc.2012.07.002.

Yilmazkuday, H. 2025a. “U.S. Tariffs and Stock Prices.” *Finance Research Letters* 83:107708. https://doi.org/10.1016/j.frl.2025.107708.

Yilmazkuday, H. 2025b. “Geopolitical Risks and Cryptocurrency Returns.” *Review of Financial Economics* 43 (2): 166–191. https://doi.org/10.1002/rfe.1223.

Zhang, K. H. 2024. “Geoeconomics of us-China Tech Rivalry and Industrial Policy.” *Asia and the Global Economy* 4 (2): 100098. https://doi.org/10.1016/j.aglobe.2024.100098.

Zhang, Y., J. He, M. He, and S. Li. 2023. “Geopolitical Risk and Stock Market Volatility: A Global Perspective.” *Finance Research Letters* 53:103620. https://doi.org/10.1016/j.frl.2022.103620.