Geopolitical Risk and Stock Returns

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Abstract

This paper systematically examines the relationship between geopolitical risk and stock returns by constructing a comprehensive Geopolitical Risk Index (GRI) using *Wall Street Journal* articles from 1984 to 2025. GRI positively predicts excess market returns in the US and globally, in and out of sample, beyond other leading risk factors. The effects of geopolitical risk have intensified since 2000. The GRI captures trade wars, a previously overlooked dimension. The trade war component adds incremental predictive power. Cross-sectionally, stocks with higher geopolitical risk exposure earn higher abnormal returns. Overall, our findings underscore the importance of geopolitical risk in asset pricing.

JEL classification: G11, G14, G23.

Keywords: Geopolitical risk, political risk, trade wars, stock returns, uncertainty

1 Introduction

Geopolitical risk has surged to unprecedented levels in recent years, driven by conflicts such as the Russia–Ukraine war, the Israel–Hamas war, and escalating trade tensions between the United States and key global partners, including Canada, China, Europe, and Mexico. Existing research has established that such risks significantly affect economic fundamentals, including firm investments (Caldara and Iacoviello, 2022) and cross-border mergers and acquisitions (Chen, Naranjo, and Tang, 2024). In addition to its real economic effects, anecdotal evidence suggests that geopolitical risk also influences financial markets, leading to increased volatility and risk-averse behaviors among investors in response to unfolding geopolitical events.[1] Despite growing attention, the empirical relationship between geopolitical risk and asset prices remains underexplored, leaving an important gap in the literature.

In this paper, we systematically examine the relationship between geopolitical risk and stock returns. We construct a Geopolitical Risk Index (GRI) using textual data from *Wall Street Journal* (WSJ) articles spanning from January 1984 to April 2025. Specifically, we develop a comprehensive dictionary for geopolitical risk, building on Caldara and Iacoviello (2022) to systematically identify and classify relevant events. Importantly, our GRI measure incorporates trade wars, which is an essential yet previously overlooked dimension of geopolitical risk in existing studies. Our expanded dictionary captures various forms of geopolitical risk, such as military conflicts, diplomatic tensions, and trade disputes.

To construct the GRI, we first identify geopolitical news articles that contain the relevant keywords from our expanded dictionary. The inclusion of trade-war-related terms results in a 33% increase in identified geopolitical news articles, underscoring the significance of trade-related geopolitical tensions in our sample period. We then calculate the GRI as the ratio of geopolitical news articles to the total number of news articles published in a given month. Given the distinct importance of trade wars, we also construct a separate Trade War Index (TWI) alongside the GRI.

[1] For example, "Stock Fall as Tariff Fears Ripple Through Economy," *Wall Street Journal* March 4, 2025. According to a survey by JP Morgan, at the end of 2023, geopolitical risk was the No. 1 potential investment risk that investors worried about, topping potential recession, higher interest rates, and U.S. elections.

Figure 1 visualizes the GRI from January 1984 to April 2025. GRI effectively captures major geopolitical risk events, such as the Gulf War, the 9/11 attacks, and the onset of the Iraq War. More recently, the GRI rose sharply during the Russian invasion of Ukraine in February 2022 and the onset of the Israel–Hamas War in October 2023. Additionally, the GRI reflects critical trade-related tensions, such as the trade dispute between the United States and Japan in the 1990s, the 2018 US–China trade war, and the ongoing trade tensions between the U.S. and its major trade partners started in February 2025.

Why does geopolitical risk matter for asset pricing? Geopolitical risk creates uncertainty about future economic conditions, foreshadowing lower investment and employment, and is associated with higher disaster probability (Caldara and Iacoviello, 2022). According to Merton (1973)'s intertemporal asset pricing model, investors adjust their portfolios to hedge against future risks affecting their investment opportunities. Furthermore, Liu, Pan, and Wang (2005) and Barro (2006) show that rare economic disasters are a priced risk factor. Both the intertemporal hedging and the rare disaster aversion motivate investors to reduce demand for risky assets such as stocks during geopolitical crises, leading to lower asset valuations and higher expected returns. Cross-sectionally, stocks with high returns when geopolitical risk is high serve as a hedge against geopolitical risk, in which case investors would require a lower risk premium to hold those stocks.

Complementing these risk-based explanations, behavioral theories offer an alternative perspective on how geopolitical risk may influence asset prices. According to prospect theory (Tversky and Kahneman, 1992), investors overweight low-probability events. Given that geopolitical shocks are typically rare and dramatic, investors may overreact to geopolitical news, leading to contemporaneous price depression and subsequent reversal.

Thus, both rational and behavioral theories suggest that geopolitical risk can influence asset pricing. To empirically test this hypothesis, we first examine whether geopolitical risk predicts aggregate U.S. stock market returns. Our GRI strongly and positively predicts future market returns. The predictability is both statistically significant and economically meaningful. In the one-month-ahead return prediction test, we find that a one-standard-deviation increase in GRI is associated with an 8.71% increase in annualized excess returns for the following month, with significance at the 1% level. Moreover, this predictive relationship persists across longer horizons, ranging from 3 to 12 months, suggesting that geopolitical uncertainty represents a non-diversifiable risk that earns a risk premium. The effect of GRI on the U.S. stock market is much stronger during the later sample period of 2000-2025. A one-standard-deviation increase in GRI is associated with a 13.21% increase in annualized excess returns for the following month, suggesting that investors are increasingly concerned about geopolitical risks in recent years.

The return predictability of GRI differs from many existing risk measures. We examine whether GRI retains its predictive power after accounting for various economic factors that have been documented as stock return predictors. These include traditional variables such as valuation ratios, inflation, and interest rates, as well as alternative measures of uncertainty and risk, including economic policy uncertainty from Baker, Bloom, and Davis (2016), news-implied volatility from Manela and Moreira (2017), and war-related risks from Hirshleifer, Mai, and Pukthuanthong (2025a,b). The results show that GRI remains a strong and statistically significant predictor of future stock market returns beyond the existing factors. Also, its predictive power persists even in models that include multiple economic predictors, suggesting that the information captured by GRI is distinct from traditional economic variables. These findings underscore the unique informational content of geopolitical risks in shaping investor expectations and asset pricing.

To gauge GRI's real-time predictability, we examine its out-of-sample performance. In a monthly test, the out-of-sample R^2 is 2.48% over the sample period of 1991-2025 and increases to 2.88% during 2000-2025, both significant at the 1% level. In contrast, the out-of-sample R^2 of the Geopolitical Risk (GPR) index from Caldara and Iacoviello (2022) is only 0.005%. The predictability of the GRI is substantial. As a benchmark, Goyal and Welch (2008) find that only 3 out of the 18 commonly known equity premium predictors have positive out-of-sample R^2. More recently, Goyal, Welch, and Zafirov (2024) examine more than 40 well-known predictors and find an average out-of-sample R^2 of -1.01%. Thus, the performance of out-of-sample R^2 further reinforces the strong return predictability of the GRI.

Taking a step further, we explore the channels through which geopolitical risk influences stock returns through two sets of evidence. First, we examine how innovations in geopolitical risk are related to contemporaneous market returns. If higher geopolitical risk commands a greater risk premium, we would expect a negative contemporaneous correlation between unexpected changes in GRI and returns. Consistent with this hypothesis, we find that increases in geopolitical risk are associated with significant declines in contemporaneous returns.

Second, we investigate whether geopolitical risk is incorporated into prices overnight or during trading hours. Building on the notion that retail investors tend to trade near the market open, while institutional investors prefer to trade near the market close (Lou, Polk, and Skouras, 2019, 2024), examining overnight versus intraday returns allows us to assess the effects of different investor clienteles on asset prices. We find that the negative contemporaneous relationship between geopolitical risk and return is driven entirely by intraday returns. Furthermore, 70% of the one-month return predictability stems from intraday activity. These results suggest that institutional investors' demand shifts in response to changing geopolitical risk are likely a key mechanism through which such risk is incorporated into asset prices.

After establishing that geopolitical risk is priced in the aggregate market return, we then examine whether GRI is priced in the cross-section of stock returns. To avoid the look-ahead bias, we follow the approach of Hirshleifer, Mai, and Pukthuanthong (2025b) by constructing a geopolitical risk factor (GRI^{res}) as the innovation from an AR(1) process estimated for GRI with an expanding window of at least 12 months starting on January 1985. To assess the pricing of geopolitical risk, we examine the performance of portfolios sorted by a stock's rolling beta on GRI^{res}. The results show that stocks with higher exposure to geopolitical risk earn significantly higher abnormal returns. The High-Low portfolio, which captures the return differential between stocks with the highest and lowest geopolitical risk exposure, delivers a value-weighted Fama-French six-factor alpha of 4.45% (annualized) over the subsequent month. These findings suggest that geopolitical risk carries a systematic risk premium in the cross-section of stock returns.

One key innovation of our paper is that we incorporate trade war into the geopolitical risk. Understanding the economic implications of trade protectionism is essential, as theoretical predictions remain ambiguous. Arguments in favor of protectionist policies emphasize mechanisms such as infant-industry support (Hamilton, 1791), anti-dumping motives (Ethier, 1982), and the enhancement of supply-chain resilience (Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2021). Conversely, classical and modern trade theories highlight the costs of protectionism, including the principle of comparative advantage (Ricardo, 1817), the gains from trade (Samuelson, 1939, 1962), scale-economy efficiencies in open markets (Krugman, 1980), rent-seeking distortions (Krueger, 1974), and the risk of retaliatory responses (Bagwell and Staiger, 1999). In this paper, we assess the aggregate economic effects of the trade war by examining stock-market reactions as a forward-looking measure of expected economic impact.

We show that the trade war component of the GRI has independent return forecasting power beyond the traditional geopolitical risk index. Our TWI positively predicts aggregate stock market returns. The effect is economically meaningful: a one-standard-deviation increase in TWI is associated with a 4.42% increase in annualized excess returns in the following month. This magnitude is comparable to that of traditional geopolitical measures such as GPR. Cross-sectionally, TWI also exhibits strong return predictability. A long-short portfolio strategy that longs high trade-war exposure stocks and shorts low exposure ones yields an annualized alpha of 4.43% in the subsequent month.

Finally, we expand our analysis to the international setting. Given that geopolitical events have global impacts beyond the U.S., we also examine whether GRI predicts international stock market returns, using data from major international indices such as the UK FTSE market index, MSCI global market index, and Dow Jones World Index excluding the US. We find that GRI positively predicts international stock market returns, with stronger effects in recent years. The magnitude of this predictability is high during the sample period of 2000-2025; a one-standard-deviation increase in GRI is associated with an increase in the annualized excess return of 7.97% to 11.06%. These findings highlight the growing impact of geopolitical risks on global stock markets.

This paper makes three important contributions to the finance and economics literature. First, it is related to the literature on political economics and finance. Prior studies show that political forces are important for the economy and financial markets, including political cycles (Santa-Clara and Valkanov, 2003), political uncertainty (Pástor and Veronesi, 2012, 2013), political beliefs (Meeuwis, Parker, Schoar, and Simester, 2022), president approval rating (Chen, Da, Huang, and Wang, 2023), firm-level political risk (Hassan et al., 2019), fiscal uncertainty (Croce, Nguyen, and Schmid, 2012), and political polarization (Sheng, Sun, and Wang, 2024; Wu and Zechner, 2024). A new literature on geopolitical risk is growing. Clayton, Maggiori, and Schreger (2025a,b,c) provide seminal theoretical foundations for modeling geopolitical forces. Hirshleifer, Mai, and Pukthuanthong (2025a) and Hirshleifer, Mai, and Pukthuanthong (2025b) show that war is related to stock market returns and disaster concerns. Engle and Campos-Martins (2020) use a statistical model for the magnitude of the common volatility shocks to measure geopolitical risk. Caldara and Iacoviello (2022) construct novel measures of geopolitical threats and acts based on news articles from 10 sources and study their implications for real economic activities. Clayton, Coppola, Maggiori, and Schreger (2025) propose a new measure of geoeconomic pressure from firm earnings conference call transcripts and sell-side research reports, emphasizing the distinct effects of geopolitical threats versus actions on firm behavior. Our paper is one of the first empirical studies that examine the return predictive power of geopolitical risk. We find that geopolitical risk has incremental return forecasting power beyond other leading risk measures.

Our paper is related to a contemporaneous study by Goncalves, Melone, and Ricciardi (2025), who utilize the widely adopted geopolitical risk measures from Caldara and Iacoviello (2022) to examine how geopolitical threats versus acts influence cross-sectional and time-varying risk premia. In contrast, our paper makes two substantive and distinct contributions. First, we construct a broader and more comprehensive measure of geopolitical risk that explicitly incorporates trade wars, a critical yet previously overlooked dimension of geopolitical uncertainty. Our GRI demonstrates superior predictive performance, both in-sample and out-of-sample, compared to the geopolitical risk measure from Caldara and Iacoviello (2022). In addition, we go beyond documenting return predictability by providing novel insights into the economic mechanisms through which geopolitical risk affects asset prices, thereby offering a deeper understanding of its role in asset pricing.

Second, our study contributes to the vast literature on forecasting the equity premium.[2] Early papers find that aggregate stock market returns can be predicted by past valuation ratios (Campbell and Shiller, 1988a,b; Fama and French, 1988; Kothari and Shanken, 1997). However, Goyal and Welch (2008) find many of the valuation ratios have poor out-of-sample forecasting performance. More recently, Goyal, Welch, and Zafirov (2024) conduct a more comprehensive analysis of 46 existing return predictors for equity premium and continue to find poor out-of-sample performance for over half of the predictors. Several papers emphasize the importance of using proper econometric techniques and measures when forecasting aggregate market returns (Stambaugh, 1999; Lewellen, 2004; Kostakis, Magdalinos, and Stamatogiannis, 2015; Lou, Polk, and Skouras, 2024). Our paper carefully addresses the econometric issues by employing various econometric techniques and shows that geopolitical risk has robust return predictive power for future market returns. The return predictability is not only strong in sample but, more importantly, strong out of sample.

Finally, this paper contributes to the growing field of big data and textual analysis in finance by developing a new measure for geopolitical risks based on news articles. Previous studies have used textual analysis to capture sentiment (Tetlock, 2007; Jha, Liu, and Manela, 2025), partisanship (Kelly, Manela, and Moreira, 2021), long-run risk (Liu and Matthies, 2022), macroeconomic attention (Fisher, Martineau, and Sheng, 2022), climate risk (Hong, Li, and Xu, 2019; Li, Shan, Tang, and Yao, 2024), business cycles (Bybee, Kelly,

[2]The literature on forecasting the equity premium is extensive, including impacting work such as Campbell and Cochrane (1999), Lettau and Ludvigson (2001), Lustig and Van Nieuwerburgh (2005), Cochrane (2011).

Manela, and Xiu, 2024), and industry classification (Hoberg and Phillips, 2016, 2018).[3] By applying textual analysis to geopolitical risk, this study provides a timely and novel measure of geopolitical uncertainty (including trade wars) and shows its implications for asset pricing.[4]

2 Data and Measure

2.1 Data

This paper utilizes a comprehensive dataset to construct and analyze geopolitical risk measures. The primary source of news data is the *Wall Street Journal*, which is particularly relevant for stock markets and investors due to its extensive coverage of financial and geopolitical events. This news data source is well-accepted in the finance literature (e.g., Manela and Moreira, 2017; Fisher, Martineau, and Sheng, 2022). The sample period spans from January 1, 1984, to April 7, 2025, providing a long-term perspective on geopolitical risk trends. Our sample period captures the most recent years, enabling the analysis to capture timely geopolitical events, such as the ongoing Russia-Ukraine war, the Israel-Hamas war, and trade wars. Stock returns and related financial data are obtained from CRSP. We also collect various predictors of the aggregate stock market from the database used in Goyal and Welch (2008) and Goyal, Welch, and Zafirov (2024).

In addition to newly constructed geopolitical risk measures, this study incorporates several existing indices for comparison, including the Geopolitical Risk (GPR) Index from Caldara and Iacoviello (2022), the Economic Policy Uncertainty (EPU) Index from Baker, Bloom, and Davis (2016), the WAR Index from Hirshleifer, Mai, and Pukthuanthong (2025a),

[3] For reviews, see Goldstein and Yang (2017), Goldstein, Spatt, and Ye (2021, 2024), and Hoberg and Manela (2025).

[4] More generally, this paper contributes to the broader finance theory literature by emphasizing the role of information in stock markets. Building on foundational work on information and market efficiency (Grossman and Stiglitz, 1980) and the role of disclosure and information diversity (Goldstein and Yang, 2015, 2019), this study demonstrates how news-based information can be used to capture important risks that affect financial markets.

and the News Implied Volatility Index (NVIX) from Manela and Moreira (2017). Since the recent GPR index starts in January 1985, most of our tests use a sample period from January 1985. By integrating these diverse data sources, the paper provides a comprehensive examination of geopolitical risk and its implications for financial markets. Our findings demonstrate that the GRI and TWI are distinct from existing measures, highlighting their unique contributions to the literature.

2.2 Measuring Geopolitical Risk

To construct the Geopolitical Risk Index (GRI), we employ a dictionary-based method, which involves developing a targeted set of keywords and identifying relevant news articles based on these terms. This method is well-established in the finance and economics literature (e.g., Fisher, Martineau, and Sheng, 2022; Caldara and Iacoviello, 2022), and is particularly suitable when the specific focus of the text analysis is well-defined, as in this study. Alternative approaches, such as supervised or unsupervised machine learning methods, are less applicable in our context, as their outcomes tend to be noisy without well-curated training datasets.[5]

We develop the dictionary of geopolitical risk based on Caldara and Iacoviello (2022), which captures the threat, realization, and escalation of adverse events associated with wars, terrorism, and political tensions that disrupt international relations. While their dictionary provides a solid foundation, it has a notable limitation: it does not account for trade wars, which have played a significant role in global economic instability. Trade disputes, such as those between the United States and Japan from 1992 to 1995 and the more recent conflicts involving the United States, China, Canada, Mexico, and Europe since 2018, have become critical sources of geopolitical uncertainty. To address this gap, we expand the dictionary of geopolitical risk to include terms related to trade wars explicitly as another key dimension, capturing both traditional threats and the evolving landscape of economic conflicts.

[5] See Gentzkow, Kelly, and Taddy (2019) for a detailed discussion of various text analysis methods and Caldara and Iacoviello (2022) for further justification of the dictionary-based approach.

To construct the Trade War Index (TWI), we draw directly on existing research in trade policy and textual analysis. Our keyword design is guided by prior studies that identify core terminology used in trade conflicts, tariff actions, retaliatory measures, and trade negotiations. In particular, Ossa (2014) highlights the central role of tariffs, trade disputes, and negotiation breakdowns in measuring trade wars using empirical trade-policy data. In parallel, Amstad, Gambacorta, He, and Xia (2021) develop a text-based measure of trade sentiment and show that terms related to tariffs, sanctions, trade tensions, and policy negotiations systematically capture shifts in trade-policy uncertainty.

Motivated by this literature, we construct the TWI using a Factiva query that links major U.S. trading partners (e.g., China, Canada, Mexico, Japan, Europe) with trade-war-related terms such as tariff, import, export, sanction, agreement, dispute, negotiation, tension, retaliation, and breakdown. This approach ensures that our keyword list is firmly grounded in established economic research rather than ad hoc construction, and allows the TWI to capture the key linguistic dimensions emphasized in prior work on trade policy and trade conflicts. The list of keywords is presented in the Internet Appendix. This expanded word list allows us to systematically capture news coverage of trade-related geopolitical tensions and incorporate them into our GRI, ensuring a more comprehensive measure of geopolitical uncertainty.

In sum, our approach introduces two key innovations, compared to existing measures. We expand the word list to include terms related to trade wars, ensuring that this crucial aspect of geopolitical risk is captured. Additionally, instead of using multiple news sources, we focus exclusively on the *Wall Street Journal*, as it is the most relevant source for financial markets and investor sentiment. This refined approach allows us to develop a more targeted and finance-relevant measure of geopolitical risk, and as demonstrated by our empirical results, has yielded a measure with substantially stronger predictive power. We present a few news articles that contain the keywords in the Internet Appendix.

3 Geopolitical Risk Index (GRI)

In this section, we introduce our Geopolitical Risk Index (GRI) and Trade War Index (TWI), providing a detailed examination of their properties both numerically and graphically. We first present summary statistics to highlight key characteristics of each index, including their distributions, trends over time, and periods of heightened geopolitical or trade-related tensions. Additionally, we visualize their historical movements to illustrate how they respond to major geopolitical and trade conflict events. By comparing the GRI and TWI, we demonstrate their distinct yet complementary roles in capturing different aspects of geopolitical risk, with the GRI focusing on broader geopolitical tensions and the TWI specifically tracking trade-related disputes. These analyses help understand the evolution of geopolitical risk over time and its implications for financial markets.

3.1 GRI and TWI: Measure and Summary Statistics

To construct the GRI, we follow a systematic two-step approach. First, we identify news articles that contain the relevant keywords from our expanded dictionary. This process yields a total of 68,410 articles that mention geopolitical risks. Second, we compute the GRI by dividing the number of articles containing these keywords by the total number of news articles published in a given month. This method ensures that the index captures the relative intensity of geopolitical risk discussions over time. The formula for the GRI is:

$$GRI_t = \frac{\text{Number of news articles with keywords in month } t}{\text{Total number of news articles in month } t} \tag{1}$$

To make the measure more interpretable, we normalize the index so that its mean equals 100. Additionally, we construct a related measure to complement the GRI: Trade War Index (TWI), which applies a similar methodology but is based on our newly developed trade war-related dictionary. This measure identifies 16,963 articles, which is 33% more than the existing geopolitical risk measure, highlighting the importance of trade-related geopolitical tensions in recent years.

Table 1 presents the summary statistics for GRI, TWI, and related measures. The GRI exhibits a high standard deviation, indicating significant variability in geopolitical risk over time. This suggests that geopolitical tensions fluctuate considerably, reflecting periods of heightened uncertainty driven by major global events. The mean and standard deviation of GRI are comparable to those of GPR, reinforcing the idea that both indices capture similar overall patterns of geopolitical risk, albeit with key differences in their composition.

In contrast, the TWI has a higher standard deviation than both the GRI and GPR, which is consistent with the nature of trade war events. Unlike broader geopolitical risks, trade conflicts tend to arise sporadically and escalate rapidly, leading to sharp variations in the index. This greater volatility in TWI highlights the episodic nature of trade-related geopolitical risks, where periods of relative stability are punctuated by sudden escalations in trade disputes. These differences underscore the value of separately tracking geopolitical risks and trade-related risks, as they exhibit distinct temporal patterns and potential market implications.

We also examine the correlations among these indices to better understand their relationships. The GRI is moderately correlated with the GPR, with a correlation coefficient of 0.56. Given the overlap in the geopolitical risks captured by both indices, this correlation is expected. However, the fact that it is far from a perfect correlation suggests that GRI and GPR, while related, are distinct in important ways, likely due to differences in methodology and scope. In contrast, GRI exhibits only a weak correlation with the EPU, the WAR, and NVIX indices, suggesting that geopolitical risk, as captured by GRI, is largely distinct from measures of policy uncertainty, actual military conflict and market volatility.

For TWI, its correlation with GRI is moderate, reflecting the fact that trade conflicts are an important but separate aspect of geopolitical risk. However, its correlations with WAR and NVIX are low, highlighting that trade war events are generally independent of direct military conflicts and financial market volatility. These correlation patterns underscore the importance of separately analyzing different dimensions of geopolitical risk to capture their unique characteristics and implications.

3.2 Historical Movements of GRI and TWI: Graphical Evidence

Once we obtain the monthly GRI data from January 1984 to April 2025, we visualize it in Figure 1. The GRI effectively captures major geopolitical risk events, with distinct spikes corresponding to significant global conflicts. The first major surge occurs in August 1990, aligning with the Gulf War in the Middle East. The second spike follows the 9/11 attacks, with another sharp increase around the onset of the Iraq War. More recently, the GRI rises sharply during the Russian invasion of Ukraine in February 2022 and again in October 2023, when Hamas launched a large-scale attack on Israel, triggering the Israel- Hamas War.

Among all these spikes, the highest GRI value is observed during the Russia- Ukraine war, which aligns with the intuition that this was the first large-scale invasion in Europe since World War II. These geopolitical shocks had profound implications for global markets, trade, and economic stability, reinforcing the importance of tracking geopolitical risks over time.

Additionally, the GRI reflects critical trade-related tensions, such as the U.S.-Japan auto trade dispute in the 1990s and the 2018 U.S.-China trade war. Since our sample covers the most recent period in 2025, it also captures the ongoing trade war between the U.S. and its major trade partners, including Canada, China, Europe, and Mexico, which escalated sharply since February 2025. The latter event highlights the increasing role of economic conflicts in shaping geopolitical risks, a dimension that traditional measures such as GPR may not fully capture.

Given the growing significance of trade wars, we construct a separate index, the Trade War Index, to specifically track trade-related geopolitical risks, as shown in Figure 2. The TWI effectively captures key trade disputes and economic conflicts, highlighting periods of heightened tensions.

This index not only reflects the major trade-related events mentioned above but also identifies other significant developments. For instance, the TWI spikes around the year 2000 amid tensions over whether China should be admitted to the World Trade Organization (WTO). Another surge occurs in 2017 following the U.S. withdrawal from the Trans-Pacific

Partnership (TPP), signaling a shift in trade policy. Among these spikes, the U.S.-China trade war in 2018 registers the highest TWI value, which is consistent with the notion that this event marked the beginning of a broader wave of anti-globalization sentiment.

We also plot GRI, TWI, and GRP together in Figure 3. While the GRI comoves with the GRP index, the two measures exhibit meaningful differences. In particular, the GPR primarily captures geopolitical tensions and military conflicts, whereas the GRI incorporates a wider scope, including trade wars and economic disputes. This distinction is crucial, as trade-related geopolitical risks have become increasingly prominent in recent years, influencing global supply chains, market volatility, and investment decisions. By differentiating between these dimensions, the GRI and TWI together provide a more comprehensive view of geopolitical risks and their impact on financial markets.

4 Geopolitical Risk and Aggregate Stock Returns

Our primary research question investigates whether geopolitical risk influences the stock market. In this section, we analyze this relationship through the lens of the aggregate stock market. The underlying hypothesis is that if geopolitical risk is systemically important and cannot be diversified away, it should have predictive power over aggregate stock market returns. Conversely, if this risk is fully diversifiable, we would not expect it to have a significant impact on market returns.

4.1 Predicting future market returns

To examine the predictive power of geopolitical risk on financial markets, we regress future excess market returns on the GRI:

$$R^e_{t+1\to t+n} = \alpha + \beta \mathrm{GRI}_t + \epsilon_{t+1}, \tag{2}$$

where $R^e_{t+1\to t+n}$ is the excessive return of the market from month $t+1$ to month $t+n$ (expressed as annualized percentage) and GRI_t is the geopolitical risk index in month t (standardized to zero mean and unit variance). To correct for the endogeneity bias in predictive regressions with persistent regressors, and to address the moving average structure in error terms in long-horizon return predictions, we use the instrument variable (IVX) method of Kostakis, Magdalinos, and Stamatogiannis (2015).[6] Given the unusually high volatility in the stock market during the COVID-19 pandemic, we exclude the period from 2020 to 2022 to ensure that our analysis is not unduly influenced by this exceptional event.

Table 2 presents the results. For the full sample period from 1985 to 2025, we find strong evidence that geopolitical risk positively predicts future market returns. The predictability is statistically significant and economically large. For the test that predicts 1-month-ahead returns, we find a one-standard-deviation increase in the GRI is associated with an 8.71% increase in annualized excess returns in the next month, significant at the 1% level. Establishing long-run predictability using robust methods that address OLS biases is challenging.[7] However, GRI's predictability still extends to the 12-month horizon, where a one-standard-deviation increase predicts a statistically significant 0.52% increase in annualized excess returns.

We also examine the period of 2000-2025 separately as it may be most relevant for future applications (Goyal and Welch, 2008), given the structural changes in information dissemination through widespread internet access and digital media. Additionally, this period encompasses several major geopolitical events, including the 9/11 terrorist attacks, the Iraq War, the Russian annexation of Crimea, the Russian invasion of Ukraine, the Israel-Hamas War, and escalating global trade tensions. The predictive power of GRI is substantially stronger in this more recent subsample (2000-2025). In this period, a one-standard-deviation increase in GRI predicts a 13.21% increase in next-month annualized excess returns (Panel B Column 1). The effect remains economically and statistically significant across all horizons. This is

[6]In Table IA1 in the Internet Appendix, we provide OLS regression with Newey-West standard errors for comparison.

[7]See Valkanov (2003), Boudoukh, Richardson, and Whitelaw (2006), and Kostakis, Magdalinos, and Stamatogiannis (2015)

economically substantial, especially considering that the average annualized monthly excess stock market return over this period is 6.51%.

In comparison, the GPR from Caldara and Iacoviello (2022) has much weaker predictability. As shown in Table IA2 in the Internet Appendix, GPR shows only marginal significance for 1-month-ahead predictions and no significance at longer horizons. The difference in performance underscores the enhanced predictive content gained by incorporating trade war dimensions and utilizing the *Wall Street Journal* as the source text for constructing a market-relevant geopolitical risk index.

Overall, these results indicate that geopolitical risks play a significant role in the U.S. aggregate stock market and positively predict future market returns across various investment horizons and sample periods. Notably, the predictability is particularly strong in the more recent period (2000-2025), highlighting the growing relevance of geopolitical risks for investors.

4.2 Comparison with other predictors

In this section, we examine whether GRI retains its predictive power when controlling for various economic factors documented as stock return predictors in the literature. We consider traditional predictors including the dividend-price ratio (DP), earnings-price ratio (EP), dividend payout ratio (DE), inflation (INFL), and the Treasury bill rate (TBL) from Goyal and Welch (2008). We also control for alternative measures of uncertainty and risk, including Economic Policy Uncertainty (EPU) from Baker, Bloom, and Davis (2016), Geopolitical Risk (GPR) from Caldara and Iacoviello (2022), the War Index (WAR) from Hirshleifer, Mai, and Pukthuanthong (2025a), and News Implied Volatility (NVIX) from Manela and Moreira (2017).

Table 3 presents the results.[8] For the full sample period (1985-2025) shown in Panel A, GRI remains statistically significant at the 1% level across all bivariate specifications, with coefficients ranging from 7.51 to 11.89. Importantly, even in the comprehensive specification

[8]See Table IA3 for the OLS results.

that includes multiple economic predictors (column 10), GRI maintains statistical significance at the 1% level with a coefficient of 11.89. This suggests that the information content in GRI is not subsumed by these traditional economic variables.

The results are even stronger in the more recent period (2000-2025) presented in Panel B. GRI exhibits larger coefficients across all specifications (ranging from 9.54 to 14.98) and maintains statistical significance at the 1% level throughout. The adjusted R^2 values are also notably higher in this period, reaching 10.81% in column 10. This further supports our earlier finding that the predictive power of geopolitical risk has strengthened in recent decades. Collectively, these results demonstrate that GRI captures unique information about future stock returns that is distinct from what is contained in traditional economic predictors and other uncertainty measures.

4.3 Out-of-sample R^2

To assess the real-time performance of GRI as a predictor of market returns, we conduct out-of-sample tests following the methodology of Campbell and Thompson (2007). This approach addresses potential concerns about in-sample overfitting and provides a more realistic evaluation of predictive performance for investors. Specifically, we compute the out-of-sample R^2 statistic (R^2_{OS}) as:

$$R^2_{OS} = 1 - \frac{\sum_{t=p}^{T-1}\left(R^e_{t+1} - \hat{R}^e_{t+1}\right)^2}{\sum_{t=p}^{T-1}\left(R^e_{t+1} - \bar{R}^e_{t+1}\right)^2}, \tag{3}$$

where R^e_{t+1} is the realized excess market return, $\hat{R}^e_{t+1}$ is the predicted excess return using information available only up to time t, $\bar{R}^e_{t+1}$ is the historical mean excess return computed over the training window, and p is the size of the initial training window. We employ an expanding estimation window to incorporate all available information into formulating future forecasts. Positive values of R^2_{OS} indicate that the predictor outperforms the historical mean benchmark. We test the statistical significance of R^2_{OS} using the Clark and West (2007) MSPE-adjusted statistic.

Table 4 presents the out-of-sample R^2 statistics for our geopolitical risk measure (GRI) alongside other economic predictors. The results are striking: GRI delivers impressive out-of-sample performance with an R^2_{OS} of 2.476% for the 1995-2025 evaluation period and 2.882% for the 2000-2025 period, both significant at the 1% level. This performance substantially exceeds that of traditional predictors such as the dividend-price ratio (DP), dividend yield (DY), and earnings-price ratio (EP), which generally show negative R^2_{OS} values.

Among alternative risk and uncertainty measures, GPR shows positive but more modest out-of-sample performance (0.843% for 2000-2025), while EPU generates negative R^2_{OS} values. Similarly, the dividend-price ratio (DP) and dividend yield (DY) only produce positive R^2_{OS} values (1.064% and 1.196%, respectively) in the 2000-2025 period. The strong out-of-sample performance of GRI is particularly notable given the documented challenges in achieving positive out-of-sample R^2 values for return predictors in the literature (Goyal and Welch, 2008; Goyal, Welch, and Zafirov, 2024).

4.4 Mechanism: Evidence from Intraday and Overnight Returns

In this section, we examine the mechanism for return predictability of geopolitical risk. We provide two sets of evidence. First, we examine the contemporaneous relationship between innovations in geopolitical risk and market returns. If GRI is associated with higher risk premiums, we would expect a negative contemporaneous correlation of innovations with returns.

Since GRI is highly persistent (with an AR(1) coefficient of 0.79), we follow Hirshleifer, Mai, and Pukthuanthong (2025a) to focus on GRI innovations rather than levels. We compute GRI innovations (GRI_t^{res}) as the residuals from an AR(1) process estimated with an expanding window of at least 12 months starting from January 1985. We then run the following contemporaneous regression:

$$R_t^e = \alpha + \beta \text{GRI}_t^{res} + \gamma z_t + \epsilon_t, \tag{4}$$

where R_t^e is the market excess return in month t and z_t includes various control variables. The coefficient β captures the immediate market reaction to geopolitical risk news.

Table 5 reports the results. Over the full sample period (1986-2025), the coefficient on GRI_t^{res} is -7.24 and statistically significant at the 1% level. This indicates that, on average, a one-standard-deviation increase in unexpected geopolitical risk index is associated with 7.24% lower in annualized contemporaneous returns. This negative contemporaneous relationship is robust to controlling for the innovations of other uncertainty measures (GPR^{res}, EPU^{res}, WAR^{res}, NVIX^{res}) and traditional economic predictors (DP, EP, INFL, TBL).

The negative contemporaneous relationship is even stronger in the more recent period (2000-2025), with a coefficient of -9.30 in the baseline specification. This suggests that markets react more strongly to geopolitical shocks in recent decades, possibly due to increased global integration and faster information diffusion.

Next, we shed light on whether the negative contemporaneous relation between geopolitical risk and stock prices is more likely due to the risk-based hypothesis or the overreaction hypothesis. Relatively speaking, retail investors are more likely to be affected by behavioral biases; therefore, by separately examining the effect of institutional investors and retail investors, we can draw inferences about the relative importance of the behavioral versus risk channel. Building on the notion that retail investors tend to trade near the market open, while institutional investors prefer to trade near the market close (Lou, Polk, and Skouras, 2019, 2024), we examine whether the relationship between geopolitical risk and returns is driven by intraday or overnight returns.

We follow Lou, Polk, and Skouras (2019) to decompose monthly returns into intraday and overnight components. As shown in Panel A of Table 6, we find that the contemporaneous relationship between GRI and market returns is entirely driven by the intraday component. In the full sample period, a one-standard-deviation increase in GRI^{res} is associated with a -7.24% annualized contemporaneous monthly return, of which -6.79% is attributed to intraday returns and only -0.25% to overnight returns. Similar patterns hold in the more recent sample period.

Panel B of Table 6 reveals a consistent pattern for the predictive relationship between geopolitical risk and returns, with the intraday component accounting for the majority of the effect—67% in the full sample and 73% in the recent period. In the full sample period, a one-standard-deviation increase in GRI predicts a 5.80% rise in intraday returns and a 2.66% rise in overnight returns (t-statistic = 38.63). These results suggest that institutional investors' demand shifts in response to changing geopolitical risk are likely a key mechanism through which geopolitical risk is priced.

5 Geopolitical Risk and Cross Section of Stock Returns

After examining the relationship between geopolitical risk and aggregate stock market returns, we now turn to its implications for the cross-section of stock returns. We follow the approach of Hirshleifer, Mai, and Pukthuanthong (2025b) by constructing a geopolitical risk factor (GRI^{res}) as the innovation from an AR(1) process estimated for GRI with an expanding window of at least 12 months starting on January 1985. This approach avoids the look-ahead bias and uses only the data up to month t. We focus on common stocks listed on NYSE, AMEX, and NASDAQ, excluding financial services firms and penny stocks (those with prices below $1). The cross-sectional analysis ends in December 2024 due to data availability constraints in CRSP for firm-level stock returns.

To calculate return sensitivity to GRI^{res}, for each stock, we run the following regression using a rolling window of 60 months:

$$R^e_{i,t} = \alpha_i + \beta^{GRI}(-\text{GRI}^{res}_t) + \boldsymbol{\beta^z z_t} + \epsilon_t, \tag{5}$$

where $R^e_{i,t}$ is the annualized excess return of stock i in month t. $-\text{GRI}^{res}_t$ is the negative of GRI^{res} in month t, so that higher beta indicates greater exposure to geopolitical risk. $\boldsymbol{z_t}$ includes the six factors from Fama and French (2015): market risk (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (MOM) factors.

Table 7 presents the performance of portfolios sorted based on their exposure to geopolitical risk. Using NYSE breakpoints, we form quintile portfolios each month by sorting stocks on their estimated β^{GRI} using a 60-month rolling window. Portfolio 1 (Low) contains stocks with the lowest sensitivity to negative GRI^{res}, while Portfolio 5 (High) contains those with the highest sensitivity. Portfolio returns are annualized.

The results for the full sample period (1991-2025) show that both low and high GRI^{res} beta portfolios earn positive and statistically significant returns. The value-weighted low-beta portfolio (Portfolio 1) earns an average (annualized) monthly return of 7.80% (t-statistic = 2.68), while the high-beta portfolio (Portfolio 10) earns 10.09% (t-statistic = 2.89), resulting in a High-Low spread of 2.28% that is statistically insignificant. However, the value-weighted High-Low alpha is 3.93% and statistically significant (t-statistics = 1.72).

When focusing on the more recent period (2000-2025), the pattern strengthens considerably. The value-weighted High-Low spread increases to 4.75% with a t-statistic of 2.04. After adjusting for factors from the Fama-French six-factor model, the value-weighted alpha rises to 5.76% (t-statistic = 2.37).

To ensure that our cross-sectional results are not driven by small stocks, we also conduct Fama-MacBeth regressions as shown in Table IA4 of the Internet Appendix. The results reveal that the positive relationship between GRI exposure and future returns is particularly strong among large stocks. For the full sample period (1991-2025), the coefficient on β^{GRI} is 2.05% (t-statistic = 2.64) for large stocks but insignificant for small stocks. In the more recent period (2000-2025), both large and small stocks exhibit significant positive coefficients, with values of 2.40% (t-statistic = 2.36) and 1.63% (t-statistic = 2.04), respectively. This indicates that the pricing of geopolitical risk is not a small-stock phenomenon but rather a market-wide effect, with large stocks actually showing stronger sensitivity to GRI exposure.

Overall, these results suggest that stocks with higher exposure to geopolitical risk command higher expected returns, particularly in recent decades when geopolitical tensions have been especially salient for investors. This phenomenon is more pronounced among large stocks.

6 Trade Wars and Stock Returns

Given the importance of trade wars, we examine the relationship between trade wars and stock market returns in this section. We first test whether the trade war index (TWI) predicts aggregate market returns, followed by an analysis of cross-section of stock returns.

6.1 TWI and Market Returns

We first test whether TWI predicts aggregate stock market returns by running the following predictive regression:

$$R^e_{t+1} = \alpha + \beta \mathrm{TWI}_t + \gamma z_t + \epsilon_{t+1}, \tag{6}$$

where R^e_{t+1} is the excessive return of the market in month $t+1$ (expressed as annualized percentage), TWI_t is the Trade War Index in month t (standardized), and z_t represents other control factors included in specific regressions. Regressions are estimated using the IVX methodology of Kostakis, Magdalinos, and Stamatogiannis (2015).

Table 8 reports the results.[9] For the full sample period from 1985 to 2025, we find strong evidence that geopolitical risk positively predicts future market returns. The predictability is statistically significant and economically large. For the test that predicts 1-month-ahead returns, we find a one-standard-deviation increase in GRI is associated with a 4.42% increase in annualized excess returns in the next month, significant at the 10% level. Such a magnitude rises to 7.55% in the more recent sample period (2000-2025), significant at the 1% level.

This predictability is robust to controlling various variables. Again, we include the dividend-price ratio (DP), earnings-price ratio (EP), dividend payout ratio (DE), inflation (INFL), and the Treasury bill rate (TBL), as well as Economic Policy Uncertainty (EPU), Geopolitical Risk (GPR), and the War Index (WAR).[10] For the full sample period (1985-

[9] See Table IA5 for the OLS results.

[10] For the test of TWI, it is important to include the sample after 2018, which is a period that trade wars raised a concern again. Thus, we do not compare it with the News Implied Volatility (NVIX), which ends in 2016.

2025) shown in Panel A, TWI remains significant across all bivariate specifications, with coefficients ranging from 4.42% to 5.72%. Results from the more recent sample period are even stronger. This suggests that the information content in TWI is not subsumed by these traditional economic variables.

In addition, we examine the contemporaneous relationship between innovations in trade war risk and market returns. If innovations in TWI are associated with higher risk premiums, we would expect a negative contemporaneous correlation of innovations with returns. Specifically, we run the following regression:

$$R_t^e = \alpha + \beta \mathrm{TWI}_t^{res} + \gamma z_t + \epsilon_t,$$

where R_t^e is the excessive return of the market in month t (expressed as annualized percentage), TWI_t^{res} is the AR(1) residual of the Trade War Index (TWI) estimated with an expanding window, and z_t is one of the economic factors. GPR_t^{res}, EPU_t^{res}, and WAR_t^{res} are AR(1) residuals calculated in a similar way.

Table IA6 reports the results of this test. Over the full sample period (1986-2025), the coefficient on TWI_t^{res} is -3.9 and statistically significant at the 10% level. This result is no longer significant after controlling for the innovations of other uncertainty measures (EPU^{res}, WAR^{res}, NVIX^{res}) and traditional economic predictors (DP, EP, INFL, TBL). This outcome is reasonable, given the relatively small number of trade war events over the full sample period. Most trade war episodes are concentrated in the post-2018 period, limiting their explanatory power in the earlier decades. As a result, the trade war signal is likely diluted when averaged across the entire sample.

For trade wars, it is important to focus on the more recent sample period (2000 to 2025). Panel B shows that TWI is negatively related to same-period market returns. Column (1) shows the coefficient on TWI_t^{res} is -6.85 and statistically significant at the 1% level. This indicates that, on average, a one-standard-deviation increase in unexpected trade war risk is associated with a 6.85 percentage point decrease in annualized contemporaneous returns.

This negative contemporaneous relationship is robust to controlling for the innovations of other uncertainty measures (GPR^{res}, EPU^{res}, WAR^{res}, NVIX^{res}) and traditional economic predictors (DP, EP, INFL, TBL).

6.2 TWI and Cross-section of Stock Returns

Building on our cross-sectional analysis of GRI, we investigate whether trade war risk is also priced in the cross-section of stocks. Following the same methodology, we construct trade war risk factor (TWI^{res}) based on AR(1) innovations and estimate stock-level betas with respect to negative TWI^{res} using a 60-month rolling window, controlling for the Fama-French six factors.

Table 9 presents the performance of portfolios sorted on their TWI betas. For the full sample period (1991-2024), the value-weighted High-Low portfolio earns a Fama-French six-factor alpha of 4.43% per year (t-statistic = 2.35). In the more recent period (2000-2024), when trade wars became more prevalent, the High-Low alpha increases to 6.00% (t-statistic = 2.48).

Our results confirm that trade war risk carries a distinct risk premium in the cross-section of stock returns, beyond that of broader geopolitical risk. Investors require significant compensation for holding stocks with higher exposure to trade tensions, especially in recent years as global trade conflicts have intensified.

7 Additional Analyses

7.1 Predicting international stock market returns

We also investigate whether the GRI predicts international stock market returns, given that most geopolitical events have global implications. To test this, we collect four international market indices from Global Financial Data: the UK FTSE Index, MSCI World Index, Dow Jones World Index (excluding the U.S.), and FTA Index (excluding the U.S.).

Table 10 presents the results for both the full sample and a more recent period (2000-2025) using the IVX method from Kostakis, Magdalinos, and Stamatogiannis (2015).[11] In general, we find that GRI positively predicts international stock market returns, with stronger effects in the recent sample. The magnitude of this predictability is slightly smaller than that observed in the U.S. stock market but still quite substantial. For instance, in the MSCI World Index from 2000 to 2025 (Column 2 in Panel B), a one-standard-deviation increase in the GRI is associated with a 11.06% increase in annualized excess returns in the following month, with statistical significance at the 1% level. Overall, these findings suggest that geopolitical risks play a crucial role in shaping global equity premiums, particularly over the past 25 years.

7.2 Industry Heterogeneity

While the aggregate analysis reveals a significant risk premium associated with geopolitical risk (GRI), its impact likely varies across different sectors of the economy due to heterogeneous exposures to global events, trade flows, and political sensitivities. To quantify this heterogeneity, we regress Fama-French 48 industry excess returns on contemporaneous GRI^{res} and on the lagged GRI, following the regression specifications in Tables 5 and 2. We present the industry results in Table 11.

Contemporaneously, there are only two industries that exhibit positive sensitivity: Guns and Gold, although only Guns is statistically significant. All other 46 industries exhibit negative sensitivity. The impact is particularly large for certain sectors: a one-standard-deviation increase in GRI^{res} is associated with statistically significant drops in contemporaneous annualized returns of 14.46% for Toys, 13.79% for Fabricated Products (FabPr), 13.17% for Automobiles and Trucks (Autos), 12.71% for Tobacco Products (Smoke), 12.30% for Aerospace (Aero), and 11.36% for Electrical Equipment (ElcEq), among others. Many of these sectors are closely tied to global manufacturing, consumer demand, and international trade, suggesting their vulnerability to the disruptions associated with heightened geopolitical risk. These

[11] See Table IA7 for the OLS results.

patterns are even more pronounced in the later sample period (2000-2025, Panel B), where the magnitudes of the negative betas for industries like Toys, Chips, and Autos increase considerably.

Predictive regressions also shows significant heterogeneity across industries. A one-standard-deviation increase in GRI predicts notably higher subsequent monthly returns for technology-related and equipment industries. For instance, such an increase predicts subsequent returns to rise by 15.66% for Semiconductors (Chips), 12.46% for Computer (Comps), 11.54% for Measuring and Control Equipment (LabEq), and 11.45% for Electrical Equipment (ElcEq). This suggests these sectors may be perceived as highly vulnerable to geopolitical risk. In contrast, there are only 9 industries where GRI predicts lower future returns. The Coal industry stands out with a large and statistically significant negative predicted response: a one-standard-deviation increase in GRI predicts a 17.12% drop in next month. Other industries like Gold (−8.22%), Oil (−4.77%), and Ships (−3.29%) also show negative predicted return sensitivities, although mostly statistically insignificant in the full sample. The results for the 2000-2025 period (Panel B) generally reinforce these patterns.[12]

In conclusion, these findings demonstrate substantial industry heterogeneity in response to our GRI. Sectors tied to global trade and manufacturing showing strong negative contemporaneous reactions and positive future return dynamics following GRI shocks. However, nearly all industries react negatively contemporaneously, and the vast majority react positively in the next month. This widespread directional alignment, despite differing magnitudes, underscores that GRI captures a systematic risk factor priced across the economy.

8 Conclusion

This paper provides a comprehensive analysis of the relationship between geopolitical risk and stock market returns. By constructing a novel Geopolitical Risk Index (GRI) using textual analysis of *Wall Street Journal* archives, we document that geopolitical risk is a

[12] We also report the industry heterogeneity results using TWI in Table IA8 in the Internet Appendix.

significant and persistent factor influencing asset prices.

Our analysis reveals that GRI positively predicts future market returns, reinforcing the idea that geopolitical uncertainty is a non-diversifiable risk that commands a risk premium. The predictability remains statistically and economically significant, persisting across various investment horizons and not being subsumed by traditional risk measures such as valuation ratios, interest rates, and economic policy uncertainty. These results highlight the unique informational content of geopolitical risk in shaping investor expectations and market dynamics.

Beyond its impact on aggregate stock returns, we also examine whether geopolitical risk is priced in the cross-section of stock returns. We find that stocks with greater exposure to geopolitical risk earn higher abnormal returns. This result is consistent with the notion that investors demand compensation for holding stocks sensitive to geopolitical shocks. The return premium remains significant even after controlling for traditional risk factors, suggesting that geopolitical risk is a distinct source of systematic risk in financial markets.

Extending our analysis to international markets, we find that geopolitical risk affects global asset prices in a manner consistent with its impact on the U.S. market. The predictability of stock returns based on GRI is particularly pronounced in recent decades, suggesting that geopolitical instability has become increasingly relevant for investors worldwide.

One of the novel contributions of our study is highlighting the role of trade war risk as a distinct and influential dimension of geopolitical uncertainty. By isolating the trade war component, we uncover its unique ability to forecast both market-wide and cross-sectional stock returns, independent of traditional geopolitical risk indices. Our evidence points to trade tensions as a meaningful driver of investor expectations and pricing dynamics, particularly in periods of heightened global economic friction.

Our findings have important implications for investors, policymakers, and future research. For investors, understanding how geopolitical risk is priced can help in designing risk management strategies and asset allocation models that incorporate geopolitical uncertainty. For policymakers, the study highlights the financial market consequences of geopolitical instability, reinforcing the need for transparency and stability in international relations. Future research could explore the interaction between geopolitical risk and bond and currency markets.

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Figure 1: Geopolitical Risk Index 1984-2025

This figure plots the monthly Geopolitical Risk Index (GRI) from January 1984 to April 2025. The GRI is based on news articles from the Wall Street Journal and defined as in Equation (1).

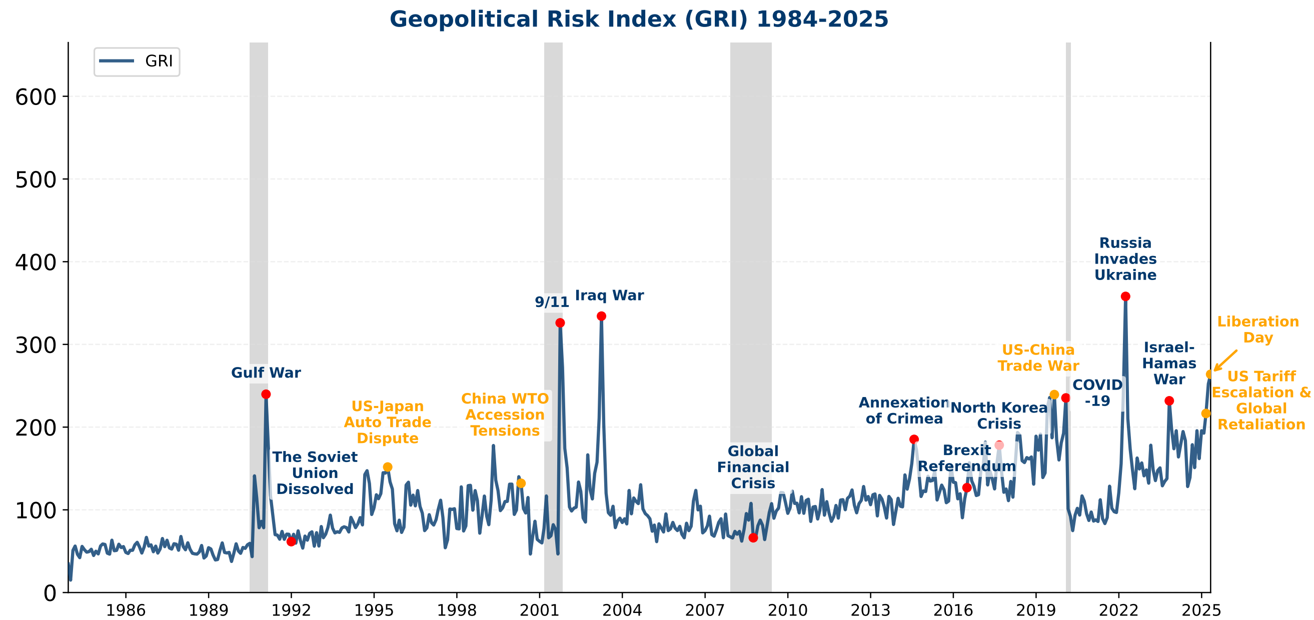

Figure 2: Trade War Index 1984-2025

This figure plots the monthly Trade War Index (TWI) from January 1984 to April 2025. TWI is based on news articles from the Wall Street Journal and defined in a similar method as in Equation (1).

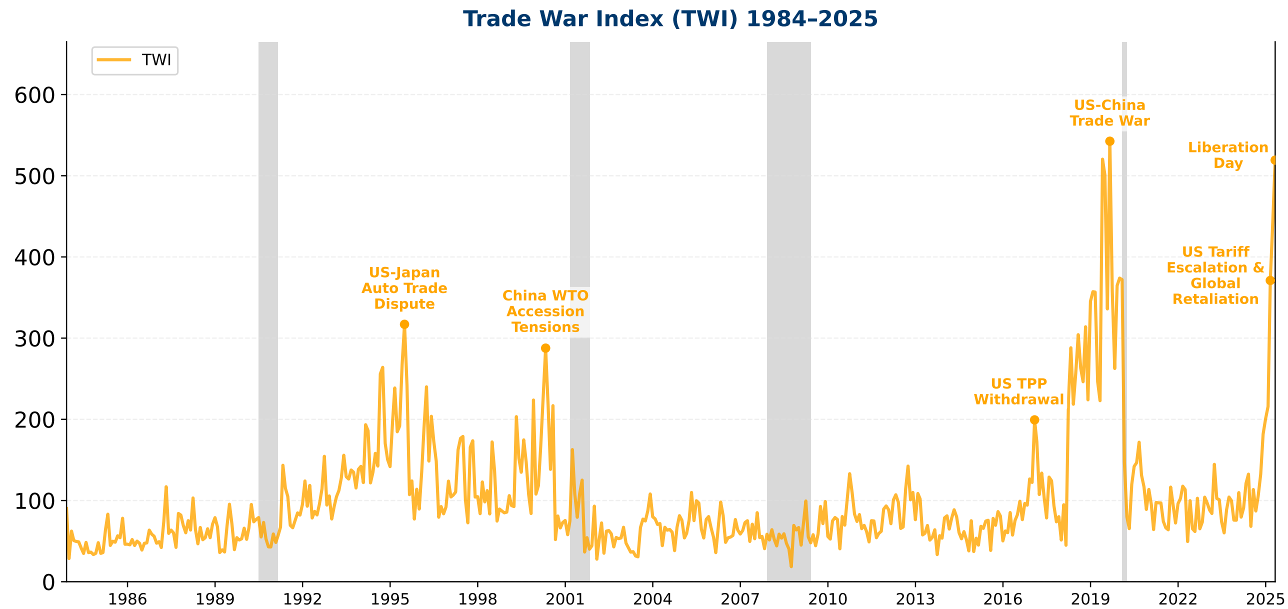

Figure 3: Geopolitical Rish Index, Trade War Index, and GPR 1985-2025

This figure plots monthly indexes from January 1985 to April 2025: GRI, TWI, and GPR. GRI is the geopolitical risk index. TWI is the trade war index. Both GRI and TWI are based on news articles from the Wall Street Journal and defined in Equation (1). GPR is Caldara and Iacoviello (2022)'s measure of geopolitical risk. The recent GPR data starts from 1985.

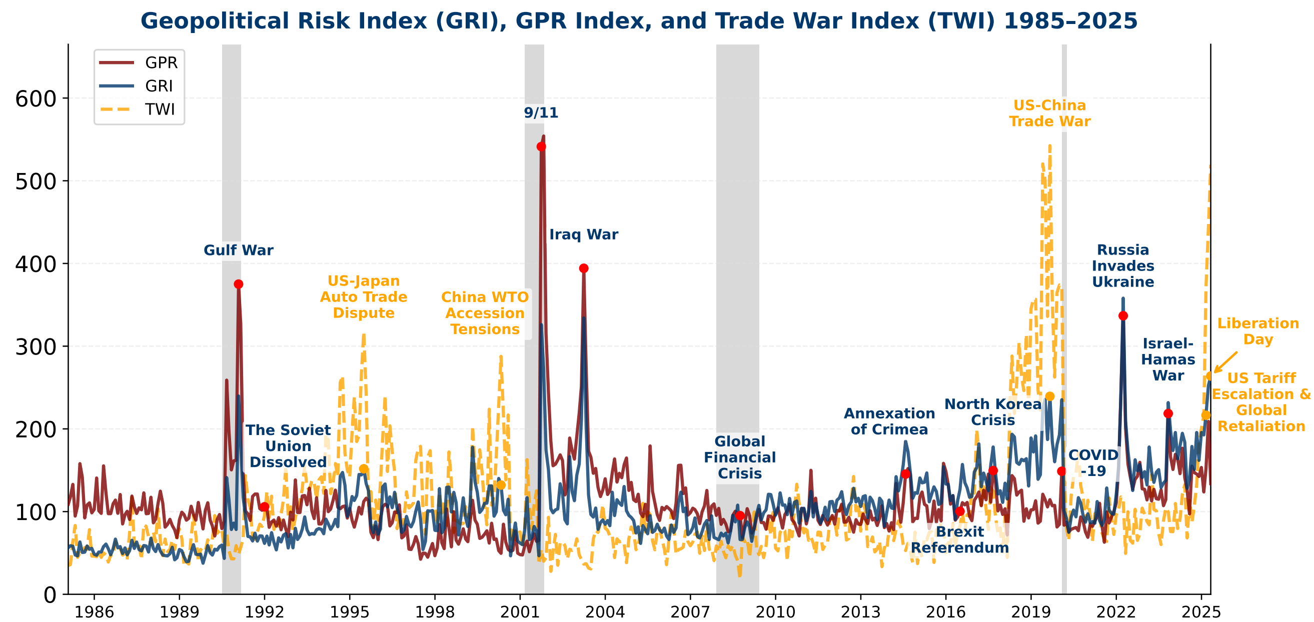

Table 1: Summary statistics

Panel A presents the summary statistics of each main variable utilized in the paper. Panel B displays the correlations among the variables. R_t^e is the excessive return of the market in month t (expressed as annualized percentage). GRI is the geopolitical risk index. TWI is the trade war index. GPR is Caldara and Iacoviello (2022)'s measure of geopolitical risk. WAR is the war index by Hirshleifer, Mai, and Pukthuanthong (2025a). NVIX is the news-implied volatility index by Manela and Moreira (2017). Sample period is from January 1985 to February 2025, excluding the three-year COVID period from 2020 to 2022.

A. Descriptive Statistics

				Percentile			
Variable	Mean	Median	Stdev	10^{th}	25^{th}	75^{th}	90^{th}
R_t^e	9.23	13.43	50.66	-54.64	-19.38	41.61	68.37
GRI	100.00	92.74	42.22	52.94	69.32	120.45	154.08
TWI	100.00	77.22	71.40	46.80	58.04	109.19	183.85
GPR	100.00	91.94	45.50	63.14	79.26	108.91	139.23
EPU	110.15	105.00	31.96	75.00	86.00	127.00	157.00
WAR	0.103	0.102	0.022	0.075	0.089	0.114	0.132
NVIX	24.47	23.88	5.99	17.63	20.42	28.07	30.98

B. Correlation Structure

	R_t^e	GRI	GPR	TWI	EPU	WAR
GRI	0.016					
GPR	-0.032	0.564				
TWI	0.012	0.466	-0.125			
EPU	-0.062	0.215	0.210	0.049		
WAR	0.056	0.278	0.517	-0.287	0.235	
NVIX	-0.268	0.232	0.069	-0.189	0.614	0.149

Table 2: Predicting future market returns

This table presents the results of the following predictive regression

$$R^e_{t+1\to t+n} = \alpha + \beta \text{GRI}_t + \epsilon_{t+1},$$

where $R^e_{t+1\to t+n}$ is the excessive return of the market in from month $t+1$ to month $t+n$ (expressed as annualized percentage) and GRI_t is the geopolitical risk index in month t (standardized to zero mean and unit variance). Regressions are estimated using the IVX methodology of Kostakis, Magdalinos, and Stamatogiannis (2015). The resultant Wald statistics, derived from the corresponding Wald tests, are shown in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

A. Sample period: 1985–2025						
	$R^e_{t+1\to t+n}$					
	$n=1$	$n=3$	$n=6$	$n=12$	$n=24$	$n=36$
	(1)	(2)	(3)	(4)	(5)	(6)
GRI	8.71***	2.42**	1.19**	0.52*	0.26	0.16
	(11.90)	(6.21)	(4.73)	(2.90)	(2.33)	(1.28)
Obs.	445	443	440	434	422	410
Adj. R^2 (%)	2.68	5.00	8.52	11.61	17.81	21.34
B. Sample Period 2000–2025						
	$R^e_{t+1\to t+n}$					
	$n=1$	$n=3$	$n=6$	$n=12$	$n=24$	$n=36$
	(1)	(2)	(3)	(4)	(5)	(6)
GRI	13.21***	4.12***	1.97***	0.96**	0.48**	0.31*
	(19.25)	(12.04)	(8.10)	(5.79)	(5.07)	(2.75)
Obs.	265	263	260	254	242	230
Adj. R^2 (%)	6.61	13.00	17.57	24.55	35.14	46.27

Table 3: Predicting future market returns: GRI versus other factors

This table presents the results of the following predictive regression

$$R^e_{t+1} = \alpha + \beta \text{GRI}_t + \gamma z_t + \epsilon_{t+1},$$

where R^e_{t+1} is the excessive return of the market in month $t+1$ (expressed as annualized percentage), GRI_t is the geopolitical risk index in month t (standardized), and z_t is one (or more in column 10) of the economic factors. GPR is Caldara and Iacoviello (2022)'s measure of geopolitical risk. EPU is the economic policy uncertainty index by Baker, Bloom, and Davis (2016). WAR is the war index by Hirshleifer, Mai, and Pukthuanthong (2025a). NVIX is the news-implied volatility index by Manela and Moreira (2017). DP, EP, DE, INFL, and TBL are the macroeconomic variables from Goyal and Welch (2008). Regressions are estimated using the IVX methodology of Kostakis, Magdalinos, and Stamatogiannis (2015). The resultant Wald statistics, derived from the corresponding Wald tests, are shown in parentheses. $*p < .1$; $**p < .05$; $***p < .01$.

A. Sample period: 1985–2025										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GRI	9.42***	8.46***	7.51**	9.39***	11.46***	9.90***	9.08***	9.04***	9.78***	11.89***
	(8.80)	(9.71)	(6.63)	(7.01)	(16.76)	(13.95)	(10.57)	(11.13)	(12.09)	(16.84)
GPR	-1.08									
	(0.13)									
EPU		-1.48								
		(0.34)								
WAR			1.83							
			(0.49)							
NVIX				-1.52						
				(0.30)						
DP					7.85					6.89
					(2.42)					(2.08)
EP						3.96				3.00
						(1.97)				(0.72)
DE							0.99			
							(0.17)			
INFL								0.10		-0.62
								(0.00)		(0.05)
TBL									2.61	0.41
									(0.69)	(0.01)
Obs.	445	299	417	374	431	431	431	431	431	431
Adj. R^2 (%)	2.55	4.91	1.82	1.65	3.95	2.92	2.43	2.43	2.40	3.66

A. Sample period: 2000–2025										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GRI	14.98***	12.51***	9.54**	14.47***	13.38***	13.85***	13.67***	13.75***	13.16***	14.05***
	(15.05)	(16.23)	(6.15)	(11.00)	(16.38)	(18.39)	(17.54)	(18.06)	(16.93)	(18.05)
GPR	-2.62									
	(0.46)									
EPU		2.63								
		(0.68)								
WAR			5.31							
			(1.81)							
NVIX				-2.48						
				(0.44)						
DP					8.52					12.77*
					(1.63)					(2.91)
EP						3.26				5.79
						(1.08)				(2.11)
DE							-0.10			
							(0.00)			
INFL								1.71		3.18
								(0.31)		(1.05)
TBL									-3.08	1.85
									(0.64)	(0.19)
Obs.	265	263	237	194	251	251	251	251	251	251
Adj. R^2 (%)	6.52	6.52	5.36	4.46	9.00	6.64	6.16	6.28	6.46	10.81

Table 4: Out-of-Sample R^2

This table presents the out-of-sample R^2 statistics (percentage points) following Campbell and Thompson (2007) to predict one-month-ahead market returns using GRI and other economic factors. GPR is Caldara and Iacoviello (2022)'s measure of geopolitical risk. EPU is the economic policy uncertainty index by Baker, Bloom, and Davis (2016). WAR is the war index by Hirshleifer, Mai, and Pukthuanthong (2025a). DP, EP, DE, INFL, TBL, and SVAR are the macroeconomic variables from Goyal and Welch (2008). Forecasts are estimated recursively using the data available in the expanding estimation window. The initial training window is 10 years starting from January 1985 and the evaluation starts from January 1995 to Feburary 2025. *$p < .1$; **$p < .05$; ***$p < .01$ (based on the Clark and West (2007) MSPE-adjusted statistic).

	Evaluation Period	
	1995–2025 (1)	2000–2025 (2)
GRI	2.476***	2.882***
GPR	0.005	0.843 *
EPU	-0.022	-0.022
WAR	0.003	0.449*
DP	-0.022	1.064*
DY	-0.020	1.196*
EP	-0.014	-0.008
DE	-0.017	-0.024
INFL	-0.015	-0.020
TBL	-0.008	-0.010
SVAR	0.013	0.022

Table 5: Contemporaneous relation between GRI innovation and stock returns

This table presents the results of the following regression

$$R_t^e = \alpha + \beta \mathrm{GRI}_t^{res} + \gamma z_t + \epsilon_t,$$

where R_t^e is the excessive return of the market in month t (expressed as annualized percentage), GRI_t^{res} is AR(1) residual of GRI estimated with an expanding window of at least 12 months from January 1985 to month t, and z_t is one of the economic factors. GPR is Caldara and Iacoviello (2022)'s measure of geopolitical risk. EPU is the economic policy uncertainty index by Baker, Bloom, and Davis (2016). WAR is the war index by Hirshleifer, Mai, and Pukthuanthong (2025a). NVIX is the news-implied volatility index by Manela and Moreira (2017). DP, EP, DE, INFL, and TBL are the macroeconomic variables from Goyal and Welch (2008). GPR_t^{res}, EPU_t^{res}, WAR_t^{res}, and NVIX_t^{res} are AR(1) residuals calculated in a similar way. All independent variables are standardized to zero mean and unit variance. Standard errors are calculated following Newey and West (1987) with 6 lags and the resultant t-statistics are shown in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

A. Sample period: 1986–2025											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
GRI_t^{res}	-7.24***	-3.29	-7.01**	-7.17**	-1.86	-6.87***	-6.88**	-6.77**	-6.77***	-6.84**	-6.88**
	(-2.87)	(-0.86)	(-2.54)	(-2.55)	(-0.86)	(-2.59)	(-2.57)	(-2.56)	(-2.63)	(-2.53)	(-2.57)
GPR_t^{res}		-5.15									
		(-1.51)									
EPU_t^{res}			-2.89**								
			(-0.84)								
WAR_t^{res}				1.91							
				(0.82)							
NVIX_t^{res}					-26.11***						
					(-8.91)						
DP						-3.08					-2.85
						(-0.98)					(-0.70)
EP							-1.82				-1.01
							(-0.52)				(-0.24)
DE								-0.66			
								(-0.16)			
INFL									-0.20		-0.03
									(-0.05)		(-0.01)
TBL										-0.69	0.43
										(-0.26)	(0.16)
Obs.	434	434	288	406	363	420	420	420	420	420	420
Adj. R^2 (%)	1.80	1.99	5.03	1.16	24.84	1.59	1.39	1.29	1.27	1.29	0.91

B. Sample period: 2000–2025											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
GRI_t^{res}	-9.30***	-6.53	-9.38**	-9.37***	-2.71	-8.64***	-8.77***	-8.74***	-8.93***	-9.07***	-9.28***
	(-3.33)	(-1.27)	(-2.84)	(-2.84)	(-1.30)	(-2.81)	(-2.93)	(-2.88)	(-3.12)	(-3.06)	(-3.34)
GPR_t^{res}		-3.57									
		(-0.90)									
EPU_t^{res}			-1.54*								
			(-0.33)								
WAR_t^{res}				2.77							
				(0.90)							
NVIX_t^{res}					-32.55***						
					(-12.00)						
DP						-1.94					-9.54
						(-0.31)					(-1.32)
EP							-1.01				-2.28
							(-0.21)				(-0.43)
DE								0.04			
								(0.01)			
INFL									2.48		2.72
									(0.59)		(0.80)
TBL										-5.50*	-12.09**
										(-1.75)	(-2.33)
Obs.	266	266	264	238	195	252	252	252	252	252	252
Adj. R^2 (%)	3.14	2.97	5.20	2.11	39.16	2.38	2.28	2.23	2.48	3.43	4.82

Table 6: GRI and market returns: Intraday vs. Overnight

This table presents the results of the following regressions

$$R^e_t = \alpha + \beta \text{GRI}^{res}_t \epsilon_t,$$
$$R^e_{t+1} = \alpha + \beta \text{GRI}^{res}_t \epsilon_{t+1},$$

where R^e_t (R^e_{t+1}) is the total, intraday, and overnight excessive return of the market in month t ($t+1$) (expressed as annualized percentage), GRI^{res}_t is AR(1) residual of GRI estimated with an expanding window of at least 12 months from January 1985 to month t. GRI^{res} is standardized to zero mean and unit variance. Predicative regressions are estimated using the IVX methodology of Kostakis, Magdalinos, and Stamatogiannis (2015), and the resultant Wald statistics are shown in parenthesis. Contemporaneous regressions are estimated using OLS, the errors are calculated following Newey and West (1987) with 6 lags, and the resultant t-statistics are shown in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

A. Contemporaneous Regressions

	Sample Period: 1986-2025			Sample Period: 2000-2025		
	Total	Intraday	Overnight	Total	Intraday	Overnight
	(1)	(2)	(3)	(4)	(5)	(6)
GRI^{res}_t	-7.24***	-6.79***	-0.25	-9.30***	-8.45***	-0.61
	(-2.87)	(-2.76)	(-0.43)	(-3.33)	(-3.14)	(-0.71)
Obs.	434	434	434	266	266	266
Adj. R^2 (%)	1.80	1.67	-0.14	3.14	2.83	-0.09

B. Predicative Regressions

	Total	Intraday	Overnight	Total	Intraday	Overnight
	(1)	(2)	(3)	(4)	(5)	(6)
GRI_t	8.71***	5.80**	2.66***	13.21***	9.58***	3.69***
	(11.90)	(5.43)	(38.63)	(19.25)	(10.80)	(29.69)
Obs.	445	445	445	265	265	265
Adj. R^2 (%)	2.68	1.14	8.46	6.61	3.69	9.98

Table 7: Portfolios sorting on GRI Beta

This table presents the results of value-weighted portfolio returns sorted on the rolling beta on GRI factor. The rolling beta of GRI is calculated using GRI^{res} and the six factors from Fama and French (2015). Stocks are sorted into quintile portfolios on the beta of GRI (using NYSE breakpoints) and are rebalanced monthly. Alphas of portfolio returns are calculated based on the six-factor model from Fama and French (2015). Portfolio returns are annualized. Standard errors are calculated following Newey and West (1987) and the resultant t-statistics are shown in parentheses. Results exclude the pandemic period. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	Sample period: 1991–2024		Sample period: 2000–2024	
	Mean	Alpha	Mean	Alpha
Low	7.80***	-2.18	3.73	-3.96***
	(2.68)	(-1.52)	(1.05)	(-2.73)
2	9.51***	-0.41	8.20***	0.34
	(4.13)	(-0.54)	(2.78)	(0.39)
3	9.43***	0.15	7.11**	-0.50
	(3.94)	(0.21)	(2.29)	(-0.56)
4	9.70***	-0.02	8.53***	0.41
	(4.07)	(-0.02)	(2.70)	(0.42)
High	10.09***	1.76	8.48*	1.72
	(2.89)	(1.21)	(1.83)	(0.97)
H-L	2.28	3.93*	4.75**	5.68**
	(1.07)	(1.72)	(2.04)	(2.36)

Table 8: Predicting market returns: TWI versus other factors

This table presents the results of the following predictive regression

$$R^e_{t+1} = \alpha + \beta \text{TWI}_t + \gamma z_t + \epsilon_{t+1},$$

where R^e_{t+1} is the excessive return of the market in month $t+1$ (expressed as annualized percentage), TWI_t is the Trade War Index in month t (standardized), and z_t represents other control factors included in specific regressions. GPR is Caldara and Iacoviello (2022)'s measure of geopolitical risk. EPU is the economic policy uncertainty index by Baker, Bloom, and Davis (2016). WAR is the war index by Hirshleifer, Mai, and Pukthuanthong (2025a). NVIX is the news-implied volatility index by Manela and Moreira (2017). DP, EP, DE, INFL, and TBL are the macroeconomic variables from Goyal and Welch (2008). Regressions are estimated using the IVX methodology of Kostakis, Magdalinos, and Stamatogiannis (2015). The resultant Wald statistics are shown in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

A. Sample period: 1985–2025										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TWI	4.42*	5.24**	4.42*	5.72**	4.64*	4.45*	4.69*	4.65*	4.68*	4.81
	(3.19)	(4.32)	(3.04)	(4.40)	(2.73)	(3.12)	(3.31)	(3.40)	(3.38)	(2.45)
GPR		4.95**								
		(4.24)								
EPU			3.54							
			(2.08)							
WAR				5.67**						
				(4.77)						
DP					7.15					5.61
					(1.97)					(1.43)
EP						4.00				3.20
						(2.05)				(0.73)
DE							0.73			
							(0.09)			
INFL								-0.56		-0.80
								(0.05)		(0.08)
TBL									-0.20	-2.63
									(0.00)	(0.45)
Obs.	445	445	445	417	431	431	431	431	431	431
Adj. R^2 (%)	0.52	1.28	0.79	1.24	1.93	0.87	0.37	0.38	0.37	1.19

B. Sample period: 2000–2025										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TWI	7.55**	8.66***	6.78**	9.25***	7.62**	7.71**	7.94**	7.92**	8.07**	7.33**
	(5.92)	(7.94)	(4.62)	(7.65)	(5.90)	(5.88)	(6.24)	(6.24)	(6.55)	(5.33)
GPR		7.21**								
		(5.53)								
EPU			3.65							
			(1.25)							
WAR				12.75***						
				(13.70)						
DP					7.51					8.84
					(1.36)					(1.48)
EP						1.84				3.66
						(0.33)				(0.85)
DE							0.76			
							(0.06)			
INFL								1.45		2.80
								(0.21)		(0.78)
TBL									-4.82	-1.06
									(1.61)	(0.06)
Obs.	265	265	265	237	251	251	251	251	251	251
Adj. R^2 (%)	1.85	3.73	1.93	6.79	3.53	1.75	1.68	1.75	2.33	3.69

Table 9: Portfolios sorting on TWI Beta

This table presents the results of value-weighted portfolio returns sorted on the rolling beta on TWI factor. The rolling beta of TWI is calculated using TWI^{res} and the six factors from Fama and French (2015). Stocks are sorted into quintile portfolios on the beta of TWI (using NYSE breakpoints) and are rebalanced monthly. Alphas of portfolio returns are calculated based on the six-factor model from Fama and French (2015). Portfolio returns are annualized. Standard errors are calculated following Newey and West (1987) and the resultant t-statistics are shown in parentheses. Results exclude the pandemic period. *p <.1; **p <.05; ***p <.01.

	Sample period: 1991–2024		Sample period: 2000–2024	
	Mean	Alpha	Mean	Alpha
Low	7.65**	-2.10*	4.65	-3.40**
	(2.49)	(-1.85)	(1.15)	(-2.48)
2	9.81***	0.27	8.34***	1.06
	(4.03)	(0.31)	(2.67)	(1.04)
3	8.96***	0.56	6.63**	-0.34
	(3.64)	(0.51)	(2.12)	(-0.30)
4	9.64***	0.22	7.79**	0.25
	(3.97)	(0.25)	(2.54)	(0.28)
High	11.79***	2.33*	10.11**	2.60*
	(3.81)	(1.87)	(2.50)	(1.72)
H-L	4.14**	4.43**	5.46**	6.00**
	(2.28)	(2.35)	(2.51)	(2.48)

Table 10: Predicting international stock market returns

This table presents the results of the following predictive regression

$$R^{e,i}_{t+1} = \alpha + \beta \text{GRI}_t + \epsilon_{t+1},$$

where $R^{e,i}_{t+1}$ is the excess return of the international market index i in month $t+1$ (expressed as annualized percentage) and GRI_t is the geopolitical risk index in month t (standardized to zero mean and unit variance). UK FTSE represents the UK FTSE market index, MSCI is the MSCI global market index, DJW is the Dow Jones World index excluding the U.S. (available from 1992), and FTA is the FTSE All-World index excluding the U.S. (available until May 2017). Regressions are estimated using the IVX methodology of Kostakis, Magdalinos, and Stamatogiannis (2015). The resultant Wald statistics are shown in parentheses. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

A. Sample period: 1985–2025				
	International Indices			
	UK FTSE	MSCI	DJW	FTA
	(1)	(2)	(3)	(4)
GRI	5.02*	6.33**	6.33*	2.97
	(3.84)	(6.14)	(3.67)	(0.61)
Obs.	445	445	360	388
Adj. R^2 (%)	0.75	1.30	0.86	-0.08

B. Sample Period 2000–2025				
	International Indices			
	UK FTSE	MSCI	DJW	FTA
	(1)	(2)	(3)	(4)
GRI	8.25***	11.06***	7.97**	8.97*
	(8.74)	(12.45)	(5.19)	(3.50)
Obs.	265	265	265	208
Adj. R^2 (%)	2.97	4.26	1.61	1.19

Table 11: GRI: Industry Heterogeneity

This table presents the results of the following regressions by Fama-French 48 industries

$$R^e_{i,t} = \alpha + \beta_1 \text{GRI}_t + \epsilon_{t+1},$$
$$R^e_{i,t+1} = \alpha + \beta_2 \text{GRI}^{res}_t + \epsilon_t,$$

where $R^e_{i,t}$ and $R^e_{i,t+1}$ are the excessive return of stock i in month t and $t+1$ (expressed as annualized percentage). Predicative regressions are estimated using the IVX methodology of Kostakis, Magdalinos, and Stamatogiannis (2015). Contemporaneous regressions are estimated using OLS and t-statistics are calculated following Newey and West (1987) with 6 lags. *p <.1; **p <.05; ***p <.01.

A. Sample Period: 1985-2025							
Contemporaneous Regressions (β_1)				**Predicative Regressions (β_2)**			
Top 10 Highest		Top 10 Lowest		Top 10 Highest		Top 10 Lowest	
Guns	8.01**	Toys	-14.46***	Chips	15.66***	Coal	-17.12**
	(2.26)		(-3.62)		(11.72)		(5.15)
Gold	2.98	FabPr	-13.79***	Comps	12.46***	Gold	-8.22
	(0.49)		(-2.97)		(8.88)		(1.80)
Agric	0.02	Autos	-13.17***	LabEq	11.54***	Oil	-4.77
	(0.00)		(-2.94)		(7.52)		(2.33)
MedEq	-2.50	Smoke	-12.71***	ElcEq	11.45**	Ships	-3.29
	(-1.00)		(-3.24)		(6.42)		(0.45)
Soda	-2.71	Chips	-12.69***	Cnstr	8.89**	Mines	-1.94
	(-0.96)		(-2.80)		(4.94)		(0.17)
Rtail	-4.00	Aero	-12.30***	Books	7.84**	Chems	-1.38
	(-1.36)		(-3.70)		(4.43)		(0.17)
Ships	-4.53	Steel	-11.86**	BusSv	7.67*	Soda	-0.62
	(-0.94)		(-2.57)		(3.81)		(0.05)
Clths	-4.67	ElcEq	-11.36**	FabPr	7.26	Food	-0.45
	(-1.26)		(-2.57)		(2.36)		(0.03)
Telcm	-5.01*	LabEq	-10.67**	Aero	6.45*	Clths	-0.34
	(-1.75)		(-2.58)		(3.53)		(0.01)
BldMt	-5.31*	Cnstr	-10.61***	Rtail	5.34*	Beer	0.16
	(-1.72)		(-2.71)		(3.13)		(0.00)

B. Sample Period: 2000-2025							
Contemporaneous Regressions (β_1)				**Predicative Regressions (β_2)**			
Top 10 Highest		Top 10 Lowest		Top 10 Highest		Top 10 Lowest	
Gold	7.06	Toys	-21.95***	Chips	17.66***	Coal	-23.46**
	(0.94)		(-4.26)		(9.37)		(4.20)
Guns	6.66	Chips	-21.64***	Comps	13.20**	Gold	-6.25
	(1.57)		(-3.67)		(6.24)		(0.69)
Soda	-2.51	FabPr	-21.38***	Cnstr	13.04**	Ships	-5.29
	(-0.87)		(-3.25)		(6.22)		(0.70)
MedEq	-3.82	ElcEq	-21.33***	Books	12.45**	Oil	-5.25
	(-1.36)		(-3.59)		(5.97)		(1.52)
Telcm	-4.13	Steel	-21.05***	Other	11.78***	Guns	-3.40
	(-1.10)		(-3.33)		(7.96)		(0.63)
Drugs	-5.72*	LabEq	-19.23***	BusSv	10.35**	Chems	-0.34
	(-1.75)		(-3.74)		(5.11)		(0.01)
Util	-6.44**	Autos	-19.15***	LabEq	10.26**	Mines	-0.27
	(-2.12)		(-2.99)		(4.60)		(0.00)
Rtail	-6.65**	Smoke	-18.18***	Fun	9.38**	Beer	0.14
	(-1.99)		(-3.99)		(3.87)		(0.00)
Agric	-6.68	Aero	-17.77***	ElcEq	9.36*	Whlsl	0.70
	(-1.54)		(-4.18)		(2.73)		(0.04)
Hshld	-6.70**	Comps	-17.00***	Rtail	8.66***	Agric	0.71
	(-2.38)		(-3.21)		(6.99)		(0.03)

Internet Appendix for
"Geopolitical Risks and Stock Returns"

This internet appendix includes two parts.

Part A provides details on how we construct the GRI and TWI.

Part B lists additional tables used in the paper. Here is the list of tables:

A. More details on the GRI and TWI measurements

A.1 Example of news articles with GRI keywords

In this section, we provide a few examples of news articles that contain GRI keywords, which are underlined.

- John R. Dorfman, “Wall Street Is Preparing For Gulf War,” *Wall Street Journal*, November 28, 1990

“Several money managers expect stock prices to fall if hostilities begin, and say they intend to buy on such a drop. "If the market falls 5% to 10%, I intend to be a major buyer," says Victor Sperandeo, president of Rand Management Corp. in Short Hills, N.J. "If it’s down less than 5%, I’d be a small buyer."

These money managers are assuming the U.S. and its allies score a quick military victory over Iraq. On that basis, some money managers say they would bargain-hunt among the stocks likely to be hit hardest if war breaks out. These are the companies that suffer when oil prices rise, such as airlines and hotels.”

- Carolyn J. Luxemburg, “Dollar Slips Against Resurging Mark As Pressures Pile Up on U.S. Currency,” *Wall Street Journal*, September 22, 1994

“Traders said the dollar is likely to come under heavy pressure during the next few days, because of the impending Sept. 30 deadline for progress in U.S.-Japan trade talks and because of persistent weakness in U.S. stock and bond markets.”

- Michael Schroeder, Kate Kelly, and Antonio Regalado, “ Attack Shuts Down U.S. Markets and Causes Global Declines,” *Wall Street Journal*, September 12, 2001

“In the wake of the destruction caused by the terrorist attack on lower Manhattan, the nerve center of U.S. finance, all major markets were closed yesterday and will remain closed today, as officials scramble to instill confidence in shaken global investors.

When U.S. markets will reopen and what will happen when trading resumes is unclear, as officials sift through the physical damage and human carnage.

There is a risk that U.S. stock markets, already shaky, could follow the jittery reaction in the global markets that did remain open yesterday. In Europe, the Dow Jones Stoxx 50 index of European blue chips plunged 6.1% to its lowest level since August 1998. British stocks fell 5.7%, French stocks 7.4% and German stocks 8.5%. ”

- Jon Sindreu, “Ukraine Changes Playbook for Markets,” *Wall Street Journal*, February 15, 2022

“On Monday, geopolitical fears rippled through stock markets. The Stoxx Europe 600 fell 1.8%, and appeared to lead U.S. indexes lower as well. Natural-gas prices jumped on both sides of the Atlantic.

Like the rest of us, professional investors have spent the past month debating Russia’s military buildup around Ukraine. Western officials have claimed it is a prelude to an invasion that could happen as early as this week, which Moscow denies. Yet it doesn’t look like markets had truly taken the risk of war into account until Friday – with the possible exception of shares in defense contractors, which have slightly recovered from a period of dismal performance.”

- James Mackintosh, “Streetwise: War Could Have Bigger Impact on Markets,” *Wall Street Journal*, October 10, 2023

“Markets on Monday morning reacted perfectly logically to the most serious attack on Israel in 50 years and the deaths of more than 1,000 Israelis and Palestinians. Oil prices initially rose 3% or so, stock futures fell a bit, gold was up about 1% and Treasury futures rose, lowering yields. ... What matters most is the potential for the war to escalate. The most likely first step is a tightening of sanctions against Iran, which helped plan the Hamas attack. That would reverse the easing of tensions with the U.S. that helped Iran increase production by about 0.5 million barrels a day over the past year. Goldman Sachs estimates that every 0.1-million-barrel-a-day cut to Iranian production next year would raise the oil price by $1.”

- Paul Kiernan, “Tariffs Erase Economy’s Solid Outlook — Recession likelihood soars as uncertainty on Trump’s course weighs on markets,” *Wall Street Journal*, April 7, 2025

“The stock market went off a cliff last week after President Trump announced the highest tariffs in more than a century, vaporizing more than $6 trillion of wealth in two days.

...

But the world changed last Wednesday, which Trump dubbed Liberation Day. He announced massive tariffs on almost every country — effectively the largest U.S. tax increase since 1968, according to JPMorgan. On Thursday, U.S. markets suffered their steepest declines since 2020, with the S&P 500 falling 4.8%. On Friday, China retaliated with 34% additional tariffs on all goods imported from the U.S., and the S&P 500 plunged an additional 6%.

The stock declines, a parallel selloff in junk bonds, the cost of tariffs, and the prospect of weaker exports from retaliatory tariffs all now weigh on the outlook."

A.2 Dictionary Query

The Geopolitical risk index (GRI) is based on the number of articles that contain keywords from GPR dictionary from Caldara and Iacoviello (2022) and the trade war-related keywords we develop in this paper. We present the actual search queries used to construct the GRI (excluding trade wars) and the TWI. The GRI that includes trade wars combines news articles from both sets of search queries.

The actual search queries for GRI (exclude trade wars) on Factiva are:

```
(((war OR conflict OR hostilities OR revolution* OR insurrection OR uprising OR
revolt OR coup OR geopolitical) NEAR2 (risk* OR warn* OR fear* OR danger* OR
threat* OR doubt* OR crisis OR troubl* OR disput* OR concern* OR tension* OR
imminen* OR inevitable OR footing OR menace* OR brink OR scare OR peril*)) OR
((peace OR truce OR armistice OR treaty OR parley) NEAR2 (menace* OR reject* OR
threat* OR peril* OR boycott* OR disrupt*)) OR ((military OR troops OR missile* OR
arms OR weapon* OR bomb* OR warhead*) AND (buildup* OR blockad* OR sanction* OR
embargo OR quarantine OR ultimatum OR mobiliz* OR offensive)) OR ((nuclear war* OR
atomic war* OR nuclear missile* OR nuclear bomb* OR atomic bomb* OR h-bomb* OR
(hydrogen bomb*) OR nuclear test*) AND (risk* OR warn* OR fear* OR danger* OR
threat* OR doubt* OR crisis OR troubl* OR disput* OR concern* OR tension* OR
imminen* OR inevitable OR footing OR menace* OR brink OR scare OR peril*)) OR
((terroris* OR guerrilla* OR hostage*) NEAR2 (risk* OR warn* OR fear* OR danger* OR
threat* OR doubt* OR crisis OR troubl* OR disput* OR concern* OR tension* OR
imminen* OR inevitable OR footing OR menace* OR brink OR scare OR peril*)) OR ((war
OR conflict OR hostilities OR revolution* OR insurrection OR uprising OR revolt OR
coup OR geopolitical) NEAR2 (begin* OR begun OR began OR outbreak OR broke out OR
breakout OR start* OR declar* OR proclamation OR launch* OR wage*)) OR ((allie* OR
enem* OR foe* OR army OR navy OR aerial OR troops OR rebels OR insurgen*) NEAR2
(drive* OR shell* OR advance* OR invasion OR invad* OR clash* OR attack* OR raid*
OR launch* OR strike*)) OR ((terroris* OR guerrilla* OR hostage*) NEAR2 (act OR
attack OR bomb* OR kill* OR strike* OR hijack*)))
```

The actual search queries for TWI on Factiva are:

```
((US NEAR2 (trade OR tariff* OR import OR export OR sanction* OR agreement* OR dispute* OR negotiation* OR tension* OR failure OR collapse OR retaliat* OR punitive* OR breakdown*)) OR (China NEAR2 (trade OR tariff* OR import OR export OR sanction* OR agreement* OR dispute* OR negotiation* OR tension* OR failure OR collapse OR retaliat* OR punitive* OR breakdown*)) OR (Canada NEAR2 (trade OR tariff* OR import OR export OR sanction* OR agreement* OR dispute* OR negotiation* OR tension* OR failure OR collapse OR retaliat* OR punitive* OR breakdown*)) OR (Europe NEAR2 (trade OR tariff* OR import OR export OR sanction* OR agreement* OR dispute* OR negotiation* OR tension* OR failure OR collapse OR retaliat* OR punitive* OR breakdown*)) OR (Japan NEAR2 (trade OR tariff* OR import OR export OR sanction* OR agreement* OR dispute* OR negotiation* OR tension* OR failure OR collapse OR retaliat* OR punitive* OR breakdown*)) OR (Mexico NEAR2 (trade OR tariff* OR import OR export OR sanction* OR agreement* OR dispute* OR negotiation* OR tension* OR failure OR collapse OR retaliat* OR punitive* OR breakdown*)))
```

B. Additional Tables

Table IA1: Predicting future market returns—OLS

This table presents the results of the following predictive regression

$$R^e_{t+1\to t+n} = \alpha + \beta \text{GRI}_t + \epsilon_{t+1},$$

where $R^e_{t+1\to t+n}$ is the excessive return of the market in from month $t+1$ to month $t+n$ (expressed as annualized percentage) and GRI_t is the geopolitical risk index in month t (standardized to zero mean and unit variance). Standard errors are calculated following Newey and West (1987) with 6 lags for columns 1–3 and with lags matching the horizon of returns (i.e., n lags for n-month returns) for columns 4–6 and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

A. Sample period: 1985–2025						
	$R^e_{t+1\to t+n}$					
	$n=1$	$n=3$	$n=6$	$n=12$	$n=24$	$n=36$
	(1)	(2)	(3)	(4)	(5)	(6)
GRI	7.39***	4.59***	3.29**	2.45	2.38**	1.92**
	(3.64)	(2.78)	(2.33)	(1.59)	(2.52)	(2.38)
Obs.	445	443	440	434	422	419
Adj. R^2 (%)	1.89	2.17	2.21	2.33	3.93	3.88
B. Sample Period 2000–2025						
	$R^e_{t+1\to t+n}$					
	$n=1$	$n=3$	$n=6$	$n=12$	$n=24$	$n=36$
	(1)	(2)	(3)	(4)	(5)	(6)
GRI	12.94***	8.91***	6.13***	4.92**	4.71***	3.62**
	(4.68)	(4.04)	(2.87)	(1.98)	(2.68)	(2.54)
Obs.	265	263	260	254	242	239
Adj. R^2 (%)	6.35	8.51	7.00	7.99	12.92	13.67

Table IA2: Predicting future market returns using GPR

This table presents the results of the following predictive regression

$$R^e_{t+1\to t+n} = \alpha + \beta \text{GPR}_t + \epsilon_{t+1},$$

where $R^e_{t+1\to t+n}$ is the excessive return of the market in from month $t+1$ to month $t+n$ (expressed as annualized percentage) and GPR is Caldara and Iacoviello (2022)'s measure of geopolitical risk in month t (standardized to zero mean and unit variance). Regressions are estimated using the IVX methodology of Kostakis, Magdalinos, and Stamatogiannis (2015). The resultant Wald statistics, derived from the corresponding Wald tests, are shown in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

A. Sample period: 1985–2025						
	$R^e_{t+1\to t+n}$					
	$n=1$	$n=3$	$n=6$	$n=12$	$n=24$	$n=36$
	(1)	(2)	(3)	(4)	(5)	(6)
GPR	4.27*	1.16	0.32	-0.03	0.09	0.08
	(3.19)	(1.47)	(0.31)	(0.01)	(0.17)	(0.18)
Obs.	445	443	440	434	422	410
Adj. R^2 (%)	0.49	1.27	1.40	2.28	6.08	9.63

B. Sample Period 2000–2025						
	$R^e_{t+1\to t+n}$					
	$n=1$	$n=3$	$n=6$	$n=12$	$n=24$	$n=36$
	(1)	(2)	(3)	(4)	(5)	(6)
GPR	5.96*	1.57	0.31	-0.17	0.04	-0.00
	(3.76)	(1.63)	(0.16)	(0.11)	(0.02)	(0.00)
Obs.	265	263	260	254	242	230
Adj. R^2 (%)	1.08	2.30	1.90	4.31	8.46	12.88

Table IA3: Predicting future market returns: GRI versus other factors—OLS

This table presents the results of the following predictive regression

$$R^e_{t+1} = \alpha + \beta \text{GRI}_t + \gamma z_t + \epsilon_{t+1},$$

where R^e_{t+1} is the excessive return of the market in month $t+1$ (expressed as annualized percentage), GRI_t is the geopolitical risk index in month t, and z_t is one of the economic factors. Standard errors are calculated following Newey and West (1987) with 6 lags and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

A. Sample period: 1985–2025										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GRI	7.20***	6.48***	6.08***	7.91***	11.50***	9.17***	7.82***	7.68***	9.22***	12.06***
	(2.84)	(3.08)	(2.79)	(2.63)	(5.55)	(3.42)	(3.84)	(3.57)	(3.94)	(5.06)
GPR	0.34									
	(0.14)									
EPU		2.83								
		(0.92)								
WAR			2.52							
			(1.02)							
NVIX				-1.43						
				(-0.35)						
DP					9.13***					7.84**
					(3.56)					(2.23)
EP						5.81				3.12
						(1.07)				(0.64)
DE							1.24			
							(0.36)			
INFL								-0.10		-0.77
								(-0.03)		(-0.26)
TBL									3.49	0.88
									(1.20)	(0.34)
Obs.	445	300	418	375	432	432	432	432	432	432
Adj. R^2 (%)	1.67	4.71	1.32	1.02	4.37	2.89	1.72	1.66	2.05	4.08

B. Sample period: 2000–2025										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GRI	13.73***	14.53***	9.50***	14.69***	13.32***	13.64***	13.49***	13.60***	13.05***	13.86***
	(3.63)	(3.53)	(3.45)	(3.82)	(4.40)	(4.62)	(4.59)	(4.80)	(4.42)	(4.53)
GPR	-1.24									
	(-0.44)									
EPU		-1.83								
		(-0.51)								
WAR			5.61**							
			(2.16)							
NVIX				-2.16						
				(-0.43)						
DP					7.70					10.35*
					(1.57)					(1.66)
EP						3.04				4.34
						(0.43)				(0.89)
DE							0.70			
							(0.12)			
INFL								1.50		2.92
								(0.48)		(0.86)
TBL									-3.88	2.42
									(-1.43)	(0.61)
Obs.	265	264	238	195	252	252	252	252	252	252
Adj. R^2 (%)	6.03	6.49	5.55	4.62	8.45	6.45	6.10	6.17	6.67	8.50

Table IA4: Predicting cross-sectional stock returns: Fama-MacBeth Regression

This table presents the results of the following regression

$$R^e_{i,t+1} = \alpha + \lambda_t^{GRI}\beta_t^{GRI} + \lambda_t^z\beta_t^z + \epsilon_{t+1},$$

where $R^e_{i,t+1}$ is the excessive return of stock i in month $t+1$ (expressed as annualized percentage), β_t^{GRI} is the rolling beta on GRI factor, β_t^z are the betas on market factor (MKT), value factor (HML), size factor (SMB), operating factor (RMW), investment factor (CMW), and momentum factor (MOM). Stocks are sorted into Big or Small based on the sample median of market capitalization in month t. All independent variables are standardized to zero mean and unit variance. Standard errors are calculated following Newey and West (1987) with 6 lags and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

	Sample Period: 1991-2025			Sample Period: 2000-2024		
	All	Big	Small	All	Big	Small
	(1)	(2)	(3)	(4)	(5)	(6)
β^{GRI}	0.88	2.05***	0.53	1.73**	2.40**	1.63**
	(1.46)	(2.64)	(0.84)	(2.24)	(2.36)	(2.04)
β^{MKT}	1.27	1.42	2.82**	1.04	1.05	2.27
	(1.01)	(0.98)	(2.23)	(0.63)	(0.57)	(1.40)
β^{SMB}	2.26**	-0.15	1.66**	1.49	-0.39	0.84
	(2.38)	(-0.15)	(2.00)	(1.60)	(-0.36)	(1.08)
β^{HML}	-0.13	0.59	-1.27	0.35	1.52	-0.71
	(-0.10)	(0.35)	(-0.91)	(0.24)	(0.83)	(-0.46)
β^{RMW}	-2.79**	0.25	-3.38**	-2.84*	0.55	-3.69**
	(-2.12)	(0.16)	(-2.53)	(-1.67)	(0.26)	(-2.17)
β^{CMA}	-1.83	-1.66	-2.93**	-1.63	-0.91	-2.63**
	(-1.57)	(-1.19)	(-2.38)	(-1.30)	(-0.59)	(-1.98)
β^{MOM}	-2.75***	-0.90	-2.66***	-2.93**	-1.08	-2.82**
	(-2.87)	(-0.83)	(-2.97)	(-2.26)	(-0.74)	(-2.34)
Obs.	762,533	381,359	381,174	512,106	256,121	255,985
Adj. R^2 (%)	2.8	7.0	1.8	3.1	7.9	2.0

Table IA5: Predicting future market returns: TWI versus other factors—OLS

This table presents the results of the following predictive regression

$$R^e_{t+1} = \alpha + \beta \mathrm{TWI}_t + \gamma z_t + \epsilon_{t+1},$$

where R^e_{t+1} is the excessive return of the market in month $t+1$ (expressed as annualized percentage), TWI_t is the trade war index in month t, and z_t is one of the economic factors. Standard errors are calculated following Newey and West (1987) with 6 lags and the resultant t-statistics are shown in parentheses. *$p <.1$; **$p <.05$; ***$p <.01$.

A. Sample period: 1985–2025										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TWI	4.16**	4.86**	4.09**	5.44**	5.15***	4.44**	4.42**	4.31**	4.33**	5.20***
	(2.19)	(2.46)	(2.07)	(2.48)	(2.65)	(2.30)	(2.41)	(2.22)	(2.27)	(2.67)
GPR		5.02**								
		(2.50)								
EPU			4.12							
			(1.36)							
WAR				5.62**						
				(1.99)						
DP					5.44**					5.46
					(2.28)					(1.55)
EP						3.76				2.79
						(0.84)				(0.61)
DE							0.89			
							(0.25)			
INFL								-0.71		-0.72
								(-0.24)		(-0.24)
TBL									-0.24	-3.05
									(-0.10)	(-1.25)
Obs.	445	445	445	418	432	432	432	432	432	432
Adj. R^2 (%)	0.43	1.18	0.85	1.16	1.37	0.80	0.28	0.27	0.25	1.14

B. Sample period: 2000–2025										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TWI	6.88***	7.87***	5.97**	9.12***	7.57***	7.00***	7.27***	7.15***	7.92***	7.56***
	(2.77)	(2.97)	(2.03)	(3.43)	(2.82)	(2.91)	(3.00)	(2.85)	(3.09)	(2.68)
GPR		8.26***								
		(3.17)								
EPU			5.07							
			(1.21)							
WAR				11.84***						
				(3.65)						
DP					8.43					8.54
					(1.62)					(1.27)
EP						2.12				3.16
						(0.35)				(0.75)
DE							1.80			
							(0.34)			
INFL								0.92		2.60
								(0.27)		(0.71)
TBL									-6.34**	-1.20
									(-2.17)	(-0.26)
Obs.	265	265	265	238	252	252	252	252	252	225
Adj. R^2 (%)	1.48	3.86	2.09	6.05	4.06	1.40	1.35	1.25	2.81	3.60

Table IA6: Contemporaneous relation between TWI innovation and stock returns

This table presents the results of the following regression

$$R_t^e = \alpha + \beta \text{TWI}_t^{res} + \gamma z_t + \epsilon_t,$$

where R_t^e is the excessive return of the market in month t (expressed as annualized percentage), TWI_t^{res} is the AR(1) residual of the Trade War Index (TWI) estimated with an expanding window, and z_t is one of the economic factors. GPR is Caldara and Iacoviello (2022)'s measure of geopolitical risk. EPU is the economic policy uncertainty index by Baker, Bloom, and Davis (2016). WAR is the war index by Hirshleifer, Mai, and Pukthuanthong (2025a). NVIX is the news-implied volatility index by Manela and Moreira (2017). DP, EP, DE, INFL, and TBL are the macroeconomic variables from Goyal and Welch (2008). GPR_t^{res}, EPU_t^{res}, and WAR_t^{res} are AR(1) residuals calculated in a similar way. All independent variables are standardized. Standard errors are calculated following Newey and West (1987) with 6 lags and the resultant t-statistics are shown in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

A. Sample period: 1986–2025										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TWI_t^{res}	-3.90*	-3.80*	-3.41	-3.29	-2.98	-3.11	-3.14	-3.13	-3.16	-2.97
	(-1.72)	(-1.76)	(-1.48)	(-1.32)	(-1.19)	(-1.27)	(-1.27)	(-1.26)	(-1.30)	(-1.19)
GPR_t^{res}		-7.89***								
		(-3.62)								
EPU_t^{res}			-3.65							
			(-1.15)							
WAR_t^{res}				-0.85						
				(-0.36)						
DP					-2.68					-2.69
					(-0.86)					(-0.67)
EP						-1.37				-0.76
						(-0.39)				(-0.18)
DE							-0.75			
							(-0.18)			
INFL								-0.75		-0.76
								(-0.20)		(-0.22)
TBL									-0.04	1.12
									(-0.01)	(0.42)
Obs.	435	435	435	406	420	420	420	420	420	420
Adj. R^2 (%)	0.35	2.53	0.63	-0.09	0.13	-0.05	-0.10	-0.10	-0.12	-0.54

B. Sample period: 2000–2025										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TWI_t^{res}	-6.85***	-6.46***	-6.43**	-6.59**	-6.06**	-6.12**	-6.16**	-6.14**	-6.05**	-5.48**
	(-2.82)	(-2.73)	(-2.42)	(-2.59)	(-2.25)	(-2.29)	(-2.30)	(-2.29)	(-2.24)	(-2.15)
GPR_t^{res}		-8.73***								
		(-4.63)								
EPU_t^{res}			-2.03							
			(-0.48)							
WAR_t^{res}				-0.68						
				(-0.23)						
DP					-2.15					-9.25
					(-0.36)					(-1.31)
EP						-0.50				-1.72
						(-0.10)				(-0.31)
DE							-0.49			
							(-0.08)			
INFL								1.76		1.86
								(0.40)		(0.52)
TBL									-4.84	-11.12**
									(-1.62)	(-2.21)
Obs.	267	267	267	238	252	252	252	252	252	252
Adj. R^2 (%)	1.48	4.19	1.27	0.76	0.76	0.59	0.59	0.70	1.51	2.50

Table IA7: Predicting international stock market returns—OLS

This table presents the results of the following predictive regression

$$R^{e,i}_{t+1} = \alpha + \beta \text{GRI}_t + \epsilon_{t+1},$$

where $R^{e,i}_{t+1}$ is the excess return of the international market index i in month $t+1$ (expressed as annualized percentage) and GRI_t is the geopolitical risk index in month t (standardized to zero mean and unit variance). UK FTSE represents the UK FTSE market index, MSCI is the MSCI global market index, DJW is the Dow Jones World index excluding the U.S. (available from 1992), and FTA is the FTSE All-World index excluding the U.S. (available until May 2017). Standard errors are calculated following Newey and West (1987) with 6 lags and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

A. Sample period: 1985–2025

	International Indices			
	UK FTSE (1)	MSCI (2)	DJW (3)	FTA (4)
GRI	3.74	5.22**	5.64*	1.81
	(1.57)	(2.12)	(1.68)	(0.47)
Obs.	445	445	361	388
Adj. R^2 (%)	0.32	0.82	0.63	-0.19

B. Sample Period 2000-2025

	International Indices			
	UK FTSE (1)	MSCI (2)	DJW (3)	FTA (4)
GRI	7.74***	10.83***	7.63*	9.56**
	(2.86)	(3.34)	(1.95)	(2.22)
Obs.	265	265	265	208
Adj. R^2 (%)	2.58	4.08	1.45	1.42

Table IA8: TWI: Industry Heterogeneity

This table presents the results of the following regressions by Fama-French 48 industries

$$R^e_{i,t} = \alpha + \beta_1 \mathrm{TWI}_t + \epsilon_{t+1},$$
$$R^e_{i,t+1} = \alpha + \beta_2 \mathrm{TWI}^{res}_t + \epsilon_t,$$

where $R^e_{i,t}$ and $R^e_{i,t+1}$ are the excessive return of stock i in month t and $t+1$ (expressed as annualized percentage), TWI_t is the predictor, and TWI^{res}_t is its residual component. Predicative regressions (β_2) are estimated using the IVX methodology of Kostakis, Magdalinos, and Stamatogiannis (2015). Contemporaneous regressions (β_1) are estimated using OLS and t-statistics are calculated following Newey and West (1987) with 6 lags. *$p < .1$; **$p < .05$; ***$p < .01$.

A. Sample Period: 1985-2025

Contemporaneous Regressions (β_1)				**Predicative Regressions (β_2)**			
Top 10 Highest		Top 10 Lowest		Top 10 Highest		Top 10 Lowest	
Industry	β_1	Industry	β_1	Industry	β_2	Industry	β_2
Gold	6.88	Toys	-19.50***	Soda	5.89**	Coal	-21.66*
	(0.91)		(-3.75)		(4.32)		(3.57)
Guns	1.62	Smoke	-16.23***	Comps	5.02	Steel	-9.89
	(0.38)		(-3.54)		(0.88)		(2.34)
Util	0.53	Ships	-14.84**	Other	4.43	Txtls	-9.04
	(0.17)		(-2.37)		(1.09)		(1.98)
Coal	0.35	ElcEq	-14.54**	Drugs	3.29	Mines	-7.56
	(0.03)		(-2.42)		(1.02)		(1.36)
Soda	-0.90	Autos	-12.47*	Toys	3.00	Oil	-7.45*
	(-0.31)		(-1.93)		(0.32)		(3.08)
PerSv	-1.12	Comps	-11.51**	Hshld	2.71	Ships	-6.46
	(-0.28)		(-2.15)		(0.90)		(1.05)
Rtail	-1.28	Chips	-11.21*	Guns	2.70	Gold	-6.28
	(-0.38)		(-1.87)		(0.40)		(0.69)
Telcm	-1.28	BusSv	-10.36**	Books	1.96	Autos	-5.98
	(-0.34)		(-2.21)		(0.15)		(0.84)
FabPr	-1.66	Chems	-9.78**	MedEq	1.87	Agric	-5.97
	(-0.25)		(-2.30)		(0.44)		(1.86)
Fun	-2.94	Books	-9.24*	Food	1.71	Chems	-5.68
	(-0.60)		(-1.81)		(0.39)		(1.75)

B. Sample Period: 2000-2025							
Contemporaneous Regressions (β_1)				**Predicative Regressions (β_2)**			
Top 10 Highest		Top 10 Lowest		Top 10 Highest		Top 10 Lowest	
Industry	β_1	Industry	β_1	Industry	β_2	Industry	β_2
Gold	7.06	Toys	-21.95***	Chips	17.66***	Coal	-23.46**
	(0.94)		(-4.26)		(9.37)		(4.20)
Guns	6.66	Chips	-21.64***	Comps	13.20**	Gold	-6.25
	(1.57)		(-3.67)		(6.24)		(0.69)
Soda	-2.51	FabPr	-21.38***	Cnstr	13.04**	Ships	-5.29
	(-0.87)		(-3.25)		(6.22)		(0.70)
MedEq	-3.82	ElcEq	-21.33***	Books	12.45**	Oil	-5.25
	(-1.36)		(-3.59)		(5.97)		(1.52)
Telcm	-4.13	Steel	-21.05***	Other	11.78***	Guns	-3.40
	(-1.10)		(-3.33)		(7.96)		(0.63)
Drugs	-5.72*	LabEq	-19.23***	BusSv	10.35**	Chems	-0.34
	(-1.75)		(-3.74)		(5.11)		(0.01)
Util	-6.44**	Autos	-19.15***	LabEq	10.26**	Mines	-0.27
	(-2.12)		(-2.99)		(4.60)		(0.00)
Rtail	-6.65**	Smoke	-18.18***	Fun	9.38**	Beer	0.14
	(-1.99)		(-3.99)		(3.87)		(0.00)
Agric	-6.68	Aero	-17.77***	ElcEq	9.36*	Whlsl	0.70
	(-1.54)		(-4.18)		(2.73)		(0.04)
Hshld	-6.70**	Comps	-17.00***	Rtail	8.66***	Agric	0.71
	(-2.38)		(-3.21)		(6.99)		(0.03)