# Geopolitical Risk and Stock Returns

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Geopolitical risks have intensified in recent years. This paper systematically examines the relationship between geopolitical risk and stock market returns by constructing a Geopolitical Risk Index (GRI) using textual analysis of Wall Street Journal archives from 1984 to 2025. We find that GRI positively predicts future aggregate market returns, suggesting that geopolitical risk is a non-diversifiable risk that commands a risk premium. A one-standard-deviation increase in GRI predicts a 7.39% increase in annualized excess returns in the following month, with predictability persisting over the next 36 months. This relationship remains robust after controlling for valuation ratios, interest rates, economic policy uncertainty, and other risk measures. Furthermore, GRI predicts global stock returns, particularly in recent decades. Examining the cross-section of stock returns, we construct a geopolitical risk factor and find that stocks with greater exposure to geopolitical risk earn higher abnormal returns. The High-Low portfolio delivers a 7.91% monthly alpha, reinforcing the idea that geopolitical risk is a priced risk factor. Overall, our findings underscore the importance of geopolitical risk in asset pricing, highlighting its role in shaping investor expectations, market dynamics, and global equity premiums.

**JEL Codes:** G11, G14, G23

**Keywords**: Geopolitical risk, stock returns, trade wars

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# 1 Introduction

Geopolitical risks have 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 impact economic fundamentals like GDP (Caldara and Iacoviello, 2022). In addition to macroeconomic effects, anecdotal evidence suggests that geopolitical instability also influences financial markets, leading to increased volatility and risk-averse behaviors among investors in response to unfolding geopolitical events.[1] Yet, there is limited understanding on the empirical relationship between geopolitical risks and asset prices, leaving an important gap in the literature.

In this paper, we systematically examine the effect of geopolitical risk on stock returns. We construct a Geopolitical Risk Index (GRI) using textual data from Wall Street Journal (WSJ) archives, spanning from 1984 to 2025. Following Caldara and Iacoviello (2022), we define geopolitical risk as the political, economic or military events that potentially disrupt global and local economic activities. We develop a comprehensive dictionary for geopolitical risks, building on existing studies to systematically identify and classify relevant events. Our dictionary captures different types of geopolitical risks—such as military conflicts, diplomatic tensions, and trade disputes. Importantly, our GRI measure includes trade wars, which are missing from Caldara and Iacoviello's geopolitical index and have not been systematically explored in text data. Trade wars were a major concern in the 1990s (the United States and Japan) but became less prominent until their resurgence between 2018 and 2025, which involved the United States, China, Canada, Mexico, and Europe. Given the importance of trade wars by itself, we also separately construct the Trade War Index (TWI) in addition to the GRI.

To construct the GRI, we first identify geopolitical news articles that contain the relevant keywords from our expanded dictionary. Including the trade-war related keywords results in

[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.

an additional 32% geopolitical news articles, which highlights the importance of trade-war related geopolitical tensions in recent years. We then calculate the GRI by dividing the number of geopolitical news articles by the total number of news articles published in a given month.

Figure 1 visualizes the GRI index from January 1983 to February 2025. GRI effectively captures major geopolitical risk events, such as Gulf War, 9/11 attacks, and the onset of the Iraq War. More recently, the GRI rises sharply during the Russian invasion of Ukraine in February 2022 and the onset of Israel-Hamas War in October 2023. Additionally, the GRI reflects critical trade-related tensions, such as 2018 US-China trade war and the ongoing trade tensions between the U.S. and its major trade partners started in 2025.

Geopolitical risk creates uncertainty about future economics 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, Barro (2006) shows that rare economic disasters is a priced risk factor. Both the intertemporal hedging and the rare disaster-aversion motivates 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.

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 a 7.39% 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 36 months, suggesting that geopolitical uncertainty represents a non-diversifiable risk that earns a risk premium. The effect of GRI on US stock market is much stronger during the

later sample period of 2000-2025. A one-standard-deviation increase in GRI is associated with a 13.73% 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, geopolitical risk, war-related risks, and news-implied volatility. The results show that GRI remains a strong and statistically significant predictor of future stock market returns beyond the existing factors. Notably, 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.

Given that several 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 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 annualized excess return of 7.6% to 10.8%. These findings highlight the growing impact of geopolitical risks on global stock markets.

To explore the channels through which geopolitical risk influences stock returns, we analyze its relationship with contemporaneous price movements and return components. First, we examine how innovations in geopolitical risk is related to the contemporaneous market returns. If higher geopolitical risk commands a greater risk premium, we expect a negative contemporaneous correlation between unexpected changes in GRI and returns. Consistent with this expectation, we find that an increase in geopolitical risk corresponds to a

notable decline in annualized contemporaneous returns. When decomposing the returns into the cash flow and the discount rate components, we find that GRI is significantly associated with both return components, suggesting that geopolitical risk not only influences investors' expectations about future economic conditions but also investors' risk aversion.

Finally, we examine whether GRI is priced in the cross-sectional of stock returns. We follow the approach of Hirshleifer, Mai, and Pukthuanthong (forthcoming) by constructing a geopolitical risk factor (GRIFac) 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 $t$. To assess the pricing of geopolitical risk, we examine the performance of portfolios sorted by their exposure to GRI. The results show that stocks with higher exposure to geopolitical risk earn significantly higher abnormal returns. Notably, during the later sample period of 2000-2025, the High-Low portfolio, which captures the return differential between stocks with the highest and lowest geopolitical risk exposure, delivers a value-weighted alpha of 7.91% over the subsequent month. These findings suggest that geopolitical risk carries a systematic premium in the cross-section of stock returns.

This paper makes three important contributions to the finance and economics literature. First, it extends the work of Caldara and Iacoviello (2022) by broadening the scope of geopolitical risk measurement. While their measure focuses on geopolitical tensions and conflicts, this paper expands it to explicitly incorporate trade wars, which have played an increasingly significant role in shaping global economic conditions. By doing so, our project provides a more comprehensive measure of geopolitical risk that captures a wider range of political and economic disruptions.

Second, our study contributes to the literature on risk and returns. Prior research has examined various forms of risk affecting asset returns, including political cycles (Santa-Clara and Valkanov, 2003), war and disaster risks (Manela and Moreira, 2017; Hirshleifer et al., 2025, forthcoming), autocorrelation and break risk (Sias and Starks, 1997; Smith and Timmermann, 2021), sovereign risk (Du and Schreger, 2016, 2022), behavioral risks (Kamstra,

Kramer, and Levi, 2000, 2003), firm-level political risk (Hassan, Hollander, Van Lent, and Tahoun, 2019), and political polarization (Sheng, Sun, and Wang, 2024), crash risk (Goetzmann, Kim, and Shiller, 2022), pandemic risk (Acharya, Engle, Jager, and Steffen, 2024), and climate risk (Engle, Giglio, Kelly, Lee, and Stroebel, 2020). Different from these studies, this paper is the first to systematically analyze the relationship between geopolitical risk and stock returns. Given the increasing frequency and severity of geopolitical events, understanding their impact on asset prices is crucial, and this paper fills an important gap in the literature.

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), long-run risk (Liu and Matthies, 2022), attention (Fisher, Martineau, and Sheng, 2022), social media (Chawla et al., 2021), and business cycles (Bybee, Kelly, Manela, and Xiu, 2024). See Goldstein and Yang (2017) and Goldstein et al. (2021, 2024) for reviews. By applying textual analysis to geopolitical risk, this study provides a timely and dynamic measure of geopolitical uncertainty and its asset pricing implications.[2]

# 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

[2]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.

January 1, 1984, to February 28, 2025, providing a long-term perspective on geopolitical risk trends. Importantly, it includes the most recent years, enabling the analysis to capture timely geopolitical events, such as 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 et al. (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 WAR Index from Hirshleifer et al. (2025), and the News Implied Volatility Index (NVIX) from Manela and Moreira (2017). By integrating these diverse data sources, the paper provides a comprehensive and rigorous 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. This method is particularly suitable for settings where we know what we are looking for from the text data, which is the case for this paper. 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.[3]

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,

[3]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.

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 explicitly include terms related to trade wars as another key dimension, capturing both traditional threats and the evolving landscape of economic conflicts.

Specifically, we develop a specialized word list for trade wars by leveraging ChatGPT. To make sure the new word list is consistent with the existing word list from Caldara and Iacoviello (2022), we begin by feeding ChatGPT the original Geopolitical Risk (GPR) dictionary and then prompt it to generate an additional category specifically focused on trade wars.

*"For the original list with all keywords, I would like to add one more type of geopolitical risk: trade wars. Let me explain, the tension between US and China, US and Canada/Mexica, US and Euro recently are mainly about international trades and tariff or embargo. Can you develop a keywords list in the same fashion for this category."*

The prompt explains that recent geopolitical tensions—particularly those involving the United States and its key trading partners, such as China, Canada, Mexico, and Europe—are largely centered around international trade disputes, tariffs, and embargoes. In response, ChatGPT produces a refined keyword list that includes relevant country names (United States, China, Canada, Europe, Japan, and Mexico) alongside trade-related terms such as tariffs, imports, exports, sanctions, agreements, disputes, negotiations, tensions, failures, collapses, retaliation, punitive measures, and breakdowns. This expanded word list allows us to systematically capture news coverage of trade-related geopolitical tensions and incorporate them into our Geopolitical Risk Index (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.

# 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 provide valuable insights into the evolution of geopolitical risk over time and its implications for financial markets.

## 3.1 GRI: Measure and Summary Statistics

To construct the Geopolitical Risk Index (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 70,323 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 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 two related measures to complement the GRI. The first, GPR_WSJ, uses the same word list as Caldara and Iacoviello (2022) but focuses exclusively on The Wall Street Journal (WSJ), resulting in 53,372 relevant articles. The second, Trade War Index (TWI), applies a similar methodology but is based on our newly developed trade war-related dictionary. This measure identifies 16,951 articles, which is 32% 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 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 not higher suggests that GRI and GPR, while related, are distinct in important ways, likely due to differences in methodology and scope. The correlation between GRI and GPR_WSJ is notably high, indicating that one key dis-

tinction between GRI and GPR stems from differences in data sources, as GPR_WSJ is specifically based on news articles from The Wall Street Journal. This suggests that variations in media coverage can influence how geopolitical risk is measured across indices. We also find a moderate correlation between GRI and the Economic Policy Uncertainty (EPU) index, which is intuitive given that geopolitical risks often contribute to broader economic uncertainty. However, the correlation is not perfect, reinforcing that these indices capture different dimensions of uncertainty. In contrast, GRI exhibits only a weak correlation with both the WAR and NVIX indices, suggesting that geopolitical risk, as captured by GRI, is largely distinct from measures of 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: Graphical Evidence

Once we obtain the monthly GRI data from January 1984 to February 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 also covers the most recent period in 2025, it also captures the on-going trade war between the U.S. and its major trade partners, including Canada, China, Europe, and Mexico, which escalated sharply since January 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 (TWI), 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 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 broader 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 risks influence 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 risks are systemically important and cannot be diversified away, they should have predictive power over aggregate stock market returns. Conversely, if these risks are fully diversifiable, we would not expect them 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 estimate the following regression model, where future excess market returns are regressed on the Geopolitical Risk Index (GRI):

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

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 $\text{GRI}_t$ 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. 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 GRI is associated with a 7.39% increase in annualized excess returns in the next month, significant at the 1% level. The results hold across various horizons. This predictive relationship extends to longer horizons, with significance persisting up to 36 months ahead, where a one-standard-deviation increase in

GRI predicts a 1.92% increase in annualized excess returns.

We also examine the post-2000 period 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 12.94% increase in next-month annualized excess returns, with an adjusted $R^2$ of 6.35%. The effect remains economically and statistically significant across all horizons, with the adjusted $R^2$ reaching 13.67% at the 36-month horizon. This is economically substantial, especially considering that the average annualzied monthly excess stock market return over this period is 6.51%.

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. This trend suggests that as global uncertainties intensify, market participants increasingly incorporate geopolitical developments into their investment decisions.

## 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 et al. (2016), Geopolitical Risk (GPR) from Caldara and Iacoviello (2022), the War Index (WAR) from Hirshleifer et al. (2025), and News

Implied Volatility (NVIX) from Manela and Moreira (2017).

Table 3 presents results. 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 6.08 to 13.61. Importantly, even in the comprehensive specification that includes multiple economic predictors (column 10), GRI maintains statistical significance at the 1% level with a coefficient of 12.06. This suggests that the information content in GRI is not subsumed by these traditional economic variables. Among the control variables, only the Treasury bill rate (TBL) shows consistent and significant negative predictive power for future returns, while the dividend-price ratio (DP) is significant in some specifications.

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 9.50 to 14.69) and maintains statistical significance at the 1% level throughout. The adjusted $R^2$ values are also notably higher in this period, reaching 8.50% 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 Predicting international stock market returns

We also investigate whether 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 4 presents the results for both the full sample and a more recent period (2000-2025). 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 GRI is associated with a 10.83% 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.

## 4.4 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:

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

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 5 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 mod-

est 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).

## 4.5 Mechanism

To understand the channels through which geopolitical risk affects stock returns, we examine the contemporaneous relation between GRI's innovations, price movements, and the components of return.

### 4.5.1 Contemporaneous Relationship between GRI and Returns

In this section, we examine the contemporaneous relationship between innovations in geopolitical risk and market returns. Through the discount channel, if innovations in GRI are associated with higher risk premiums, we would expect a negative contemporaneous correlation of innovations with returns. Moreover, if GRI contains negative information about future cash flows, it will result in a negative contemporaneous correlation between GRI innovations and returns.

Since GRI is highly persistent (with autocorrelation of 0.78), we follow Hirshleifer, Mai, and Pukthuanthong (2025) to focus on GRI innovations rather than levels. We compute GRI innovations ($\text{GRI}_t^{res}$) 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:

$$R_t^e = \alpha + \beta \text{GRI}_t^{res} + \gamma z_t + \epsilon_t, \tag{3}$$

where $R_t^e$ is the market excess return in month $t$ and $z_t$ includes various control variables.

The coefficient $\beta$ captures the immediate market reaction to geopolitical risk news.

Table 6 reports the results. Over the full sample period (1986-2025), the coefficient on $\text{GRI}_t^{res}$ is -7.24 and statistically significant at the 1% level. This indicates that, on average, a one-standard-deviation increase in unexpected geopolitical risk is associated with a 7.24 percentage point decrease in annualized contemporaneous returns. This negative contemporaneous relationship is robust to controlling for the innovations of other uncertainty measures ($\text{GPR}^{res}$, $\text{EPU}^{res}$, $\text{WAR}^{res}$, $\text{NVIX}^{res}$) 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.

This negative contemporaneous correlation suggests that investors initially perceive geopolitical tensions as bad news, leading to immediate market declines when GRI unexpectedly increases. The magnitude of this contemporaneous effect is economically substantial—roughly 30% as large as the average annualized excess stock market return over our sample period.

#### 4.5.2 Decomposing returns: cash flow news versus discount rate news

To further explore the source of GRI's predictive power, we decompose returns into three components following the approach of Campbell (1991):

$$r_{t+1} = \mathbb{E}_t r_{t+1} + CF_{t+1} - DR_{t+1}, \tag{4}$$

where $E_t r_{t+1}$ is the expected return component, $CF_{t+1}$ is cash flow news, and $DR_{t+1}$ is discount rate news. The cash flow news ($CF_{t+1}$) represents revisions in expectations about future cash flows from period $t$ to $t+1$, while discount rate news ($DR_{t+1}$) captures revisions in expectations about future discount rates.

To estimate these components, we employ a VAR(1) model following Rapach et al. (2016):

$$Y_{t+1} = AY_t + U_{t+1}, \tag{5}$$

where $Y_{t+1}$ is a vector consisting of log return $r_{t+1}$, log dividend-price ratio $d_t - p_t$, and other return predictors, $A$ is a matrix of VAR slope coefficients, and $U_{t+1}$ is a vector of zero-mean innovations.

Let $e_1$ be a vector with one as its first element and zeros for the remaining elements. The three components of return are given by:

$$\mathbb{E}_t r_{t+1} = e_1' A Y_t, \tag{6}$$

$$DR_{t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} = e_1' \rho A (I - \rho A)^{-1} U_{t+1}, \tag{7}$$

$$CF_{t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=0}^{\infty} \rho^j d_{t+1+j} = r_{t+1} - \mathbb{E}_t r_{t+1} + DR_{t+1}, \tag{8}$$

where $\rho$ is the log-linearization constant set to 0.96. We use the VAR model to directly estimate the expected return component and discount rate news, and extract cash flow news as the residual.

We estimate different VAR specifications using various combinations of predictors, always including the log dividend-price ratio (DP) because this predictor is important for properly estimating the cash flow and discount rate components. Additional predictors include log earnings-price ratio (EP), Treasury bill rate (TBL), and stock variance (SVAR).

We examine the contemporaneous relationship between GRI innovations and return

components:

$$r_t = \alpha + \beta \, \text{GRI}_t^{res} + \epsilon_t, \tag{9}$$

$$E_t r_t = \alpha^E + \beta^E \, \text{GRI}_t^{res} + \epsilon_t^E, \tag{10}$$

$$CF_t = \alpha^{CF} + \beta^{CF} \, \text{GRI}_t^{res} + \epsilon_t^{CF}, \tag{11}$$

$$DR_t = \alpha^{DR} + \beta^{DR} \, \text{GRI}_t^{res} + \epsilon_t^{DR}. \tag{12}$$

Table 7 presents these results. We find that GRI innovations are strongly negatively related to contemporaneous cash flow news. For the full sample period, a one-standard-deviation increase in GRI innovations is associated with a decrease in contemporaneous return due to cash flow news by 8.20 to 9.64 percentage points (annualized) across different VAR specifications. The relationship with contemporaneous discount rate news is also negative but smaller in magnitude, with a one-standard-deviation increase in GRI innovations associated with a decrease of approximately 0.60 to 1.55 percentage points. This pattern is similar in the more recent period (2000-2023), with even larger negative coefficients for cash flow news.

# 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 (forthcoming) by constructing a geopolitical risk factor (GRIFac) as the innovation from an AR(1) process estimated for GRI with a expanding window of at least 12 months starting on January 1985. This approach avoids the look-ahead bias an 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).

## 5.1 Portfolio Sorts

To calculate return sensitivity to GRIFac, for each stock, we run the following regression using a rolling window of 60 months:

$$R^e_{i,t} = \alpha_i + \beta^{GRI}(-\text{GRIFac}_t) + \boldsymbol{\beta^z z_t} + \epsilon_t, \tag{13}$$

where $R^e_{i,t}$ is the annualized excess return of stock $i$ in month $t$. $-\text{GRIFac}_t$ is the negative of GRIFac 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. Sheng, Simutin, and Zhang (2023) highlights the importance of using the factor model including investments and profitability.

Table 8 presents the performance of portfolios sorted based on their exposure to geopolitical risk. We form decile portfolios each month by sorting stocks on their estimated $\beta^{GRI}$ using a 60-month rolling window. Portfolio 1 (Low) contains stocks with the lowest sensitivity to negative GRIFac, while Portfolio 10 (High) contains those with the highest sensitivity.

The results for the full sample period (1991-2025) show that both low and high GRIFac beta portfolios earn positive and statistically significant returns. The value-weighted low-beta portfolio (Portfolio 1) earns an average monthly return of 8.31% (t-statistic = 2.13), while the high-beta portfolio (Portfolio 10) earns 10.96% (t-statistic = 2.52), resulting in a High-Low spread of 2.65% per month that is statistically insignificant.

Interestingly, when focusing on the more recent period (2000-2025), the pattern strengthens considerably. The value-weighted High-Low spread increases to 5.24% with a t-statistic of 1.54, though still not statistically significant at conventional levels. However, after adjusting for factors from the Fama-French six-factor model, the value-weighted alpha of the High-Low portfolio becomes statistically significant at 7.91% monthly (t-statistic = 2.23).

Overall, these portfolio sorting 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.

## 5.2 Cross-Sectional Regression Tests

We further run the Fama-MacBeth regression:

$$R^e_{i,t+1} = \alpha + \lambda^{GRI}_t \beta^{GRI}_t + \boldsymbol{\lambda^z_t \beta^z_t} + \epsilon_{t+1}, \tag{14}$$

where $R^e_{i,t+1}$ is the excessive return of stock $i$ in month $t+1$ (expressed as annualized percentage), $\beta^{GRI}_t$ and $\boldsymbol{\beta^z_t}$ are the rolling betas on negative GRIFac and the Fama-French six factors estimated in regression (13).

Table 9 presents the results of our cross-sectional tests, examining whether exposures to GRIFac are associated with return premiums across individual stocks. Our results show that a one-standard-deviation increase in GRIFac beta is associated with 0.92% higher returns in the next month for the sample period 1991-2025, and the magnitude increases to 1.74% for the more recent period 2000-2025 (column 2).

Since GRIFac is a nontraded factor, we construct a GRIFac mimicking portfolio (GMP). We adopt the cross-sectional approach proposed by Lehmann and Modest (1988). We use the cross-sectional estimate of the slope of GRIFac betas in predicting one-month returns as the mimicking portfolio return, where GRIFac betas for a given asset is estimated using a 60-month rolling window by regressing returns on negative GRIFac.

Using the GMP returns, we first calculate rolling betas using Equation (13) and then perform the Fama-MacBeth regression in Equation (14). The results are presented in columns 3 and 4 in Table 9. We find stronger predictive power of cross-sectional returns with GMP. A one-standard-deviation increase in GMP beta is associated with 1.61% annualized returns in the full sample period and 1.70% in the later sample period.

# 6 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 significant and persistent factor influencing asset prices. Our findings suggest that geopolitical risk is a priced risk factor, meaning that investors demand compensation for bearing uncertainty associated with political, economic, and military disruptions.

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.

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. The broad applicability of our findings underscores the global nature of geopolitical risk, influencing capital flows, investment decisions, and market sentiment across different economies.

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.

These findings contribute to the growing literature on the role of non-traditional risk

factors in asset pricing and highlight the importance of considering geopolitical uncertainty in portfolio construction. 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 firm-level investment decisions.

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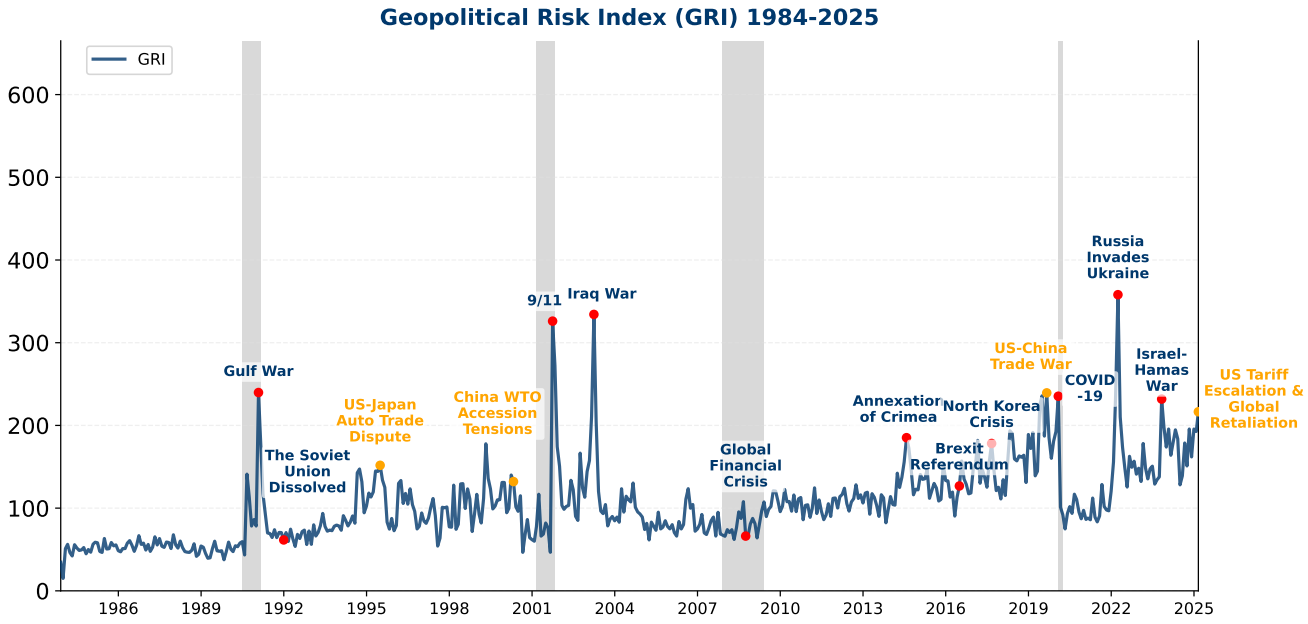



Figure 1: Geopolitical Risk Index 1984-2025

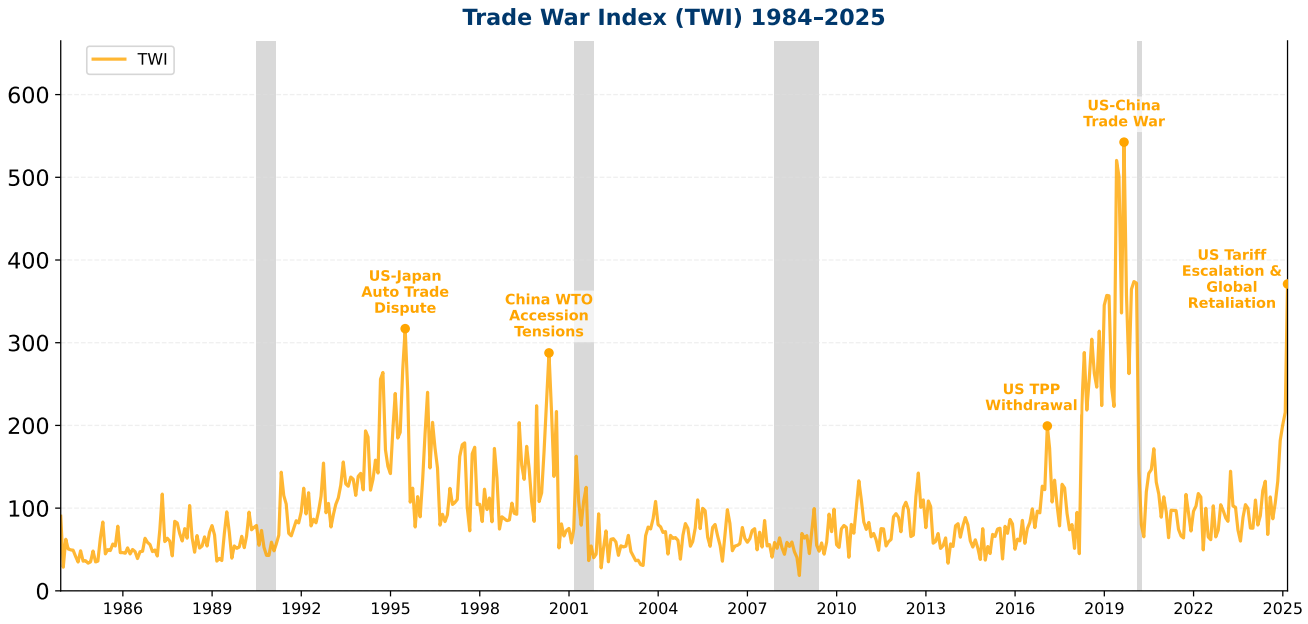



Figure 2: Trade War Index 1984-2025

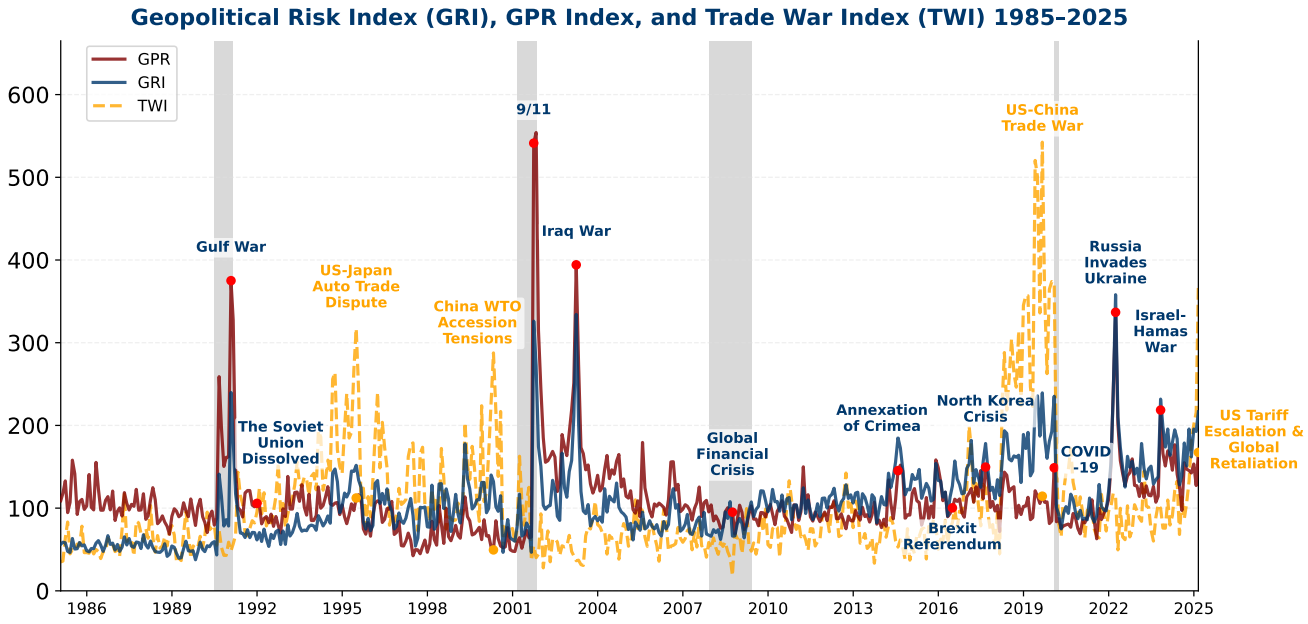



Figure 3: GRI, GRP, and TWI 1985-2025

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. GRI is the geopolitical risk index. TWI is the trade war index. GPR is Caldara and Iacoviello (2022)'s measure of geopolitical risk. $GPR_{wsj}$ is GPR using only Wall Street Journals. EPU is the economic policy uncertainty index by Baker et al. (2016). WAR is the war index by Hirshleifer et al. (2025). 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 | $10^{th}$ | $25^{th}$ | $75^{th}$ | $90^{th}$ |
| GRI | 103.98 | 96.42 | 43.90 | 55.05 | 72.09 | 125.24 | 160.23 |
| TWI | 101.14 | 78.10 | 72.21 | 47.34 | 58.70 | 110.44 | 185.95 |
| GPR | 109.20 | 100.40 | 49.69 | 68.97 | 86.54 | 118.96 | 152.04 |
| $GPR_{wsj}$ | 105.16 | 99.17 | 52.08 | 49.81 | 65.29 | 130.98 | 166.00 |
| EPU | 128.27 | 110.78 | 62.56 | 64.11 | 78.89 | 159.13 | 227.60 |
| WAR | 0.10 | 0.10 | 0.02 | 0.08 | 0.09 | 0.11 | 0.13 |
| NVIX | 24.47 | 23.88 | 5.99 | 17.63 | 20.42 | 28.07 | 30.98 |

*B. Correlation Structure*

| | GRI | GPR | $GPR_{wsj}$ | TWI | EPU | WAR |
|---|---|---|---|---|---|---|
| GPR | 0.56 | | | | | |
| $GPR_{wsj}$ | 0.92 | 0.69 | | | | |
| TWI | 0.47 | -0.13 | 0.08 | | | |
| EPU | 0.61 | 0.18 | 0.45 | 0.48 | | |
| WAR | 0.28 | 0.52 | 0.44 | -0.29 | 0.23 | |
| NVIX | 0.23 | 0.07 | 0.29 | -0.19 | 0.73 | 0.15 |

Table 2: Predicting future market returns

This table presents the results of the following predictive regression

$$R^e_{t+1\to t+n} = \alpha + \beta \mathrm{GRI}_t + \epsilon_{t+1}, \tag{15}$$

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 $\mathrm{GRI}_t$ 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 3: Predicting future market returns: GRI versus other factors

This table presents the results of the following predictive regression

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

where $R^e_{t+1}$ is the excessive return of the market in month $t+1$ (expressed as annualized percentage), $\mathrm{GRI}_t$ 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*** | 13.61*** | 6.08*** | 7.91*** | 11.50*** | 9.17*** | 7.82*** | 7.68*** | 9.22*** | 12.06*** |
| | (2.84) | (3.35) | (2.79) | (2.63) | (5.55) | (3.42) | (3.84) | (3.57) | (3.94) | (5.06) |
| GPR | 0.34 | | | | | | | | | |
| | (0.14) | | | | | | | | | |
| EPU | | -2.04 | | | | | | | | |
| | | (-0.60) | | | | | | | | |
| 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 4: Predicting international stock market returns

This table presents the results of the following predictive regression

$$R_{t+1}^{e,i} = \alpha + \beta \text{GRI}_t + \epsilon_{t+1}, \tag{16}$$

where $R_{t+1}^{e,i}$ is the excess return of the international market index $i$ in month $t+1$ (expressed as annualized percentage) and $\text{GRI}_t$ 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 | MSCI | DJW | FTA |
| | (1) | (2) | (3) | (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 | MSCI | DJW | FTA |
| | (1) | (2) | (3) | (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 5: 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. 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 | 2000–2025 |
| | (1) | (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 6: 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), $\mathrm{GRI}_t^{res}$ 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. $\mathrm{GPR}_t^{res}$, $\mathrm{EPU}_t^{res}$, $\mathrm{WAR}_t^{res}$, and $\mathrm{NVIX}_t^{res}$ 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) |
| $\mathrm{GRI}_t^{res}$ | -7.24*** | -3.29 | -6.43** | -7.17** | -1.86 | -6.87*** | -6.88** | -6.77** | -6.77*** | -6.84** | -6.88** |
| | (-2.87) | (-0.86) | (-2.38) | (-2.55) | (-0.86) | (-2.59) | (-2.57) | (-2.56) | (-2.63) | (-2.53) | (-2.57) |
| $\mathrm{GPR}_t^{res}$ | | -5.15 | | | | | | | | | |
| | | (-1.51) | | | | | | | | | |
| $\mathrm{EPU}_t^{res}$ | | | -8.67** | | | | | | | | |
| | | | (-2.13) | | | | | | | | |
| $\mathrm{WAR}_t^{res}$ | | | | 1.91 | | | | | | | |
| | | | | (0.82) | | | | | | | |
| $\mathrm{NVIX}_t^{res}$ | | | | | -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 | -7.63** | -9.37*** | -2.71 | -8.64*** | -8.77*** | -8.74*** | -8.93*** | -9.07*** | -9.28*** |
| | (-3.33) | (-1.27) | (-2.56) | (-2.84) | (-1.30) | (-2.81) | (-2.93) | (-2.88) | (-3.12) | (-3.06) | (-3.34) |
| $GPR_t^{res}$ | | -3.57 | | | | | | | | | |
| | | (-0.90) | | | | | | | | | |
| $EPU_t^{res}$ | | | -8.05* | | | | | | | | |
| | | | (-1.93) | | | | | | | | |
| $WAR_t^{res}$ | | | | 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 7: Contemporaneous relationship between GRI innovations and return components

This table reports results from the following univariate regressions with contemporaneous components:

$$
\begin{aligned}
r_t &= \alpha + \beta\, GRI_t^{res} + \epsilon_t, \\
E_t r_t &= \alpha^E + \beta^E\, GRI_t^{res} + \epsilon_t^E, \\
CF_t &= \alpha^{CF} + \beta^{CF}\, GRI_t^{res} + \epsilon_t^{CF}, \\
DR_t &= \alpha^{DR} + \beta^{DR}\, GRI_t^{res} + \epsilon_t^{DR},
\end{aligned}
$$

where $r_t$ is the log market return, $E_t r_t$ is the expected return, $CF_t$ is cash flow news, and $DR_t$ is discount rate news. Each row shows results for a different combination of return predictors. $\text{GRI}_t^{res}$ is the AR(1) residuals of GRI estimated with an expanding window of at least 12 months from January 1985 to month $t$. The returns are expressed as annualized percentages, and the 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: 1990–2023* | | | | |
|---|---|---|---|---|
| | $\beta$ | $\beta^E$ | $\beta^{CF}$ | $\beta^{DR}$ |
| | (1) | (2) | (3) | (4) |
| R, DP | -7.69*** | -0.08* | -8.20*** | -0.60*** |
| | (-3.35) | (-1.86) | (-3.32) | (-3.27) |
| R, DP, EP | -7.69*** | -0.10** | -8.22*** | -0.63*** |
| | (-3.35) | (-2.15) | (-3.32) | (-3.32) |
| R, DP, SVAR | -7.69*** | 0.24* | -9.39*** | -1.47** |
| | (-3.35) | (1.87) | (-3.47) | (-2.09) |
| R, DP, TBL | -7.69*** | 0 | -8.69*** | -1.01*** |
| | (-3.35) | (-0.02) | (-3.60) | (-4.16) |
| R, DP, EP, SVAR, TBL | -7.69*** | 0.41*** | -9.64*** | -1.55** |
| | (-3.35) | (3.35) | (-3.68) | (-2.31) |
| *B. Sample period: 2000–2023* | | | | |
| | $\beta$ | $\beta^E$ | $\beta^{CF}$ | $\beta^{DR}$ |
| | (1) | (2) | (3) | (4) |
| R, DP | -8.85*** | -0.24 | -9.55*** | -0.94*** |
| | (-3.61) | (-1.48) | (-3.43) | (-3.42) |
| R, DP, EP | -8.85*** | -0.24 | -9.53*** | -0.93*** |
| | (-3.61) | (-1.50) | (-3.43) | (-3.37) |
| R, DP, SVAR | -8.85*** | 0.17 | -10.62*** | -1.60* |
| | (-3.61) | (1.04) | (-3.65) | (-1.67) |
| R, DP, TBL | -8.85*** | -0.21 | -8.15*** | 0.5 |
| | (-3.61) | (-0.68) | (-2.60) | (0.66) |
| R, DP, EP, SVAR, TBL | -8.85*** | 0.43 | -8.69*** | 0.6 |
| | (-3.61) | (1.61) | (-2.84) | (0.88) |

Table 8: Portfolios sorting

This table presents the results portfolio returns sorted on the rolling beta on GRI factor. The rolling beta of GRI is calculated using GRIFac and the six factors from Fama and French (2015). Stocks are sorted into decile portfolios on the beta of GRI and are rebalanced monthly. Alphas of portfolio returns are calculated based on the six-factor model from Fama and French (2015). 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: 1990-2025 | | | | Sample period: 2000-2025 | | | |
|---|---|---|---|---|---|---|---|---|
| | Value-Weighted | | Equal-Weighted | | Value-Weighted | | Equal-Weighted | |
| | Mean | Alpha | Mean | Alpha | Mean | Alpha | Mean | Alpha |
| Low | 8.31** | 9.89** | 19.14*** | 18.60*** | 3.19 | 5.41 | 15.57*** | 16.98*** |
| | (2.13) | (2.30) | (4.82) | (4.61) | (0.71) | (1.14) | (3.21) | (3.53) |
| 2 | 7.87** | 9.61*** | 15.58*** | 16.05*** | 3.92 | 6.36 | 14.29*** | 16.46*** |
| | (2.44) | (2.65) | (4.79) | (4.61) | (1.01) | (1.56) | (3.45) | (3.81) |
| 3 | 8.40*** | 10.09*** | 13.36*** | 13.83*** | 6.12* | 8.02** | 12.39*** | 14.20*** |
| | (3.32) | (3.58) | (4.54) | (4.38) | (1.92) | (2.46) | (3.23) | (3.57) |
| 4 | 9.28*** | 11.76*** | 13.36*** | 13.80*** | 8.54*** | 11.14*** | 13.01*** | 14.61*** |
| | (4.08) | (4.30) | (4.41) | (4.15) | (2.90) | (3.46) | (3.28) | (3.49) |
| 5 | 10.30*** | 12.15*** | 13.60*** | 14.13*** | 8.38*** | 10.25*** | 13.31*** | 14.75*** |
| | (4.44) | (4.47) | (4.73) | (4.43) | (2.78) | (3.23) | (3.52) | (3.63) |
| 6 | 9.61*** | 12.08*** | 14.20*** | 14.71*** | 8.00** | 10.54*** | 14.35*** | 16.01*** |
| | (3.95) | (4.42) | (4.99) | (4.67) | (2.53) | (3.22) | (3.84) | (4.02) |
| 7 | 8.85*** | 11.03*** | 13.55*** | 14.70*** | 7.70** | 10.24*** | 13.24*** | 15.59*** |
| | (3.50) | (3.82) | (4.58) | (4.53) | (2.30) | (3.03) | (3.38) | (3.73) |
| 8 | 10.66*** | 13.24*** | 16.42*** | 17.26*** | 9.57** | 12.39*** | 16.13*** | 18.10*** |
| | (3.39) | (3.80) | (5.23) | (5.13) | (2.30) | (2.94) | (3.95) | (4.24) |
| 9 | 8.73** | 11.04*** | 17.35*** | 18.25*** | 6.36 | 9.29** | 16.90*** | 19.55*** |
| | (2.54) | (3.10) | (4.87) | (4.77) | (1.41) | (2.15) | (3.67) | (4.06) |
| High | 10.96** | 13.91*** | 21.19*** | 21.81*** | 8.43 | 13.32** | 19.90*** | 22.83*** |
| | (2.52) | (2.98) | (4.84) | (4.55) | (1.65) | (2.48) | (3.72) | (3.96) |
| H-L | 2.65 | 4.01 | 2.05 | 3.22 | 5.24 | 7.91** | 4.33* | 5.84** |
| | (0.80) | (1.06) | (1.05) | (1.41) | (1.54) | (2.23) | (1.89) | (2.22) |

Table 9: Predicting cross-sectional stock returns

This table presents the results of the following regression

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

where $R^e_{i,t+1}$ is the excessive return of stock $i$ in month $t+1$ (expressed as annualized percentage), $\beta^{GRI}_t$ is the rolling beta on GRI factor, $\beta^z_t$ are the betas on market factor (MKT), value factor (HML), size factor (SMB), operating factor (RMW), investment factor (CMW), and momentum factor (MOM). In columns 1–2, betas are calculated by regressing returns on the AR(1) innovations of GRI (GRIFac) and the six factors. In columns 3–4, the GRIFac mimicking portfolio (GMP) returns are used instead. 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.

| | $\beta^{GRI}$ based on GRIFac | | $\beta^{GRI}$ based on GMP | |
|---|---|---|---|---|
| | 1991–2025 | 2000-2025 | 1990–2024 | 2000–2024 |
| | (1) | (2) | (3) | (4) |
| $\beta^{GRI}$ | 0.92 | 1.74** | 1.61*** | 1.70*** |
| | (1.63) | (2.40) | (3.02) | (2.84) |
| $\beta^{MKT}$ | 1.49 | 1.05 | 1.37 | 1.17 |
| | (1.12) | (0.60) | (0.85) | (0.65) |
| $\beta^{SMB}$ | 2.39*** | 1.50* | 1.77* | 1.40* |
| | (2.59) | (1.80) | (1.81) | (1.66) |
| $\beta^{HML}$ | -0.17 | 0.40 | -0.60 | 0.24 |
| | (-0.11) | (0.23) | (-0.37) | (0.14) |
| $\beta^{RMW}$ | -2.80* | -2.83 | -3.00 | -2.70 |
| | (-1.75) | (-1.34) | (-1.61) | (-1.27) |
| $\beta^{CMA}$ | -1.94 | -1.59 | -2.15 | -1.68 |
| | (-1.55) | (-1.14) | (-1.61) | (-1.24) |
| $\beta^{MOM}$ | -2.77*** | -2.93** | -2.61** | -2.77** |
| | (-2.99) | (-2.33) | (-2.47) | (-2.23) |
| Intercept | 15.88*** | 14.76*** | 15.47*** | 15.24*** |
| | (4.63) | (3.39) | (3.80) | (3.45) |
| Obs. | 766,195 | 512,993 | 624,330 | 510,734 |
| Adj. $R^2$ (%) | 2.80 | 3.10 | 3.10 | 3.20 |