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Do Corporate Bonds Hedge Geopolitical Risk?

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Keywords: geopolitical risk, corporate bonds, risk premium, hedging, supply-chain risk, international exposure
JEL Classification: G11, G12, C13, C21, C58, E20, E30

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We examine whether corporate bonds react to geopolitical risk by analyzing how firms' bond return sensitivity to the geopolitical risk index influences subsequent performance. Our regressions show that higher geopolitical risk beta predicts lower future returns, reflecting investors' willingness to pay premiums for bonds that hedge rising geopolitical tensions. Difference-in-differences regressions indicate greater demand for high-beta bonds following intensified conflicts. The risk premium is larger for firms with elevated downside, international, supply-chain, and credit risks, particularly during volatile and uncertain economic conditions. Overall, we contribute to the literature by documenting the pricing effect of GPR on corporate bonds.

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Do Corporate Bonds Hedge Geopolitical Risk?

1. Introduction

Geopolitical risk (GPR) refers to the "threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political factors that affect the peaceful course of international relations" (Caldara and Iacoviello, 2022). Recent geopolitical developments—such as the Russia–Ukraine conflict, the Israel–Palestine war, semiconductor export restrictions, the enactment of the CHIPS (Creating Helpful Incentives to Produce Semiconductors) Act in August 2022, and the ongoing strategic rivalry between China and the United States—illustrate the increasing prevalence of such risks and their potential economic implications. Geopolitical actions include targeted sanctions and tariffs, which can exert substantial financial pressure on affected firms and nations, respectively, and create broader disruptions in local markets.[1,2,3] Moreover, escalating tensions among major global powers can lead to economic and financial fragmentation on an international scale.[4] GPR therefore presents a distinctive phenomenon wherein adverse external shocks, unrelated to underlying economic fundamentals, can exert far-reaching influence on financial markets, including corporate bond markets, which play a crucial role in firm financing.

In this paper, we study how GPR beta, i.e., the relationship between a firm's bond return sensitivity to the GPR index, is related to subsequent corporate bond returns. We show that for

[1] See "The Trump administration's sanctions policy could matter more than its use of tariffs", Jan 28,2025 (Source : Chatham House).

[2] See "US adds Tencent, CATL to list of Chinese firms allegedly aiding Beijing's military", Jan 9,2025 (Source: Reuters); "China's biggest shipping line Cosco added to US military blacklist", Jan 7,2025 Source (Bloomberg); and " TSMC walks a geopolitical tightrope" Nov 14, 2024 (Source: The Economist).

[3] GPR could have significant dislocations in local markets such as Russia-Ukraine War & Impact on German manufacturing and gold markets, Chinese aggression & Hongkong versus Singapore real estate market. See "How do geopolitical shocks impact markets?" May 24, 2024 (Source J.P. Morgan).

[4] Financial fragmentation induced by geopolitical tensions could have potentially important implications for (a) global financial stability by affecting the cross-border allocation of capital, international payment systems, and asset prices, (b) asset allocation by exacerbating macro-financial volatility in the longer term by reducing international risk diversification opportunities in the face of adverse domestic and external shocks, and (c) sudden fire-sales in financial markets leading to vicious balance sheet deleveraging by financial institutions. See IMF Financial stability report, 2023.

positive GPR beta bonds, investors are willing to pay a premium and hence accept lower returns. Such bonds generate higher returns during higher GPR states and carry negative premiums because of the hedging effect. Equivalently, negative GPR beta bonds that generate lower returns during high GPR periods show positive risk premiums because of the risk effect. Our results imply evidence of the hedging or risk premium hypothesis for corporate bonds.

Studying the relevance of GPR through the lens of the corporate bond market is pertinent for many reasons. Firstly, the bond markets are dominated by sophisticated institutional investors who are likely to factor in evolving GPR risks in their risk assessment. Secondly, compared to stockholders, bondholders are more vulnerable to downside risk due to their concave payoff structures and have larger exposure to potential bankruptcy and illiquidity risks (see, for example, Hong & Sraer, 2013; Duan, Li, and Wen, 2025; Gul, 1991; Routledge and Zin, 2010; Augustin, Cong, Lopez, and Tedongao, 2020). As a result, geopolitical adversity can imply a tail-risk event for future firm cash flows and hence expected corporate bond returns. Thirdly, there has been an unprecedented increase in corporate bond issuance since the financial crisis (Çelik, Demirtaş & Isaksson 2020). Corporate debt forms a sizeable component of corporate capital structure with current outstanding debt of over 11.5 trillion at the end of Q3, 2025 (Source: SIFMA), and hence risk assessment of bonds can be significantly affected by GPR and fragility of the underlying bond market (Henderson, Jegadeesh & Weisbach 2006; Strebulaev & Yang, 2013; Goldstein, Jiang & Ng, 2017). Finally, findings in the secondary bond market can inform pricing in the primary debt market securities and influence the firms' borrowing costs (Augustin & Tédongap, 2014; Goldstein, Jiang & Ng, 2019; Huang et al., 2019).

We measure GPR exposure by assessing a bond's capacity to hedge against such risks, specifically through the estimation of its covariance with the GPR index—a news-based measure of adverse geopolitical events developed by Caldara and Iacoviello (2022). To quantify this, we compute the GPR beta for each bond using a 36-month rolling-window regression of the bond's excess returns on changes in the GPR index, along with relevant bond-specific risk factors. Additionally, we extract firm-level GPR risk measure based on textual analysis of quarterly earning calls.

We begin our analysis by employing univariate portfolio sorts to explore the effect of GPR beta on bond returns. We find that bonds in the highest GPR quintile (or Q5) earn significantly lower monthly returns (measured alternatively as excess returns, ratings/maturity adjusted returns, 3-factor and 6-factor adjusted returns) compared to the lowest GPR quintile (or Q1). We also find that the high-low (Q5-Q1) long-short portfolio earns a significant negative monthly alpha ranging from -0.17% to -0.19% (or about -2% to -2.3% on an annual basis)[5]. Univariate tests overall show that high GPR-sensitive firms earn significantly lower returns compared to low GPR-sensitive firms, implying support for the hedging or risk premium hypothesis.

We next conduct Fama-Macbeth cross-sectional regressions and find significant evidence of a negative relationship between GPR beta and bond returns. Robust fixed effects panel regressions further validate the negative relationship between GPR beta and subsequent bond returns, implying that bonds with high covariance of their returns with GPR risk earn lower returns next period. Higher GPR beta bonds can help hedge GPR, and bond investors pay higher prices to hedge the GPR risk, thereby earning lower subsequent returns. The results are also economically significant, implying that a one-sigma increase in the geopolitical risk beta is associated with a 6.23% to 8.70% drop in annual bond returns.[6]

[5] Notably, the Q5-Q1 alphas have a *t*-stat above 3.0, a threshold recommended by Harvey, Liu, and Zhu (2016) for long-short returns in the stock markets.

[6] In comparison, Huynh and Xia (2020) find a decline of 12.6% annualized bond returns for a one-standard deviation increase in climate-change risk. Similarly, Bali, Subrahmanyam and Wen (2021) find a premium of 0.64% monthly bond returns (or 7.9% annualized) for increase in economic uncertainty. Chung, Wang and Wu (2019) find that a one standard deviation below the cross-sectional mean of VIX beta is associated with an increase of 0.14% monthly bond returns (or 1.68% annualized).

We further implement a causal test by exploiting an exogenous shock to geopolitical tension. We employ a staggered difference-in-differences (DiD) design to study the differential impact of high tercile GPR-beta firms compared to the propensity-score matched low tercile GPR-beta firms on subsequent bond returns following the GPR crisis events in our sample. We find that high GPR-beta firms are associated with lower subsequent bond returns after the GPR stress events. The DiD regression results remain robust to the parallel trend test using a dynamic DiD specification. We also conduct a placebo test by implementing the DiD on stress events identified by the corporate bond stress index and find no evidence of a hedging effect. Pástor, Stambaugh, and Taylor (2021) show that the effect of investor preference is more prominent in the presence of a shock that shifts investors' tastes. Hence, for investor preference theory to hold, we should observe a positive association between GPR beta and bond returns in response to a geopolitical stress event. Evidence from staggered DiD regressions shows that high GPR-beta bonds produce lower returns compared to low GPR-beta bonds following a GPR event, clearly rejecting the preference hypothesis, and favoring hedging or risk premium.

We perform several additional cross-sectional tests to further understand the firm-level heterogeneity channels that underlie the demand for bonds with higher GPR hedging ability. First, we evaluate whether the negative relation is attenuated in high-risk environments when investors pay more attention to risk-related news events. The underreaction hypothesis posits that bond markets may underreact to GPR-related risks so that firms with higher GPR beta are underpriced. Those bonds tend to undergo a subsequent price correction once investors start to realize the importance of risk hedging. We find that the negative relationship is even stronger for firms with higher downside risk, and in times of higher VIX and economic uncertainty. The underreaction hypothesis predicts that the relationship between GPR beta and subsequent bond return should be positive during periods when investors pay closer attention to GPR issues. Our significantly negative result of the interaction between GPR-beta and other risk factors, measured by downside risk, VIX, or economic policy uncertainty, invalidates the underreaction hypothesis.

Second, we examine the effect of higher international exposure on GPR hedging. We measure international exposure for each firm by the percentage of sales revenues generated abroad versus domestically. Internationally exposed firms are hence more susceptible to risks arising from geopolitical conflicts. We find that the negative GPR beta is larger for firms that have higher international exposure, showing a stronger hedging effect.

Third, we study how supply chain distress can impact the GPR effect. The firm-level supply chain distress is measured using a firm-level text-based measure of supply chain risk estimated using firms' 10-K filings based on the intersection of the two word lists, i.e., the supply-chain-related word list from Wu (2023) and the risk word list from Hassan et al. (2019). We find that the hedging effect is significantly stronger for firms with higher supply chain distress. GPR risk premium also increases if the country-level distress goes up based on the adverse performance of the macro-level logistics performance index.

Fourth, we analyze how firm-level distress risk influences GPR hedging. We employ three proxies for distress risk, viz., distance to default, bank loan spreads, and CDS dummy (capturing the availability of a CDS contract on a given firm), and find that the negative GPR risk premium is significantly higher for firms with higher implicit distress risk.

Finally, we assess how firm-level equity and bond characteristics shape this relation. The negative GPR risk premium is more pronounced for firms with riskier equity—specifically, higher idiosyncratic volatility or greater systematic risk exposure (Bhandari (1988), Fama and French (1992))—and for bonds featuring shorter maturities or higher illiquidity.

We perform several robustness checks. (i) First, we use several alternate GPR indices including the construction of the Google Trends GPR sentiment indices, bond return sensitivity to global (vis-à-vis domestic) geopolitical risk index and global GPR exposure decomposed into threat and act indices, and bond return sensitivity to firms' international exposure to geopolitical risk weighted by the firm's geographical segment sales as alternative measures of GPR exposure, and show a robust negative relationship between GPR beta and subsequent bond returns. (ii) Second, we control for firm-level political risk from Hassan et al. (2019) and firm-level geopolitical risk extracted from quarterly earnings call transcripts following Caldara and Iacoviello (2022), and find our results robust. (iii) Third, we re-estimate the β_{GPR} using only the bond-market factor based on the recommendation by Dickerson, Mueller, and Robotti (2023) and, in a separate specification that additionally controls for macroeconomic uncertainty (Bali, Subrahmanyam, & Wen, 2021), find that the negative GPR risk premium remains robust. (iv) Fourth, we show that the risk premium for GPR beta is higher when the level of GPR is high, showing possible nonlinear effects. (v) We find the negative significance of GPR beta for subsequent bond returns holds up to four months, showing the shock persistence in bond markets. (vi) We conduct industry-level analysis and show that the GPR hedging effect mainly derives from the technology, oil and gas, consumer non-durables & durables sector, real estate, and healthcare, showing that the hedging evidence is more prevalent in downstream industries where investors are more exposed to GPR risk. (vii) We examine the GPR effect for the CDS markets and find robust evidence for the GPR hedging premium. And (viii) finally, we examine equity returns and find no support for the hedging hypothesis, showing that the hedging hypothesis is mainly obtained in the credit market.

Our paper makes two important contributions to literature. First, the work is closely related to empirical studies on corporate bond pricing. Among those, Lin, Wang & Wu (2011) shows that the return on bonds with high sensitivities to aggregate illiquidity is lower than that on bonds with low sensitivities. Chung, Wang & Wu (2019) draw on a risk-based explanation and show that bonds with high volatility beta exhibit lower expected returns. Huynh & Xia (2021a) study the impact of climate risk and present evidence that bonds with high return sensitivity to climate change news index offer lower returns (see also Huynh & Xia, 2021b, Massa & Zhang, 2021 for the exploration of the impact of climate change on bond returns). Bali, Subrahmanyam & Wen (2021) examine the risk exposure to macroeconomic uncertainty and demonstrate that bonds with high uncertainty beta are regarded as safer securities and deliver lower returns. Our paper focuses on the potential disruptive impact of GPR on corporate bond market pricing. We unpack the impact of geopolitical risk by examining several alternative channels, such as economic uncertainty, default risk, and volatility risk.

Second, by exploring the role geopolitical risk plays in asset returns, we contribute to the literature that discusses the impact of geopolitical risk on economic activity and the stock market. Caldara & Iacoviello (2022) show that a news-based measure of geopolitical risk lowers employment and investment. Ma, Lu & Tao (2022) show that the geopolitical index can forecast stock returns beyond traditional economic indicators. Earlier literature also examined the impact of GPR on stock returns (e.g., Alqahtani, Bouri & Vo 2020; Chesney, Reshetar & Karaman 2011; Ma, Lu & Tao 2022; Salisu, Lasisi & Tchankam 2022; Jung, Lee & Lee 2021; Zaremba et al. 2022 among others), exchange rates (Iyke, Phan & Narayan 2022), country exchange-traded funds returns (Lee & Chen 2020), and the pricing of cryptocurrency (Aysan et al. 2019; Su et al. 2020). Ambrocio & Hasan (2021) find that stronger political ties with the US are associated with both better sovereign credit ratings and lower yields on sovereign bonds, especially among lower-income countries. Ambrocio, Hasan & Li (2025) show that stronger political ties with the US amplify the sensitivities of stock returns in developing countries to the global financial cycle. In this paper, we contribute to the literature by specifically focusing on the GPR effects on the corporate bond markets.

The rest of the paper is structured as follows. In Section 2, we describe our data and methodology. Section 3 presents our key hypotheses and main empirical findings, including the results from our portfolio formation analyses, panel fixed effects, and Fama Macbeth regressions. Section 4 discusses the difference-in-differences analysis and placebo test. Section 5 describes the results from cross-sectional analyses. Section 6 presents the additional robustness tests, and Section 7 concludes.

2. Data and Variable Construction

2.1. Corporate Bond Data

To formally test our ideas, we construct our dataset using corporate bond transaction records obtained from the Financial Industry Regulatory Authority's (FINRA) Trade Reporting and Compliance Engine (TRACE) Enhanced dataset, covering the period from July 2002 to December 2020. We augment this data with bond- and issuer-specific characteristics by merging the Mergent Fixed Income Securities Database (FISD) with TRACE. Our data cleaning procedures for the TRACE Enhanced closely follow the methodologies proposed by Dick-Nielsen (2009, 2014).[7] Consistent with Bao, Pan, and Wang (2011), we restrict our sample to bonds that are actively traded—specifically, those with trading activity on at least 75% of the trading days—to ensure robust estimation of liquidity measures. Additionally, following prior studies, we limit the sample to U.S. publicly traded corporate bonds and exclude convertible instruments, priced below $5 or above $1,000, bear floating interest rates, or have less than one year to maturity. We obtain equity data and firm-level accounting information from the Center for Research in Security Prices (CRSP) and the Compustat Annual Fundamentals file, respectively. Thus, our final sample represents the intersection of the corporate bond dataset with CRSP stock data and Compustat accounting records. The resulting panel comprises 578,751 bond-month observations, covering 14,271 distinct bonds issued by 1,555 firms over the period from July 2005 to December 2020. This sample size is comparable

[7] We start the sample in 2002 because FINRA makes the TRACE data available from 2002. Additionally, we use the code available from Wharton Research Data Service (WRDS) to clean the enhanced TRACE dataset.

to those used in prior research, such as Huynh and Xia (2021), Duan, Li, and Wen (2025), and Chung, Wang, and Wu (2019).

2.2. Geopolitical risk index betas

For our analysis, we obtain the Geopolitical Risk Index (GPR) developed by Caldara & Iacoviello (2022). Based on the idea that major geopolitical events attract wide attention from the media in times of elevated concerns about geopolitical risk. For example, the Gulf War, 9/11, the 2003 invasion of Iraq, the 2014 Russia-Ukraine crisis, and the Paris terrorist attacks indicate heightened geopolitical risks during these periods. The authors construct the index using 10 major international newspapers through textual analysis, searching for around 200 keywords related to geopolitical tensions and events.[8] Caldara & Iacoviello (2022) perform a series of validation tests and demonstrate that their index effectively reflects the prevailing negative investor sentiment surrounding geopolitical risk. Inspired by their seminal study, our analyses use sensitivity to the changes in the geopolitical risk index, which are the GPR betas. For each bond *i* in each month *t,* we estimate the geopolitical risk (GPR) beta (β^{GPR}) from the monthly rolling regression of bond excess returns on the monthly change in geopolitical risk index over a 36-month window with a minimum of 12 valid monthly return observations.[9] We control for the bond market factors (i.e., bond market illiquidity, default spread, and term spread) and Fama-French three stock market factors (i.e., excess stock market return *SMKT*, the size factor *SMB,* and the book-to-market factor *HML*) because prior studies suggest that several factors are priced in expected bond returns. Fama & French (1993) show that term and default factors are priced in corporate bonds, and Elton, Gruber, Agrawal, & Mann (2001) find

[8] See for example Balcilar, Bonato, Demirer, & Gupta (2018), Baur & Smales (2020), Caldara, Conlisk, Iacoviello, & Penn (2024), Choi (2022), Liu, Ma, Tang, & Zhang (2019), Ma, Lu, & Tao (2022), Smales (2021), Umar, Bossman, Choi, & Teplova (2022), Wang, Su, & Umar (2021), Wang, Wu, & Xu (2023), and Zhang, He, He, & Li (2023), among others.

[9] We obtain the geopolitical risk index from Matteo Iacoviello's website, available at https://www.matteoiacoviello.com/gpr.htm

that the Fama & French (1993) three factors are priced. Liquidity factor is based on Dick-Nielsen, Feldhütter & Lando (2012) and is also regarded as a pricing factor for corporate bonds (see Lin, Wang, He, and Wu, 2009, and Lin, Wang, & Wu, 2011, and more recently, Chung, Wang, & Wu, 2019). We then gauge the effect of aggregate geopolitical risks on bond returns after controlling for those factors. We adopt the following multi-factor model to estimate bond betas:

$$R_{it}=\alpha_{it}+\beta^{GPR}\Delta GPR_t+\beta^{DEF}DEF_t+\beta_{TERM}TERM_t+\beta_{BLIQ}BLIQ_t+\beta_{SMKT}SMKT_t+\beta_{SMB}SMB_t$$
$$+\beta_{HML}HML_t+\epsilon_{it} \quad (1)$$

where R_{it} is the bond excess returns (over the risk-free rate), β^{GPR} capture the bond's sensitivity to changes in GPR, β^{DEF} which captures the bond's sensitivity to changes in default spread. Similarly, β_{TERM} , β_{BLIQ} , β_{SMKT} , β_{SMB} , β_{HML} capture the bond's sensitivity to term spread, liquidity, stock market returns, size factor, and value factor, respectively.[10] We also validate our results through alternative measures of the GPR index discussed in Section 6.

2.3. Other control variables

To account for known determinants of corporate bond returns documented in the literature, we incorporate a comprehensive set of control variables. We control for corporate bond illiquidity (*Illiquidity*) measured following the method proposed by Chung, Wang, and Wu (2019), using transaction-level data from TRACE. Specifically, bond illiquidity is computed monthly as the autocovariance of daily price changes within each month. Bond size is captured by the natural logarithm of the total amount outstanding. We also include bond ratings as a control variable by retaining only bonds with valid credit ratings, converting letter-

[10] We obtain the stock market, size, and value factors from Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The data to compute the term spread and the default spread, used by Welch & Goyal (2008), are available on Amit Goyal's website at http://www.hec.unil.ch/agoyal.

based ratings into numerical scores ranging from 1 (AAA) to 22 (D). Bonds rated AAA to BBB are categorized as investment-grade, while those rated below BBB are considered non-investment-grade. To control for bond market risk, following Bali, Subrahmanyam & Wen (2021), we include the bond's market beta (β^{BMKT}), estimated using a 36-month rolling regression of excess bond returns on the value-weighted average return of all bonds in the sample minus the one-month T-bill rate. Macroeconomic exposures are further captured by including term and default betas (β^{TERM} and β^{DEF}), estimated via Equation (1). In line with prior studies (e.g., Huynh & Xia, 2021; Duan, Li, & Wen, 2025; Chung, Wang, & Wu, 2019; Greenwood & Hanson, 2013), we include additional bond- and firm-level characteristics. These include bond age, the natural logarithm of time to maturity, and downside risk is measured as 5% VAR of bond returns. We also account for leverage ratio, defined as the sum of long-term debt, short-term debt, minority interest, and preferred stock, scaled by total assets, firm size (*Log_MV*), calculated as the natural logarithm of the issuer's market capitalization, and return on equity (*ROE*), measured as income before extraordinary items divided by the book value of common equity, to capture firm-specific risk and cash flow variation.

2.4. Sample and Summary Statistics

After implementing the filtering criteria and ensuring that each bond has sufficient data to compute the required beta estimates. We utilize the resulting final sample to present descriptive statistics. Panel A of Table 1 reports the summary statistics of the variables used in our baseline tests. Over the sample period, the average monthly excess return on corporate bonds is 0.56% (median = 0.4%), with a standard deviation of 2.63%, consistent with previous studies. For example, Huynh & Xia (2021) find an average bond excess return of 0.5% in their sample from 2005 through 2016. Similarly, Duan, Li, & Wen (2025) report an average monthly bond return of 0.69% in their sample from 2006 through 2019. The average corporate bond in our sample exhibits a geopolitical risk change beta of -0.001, with a standard deviation of

0.013. In line with the findings of Bao, Pan, and Wang (2011) and Huynh & Xia (2021), the typical bond is investment-grade, with a mean rating score of 8.43, corresponding approximately to a BBB+ rating. On average, bonds have an illiquidity measure of 1.3, a downside risk of 3.8%, a maturity of 9.44 years, and an outstanding amount of $0.7 billion. The mean values for the market beta, default spread beta, and term spread beta are 0.51, 0.48, and 0.98, respectively. At the firm level, the average issuer has a leverage ratio of 0.36, a market capitalization of $51.95 million, and an annual return on equity (*ROE*) of 0.13. Overall, the descriptive statistics align closely with those reported in prior studies on corporate bond markets.

[Insert Table 1 here]

Panel B of Table 1 reports the average correlation coefficients between the variables used in our regressions. From Panel B, we do not find any significantly high correlations between the explanatory variables and β^{GPR}, suggesting that our results are not driven by multicollinearity issues. Although we find that the correlation between the betas for the bond market, the default spread, and the term spread is high, the variance inflation factor (VIF) for the control variables used in our analysis is below the general threshold. A frequently referenced rule of thumb is that a VIF value of less than 10 indicates no potential multicollinearity issue. The VIF values in our model specification, with all the explanatory variables taken together, range from 1.03 to 3.54 with a mean VIF of 1.78, indicating no significant multicollinearity issues in our estimates.

3. Hypotheses & Empirical tests

3.1. Key Hypotheses

Our paper focuses on a key cross-country risk – i.e., geopolitical risk – that imposes considerable costs to the economy, conditioning for all other risks (Caldara & Iacoviello 2022; Demir & Danisman 2021; Hailemariam & Ivanovski 2021). The relationship between firms' sensitivity to geopolitical risk and subsequent bond returns can be evaluated through the lens of three alternative hypotheses:

i. **The Hedging or Risk Premium Hypothesis:** This hypothesis (Merton, 1973; Campbell, 1993, 1996; Bali, Brown, and Tang , 2017; Addoum, Delikouras, Korniotis, and Kumar, 2019) posits that investors are willing to pay higher prices or accept lower returns for high GPR-beta firms, as these firms better hedge against GPR events. Specifically, the bond market payoffs of higher GPR beta firms are greater in high GPR states or periods of economic stress, when investor consumption is low, and the marginal utility of consumption is high (Cochrane, 2000). Therefore, investors are willing to pay higher prices and accept lower returns to hold corporate bonds that are highly sensitive to geopolitical risk, i.e., bonds with high GPR beta, due to their hedging ability. Within a risk-based framework, bonds with high GPR sensitivity are seen as hedging instruments and therefore carry negative risk premiums. In summary, this should lead to a negative return for high GPR-beta bonds, and the return premium required for low-GPR-beta bonds reflects the additional return for bearing downside geopolitical risk.

ii. **The Preference Hypothesis:** This alternate hypothesis (Chen, Huang, Sun, Yao and Yu, 2020; Jiang, Sun and Wang, 2022; Ge and Weisbach, 2021; Bongaerts and Schoenmaker, 2024) suggests that bonds with high GPR betas earn higher returns because investors prefer holding these bonds and reallocate capital accordingly. As investors tilt their portfolios towards high GPR-hedge bonds and away from low GPR-hedge ones, they go long on high GPR-beta bonds while shorting low GPR-beta bonds. This preference behavior leads to elevated prices (and thus higher realized returns) for high GPR-beta bonds, alongside depressed prices (lower realized returns) for low GPR-beta bonds.

Consequently, a positive relationship for GPR-beta bonds and subsequent returns is expected, reflecting the GPR premium favoring high GPR bonds.[11]

iii. **The Underreaction Hypothesis:** Finally, bond markets may underreact to GPR-related risks (Chen, Gan and Vasquez, 2025; Singleton, 2021; Hong and Stein, 2002; Daniel, Hirshleifer and Subrahmanyam, 2001; Lochstoer and Muir, 2022). In this scenario, firms with higher GPR betas exhibit higher returns due to informational or liquidity frictions that hinder the timely incorporation of geopolitical risk into bond prices. These inefficiencies may prevent full adjustment to GPR exposures and induce investors to underreact or underprice the hedging benefits of high GPR-beta bonds. Those bonds tend to undergo a subsequent price correction and overperform once investors start to realize the importance of risk hedging (Atilgan et al., 2024). The underreaction hypothesis thus predicts that the relationship between GPR and subsequent bond returns should be positive during periods when investors pay closer attention to risk-related matters.

To test the alternate hypotheses, we next conduct a comprehensive empirical analysis and evaluate alternative explanations.

3.2. Portfolio Analyses

We employ a portfolio-sorting methodology inspired by Daniel and Titman (1997), Gebhardt, Hvidkjaer, and Swaminathan (2005), Bali, Subrahmanyam & Wen (2019), and others in equity and bond pricing literature to investigate the relationship between geopolitical risk sensitivity and expected bond returns. Bonds are sorted into quintiles at the end of each month $t-1$ based on their geopolitical risk betas (β^{GPR}), calculated over a 36-month rolling

[11] Pástor, Stambaugh, and Taylor (2023) show that green stock prices are driven by investor preferences. While in equilibrium, green assets do not outperform, they tend to have higher returns than brown assets when there is a shock in the ESG factor, e.g., bad news about climate change. It indicates that the pricing for green stocks is driven by shock that shifts investors' tastes.

window using the multifactor model specified in Equation (1). Table 2 presents the average β^{GPR} values for each quintile (Column 1) and the corresponding average monthly excess returns over the one-month T-bill rate (Column 2). The results indicate a decreasing trend in excess returns across quintiles as β^{GPR} increases. Specifically, the return spread between the highest and lowest β^{GPR} portfolios is -11 basis points (bps) per month, statistically significant at the 5% level.

[Insert Table 2 here]

Column 3 reports the average ratings and maturity benchmark adjusted return for each quintile. To account for the influence of bond characteristics, we adjust returns by rating and maturity. Bonds are grouped into 15 categories based on five rating levels (Aaa, Aa, A, Baa, and high-yield) and three maturity segments (short: <5 years, medium: 5–10 years, and long: >10 years). For each bond, we subtract from each bond return the average return on its corresponding benchmark bond portfolio matched based on rating and maturity to derive a characteristics-adjusted return. The spread between the highest and lowest quintiles remains significant at -9 bps (*t-statistics* = -2.73), confirming the robustness of the negative return-β^{GPR} relationship.

To determine whether these spreads can be attributed to traditional risk factors, we estimate time-series alphas using both a bond-specific 3-factor model (*BLIQ, DEF, TERM*) in column 4 and an extended 6-factor model that includes equity market factors (*SMKT, SMB, HML*) in column 5. The low-β^{GPR} portfolio (Q1) yields higher alphas than the high-β^{GPR} portfolio (Q5). The Q5–Q1 return spread generates monthly alphas of -17 bps and -19 bps under the 3- and 6-factor models, respectively, both statistically significant at the 1% level with t-statistics of 3.28 and 3.65, meeting the empirical significance threshold (*t-statistics* > 3.0) suggested by Harvey, Liu, and Zhu (2016). Our univariate results imply that bonds with high geopolitical risk sensitivity act as a hedge against downside market risk, attracting investor demand and thus commanding lower expected returns (Bakshi & Kapadia, 2003; Campbell, Ramadorai & Ranish, 2014).

3.3. Multivariate analyses

In this section, we examine the relationship between a bond's geopolitical risk beta and future returns at the bond-month level. We employ fixed effects panel regressions as well as the Fama–MacBeth (1973) approach. Following prior literature on corporate bond returns (Bessembinder, Kahle, Maxwell, & Xu, 2008; Lin, Wang, & Wu, 2011; and Huynh & Xia, 2021), fixed effect panel regressions include various bond- and firm-level covariates as follows:

$$Ret_{i,t+1} = \alpha+\gamma\beta_{i,t}^{GPR}+\delta X_{i,t}+\varphi Y_{j,t}+\theta_i+\vartheta+\tau+\varepsilon_{i,t} \quad (2)$$

where, for bond, i month t, and firm j, $X_{i,t}$represents a vector of bond-level control variables (i.e., downside risk, maturity, ratings, the amount outstanding, illiquidity, short-term reversal, bond market beta, term spread beta, default spread beta); $Y_{j,t}$ is a set of firm-level control variables (i.e., leverage ratio, market capitalization, and return on equity); and, finally, θ_i, ϑ, τ and μ are vectors for the bond, year and month fixed effects, respectively. In line with recent advances in asset pricing literature (e.g. Patton & Verardo, 2012; Ben-Rephael, Carlin, Da, & Israelsen, 2021), we estimate Equation (2) using panel regressions with bond and year-month fixed effects and bond-level clustered standard errors. The inclusion of fixed effects controls for unobserved heterogeneity across bonds, macroeconomic trends, and time-specific seasonal effects. Compared to the traditional Fama–MacBeth (1973) (FM) approach, the fixed effects panel regressions can provide more robust coefficient estimates and standard errors (Petersen, 2009; and Patton & Verardo, 2012).

Panel A of Table 3 reports the results from the regression of 1-month-ahead corporate bond excess returns on β^{GPR}. Panel A1 reports the results for fixed effects regression, while

Panel A2 reports the results for Fama-MacBeth regressions. In both panels, Column 1 reports the results of regressions without control variables. Column 2 augments the specification in column 1 with bond characteristics, and column 3 presents the results of baseline regressions with both bond- and firm-level control variables. We add bond, year, and month fixed effects in all specifications, and the robust standard errors are estimated by clustering at the bond level. Across all model specifications in Panel A, the point estimates on β^{GPR} are negative and statistically significant at the 1% level, indicating a negative relation between the geopolitical risk beta and future bond returns. The coefficients are also economically significant. For example, in the fixed-effect regressions in column 1 of Table 3, the coefficient estimate on β^{GPR} of -4.03 indicates that a one-standard-deviation increase in the geopolitical risk beta is associated with a decrease of 5 bps on the monthly bond returns in the following month (4.03% x 0.013 = 0.05% per month) [i.e., coefficient x S.D of β^{GPR}], or a decrease of 0.60% of the average annual bond returns. This translates to a decrease in annual bond returns to the extent of (0.6% ¸ 6.9%) [i.e., the annual returns ¸ annualized mean bond returns] of 8.7%. Similarly, in columns 2 (3) of Table 3, the coefficient estimates on β^{GPR} of -3.63 (-3.64) indicate that a one-standard-deviation increase in the geopolitical risk beta is associated with a decrease of 0.43% (0.46%) of the average annual bond returns. This translates to a decrease in annual bond returns to the extent of (0.43% ¸ 6.9%) of 6.23%.[12] To further assess the economic relevance of our findings, we quantify the impact of geopolitical risk exposure on bond returns in monetary terms. We can interpret the estimated coefficient on β^{GPR} in terms of its economic implications for new debt financing. Assuming that an average firm issues a new bond with characteristics similar to the mean bond in our sample, priced at $105.92 and based on the

[12] This premium is comparable to those reported by recent studies in corporate bond returns. For example, Huynh and Xia (2020) find a climate risk premium of 6.29 basis points per month (or 0.99% per month translating to 12.6% annualized excess returns). Similarly, Bali, Subrahmanyam & Wen (2021) find a premium of 0.64% monthly bond returns (or 7.9% annualized) for increase in economic uncertainty. Chung, Wang & Wu (2019) find that a one standard deviation below the cross-sectional mean of VIX beta is associated with an increase of 0.14% monthly bond returns (or 1.68% annualized).

issuance of 578,751 bonds, a monthly decline of 5 basis points (regression 1, Table 3) in excess bond returns implies an estimated reduction of approximately \$3.06 million (\$105.92 × 578,751 × 5 bps) in the cost of debt financing for the average issuer. These results are consistent with both our central hypothesis and the theoretical predictions of asset pricing models that incorporate hedging motives for geopolitical risk. Specifically, bonds with higher β^{GPR} values tend to perform better during periods of rising geopolitical risk. As a result, these securities become more attractive to investors seeking downside protection, investors pay higher prices and accept lower expected returns on these bonds, reflecting their hedging value. Additionally, the estimated coefficients for other control variables conform to findings from existing literature. For instance, as reported in column 3 of Table 3, bonds with greater downside risk, longer maturities, larger issuance sizes, lower firm leverage, higher illiquidity, and lower sensitivity to term and default spreads tend to exhibit higher future returns. We find that the corresponding coefficients for downside risk, Maturity, issue Size, Leverage, Illiquidity (%), β^{TERM}, and β^{DEF} are 9.38, 0.14, 0.091, -0.26, 2.40, -0.22, and -0.13, respectively. We also find that these coefficients are statistically significant at 1%.

[Insert Table 3 here]

Furthermore, in Table 3, we also examine the cross-sectional relation between β^{GPR} and future bond returns, using the Fama–MacBeth (1973) approach. Panel A2 reports the results for Fama–MacBeth, where we find that the average point estimates on β^{GPR} are negative and statistically significant at the 1% level, indicating a negative relation between the geopolitical risk beta and future bond returns. The coefficients are also economically significant and consistent with the panel regressions reported in Panel A1. Our findings, therefore, favor the hedging or risk premium hypothesis.[13]

[13] Note that positive (negative) GPR beta bonds generate higher (lower) returns during higher GPR periods and hence have negative (positive) premiums because of the hedging (risk) effect.

Finally, in Panel B, we examine whether the effect of geopolitical risk has any effect on the long-term bond returns over one month. We estimate the models from Panel A1 on *t+2*, *t+3*, and *t+4* months' bond returns, and we find that indeed the relationship between β^{GPR} and excess bond returns is negative and significant at 1% across all three horizons. Moreover, the coefficient for β^{GPR} is qualitatively similar in magnitude compared to those in Panel A1, suggesting that the geopolitical risk has a persistent effect on expected bond returns over 1 to 4-month horizon. Overall, Table 3 results validate the negative relationship between GPR beta and subsequent bond returns, implying that bonds with high covariance of their returns with GPR risk earn lower returns next period, and support the hedging hypothesis.

4. Difference-in-Differences (DiD) approach with a quasi-natural experiment

In this section, we study how bond investors respond differently to high- versus low-beta GPR bonds in the presence of exogenous shocks that heighten perceptions of geopolitical tension.

4.1. DiD regressions

We aim to provide a causal interpretation by examining whether β^{GPR} exerts a stronger impact on bond returns following significant geopolitical events using a difference-in-differences methodology. We hypothesize that following the GPR events, the bonds that have high β^{GPR} would have lower excess returns relative to those with high β^{GPR}. Following six major geopolitical events are identified based on one-step probabilities extracted from a two state Markov-switching model: the London bombing in 2005, the 2011 military intervention in Libya; the 2014 Annexation of Crimea by the Russian Federation; the 2015 Paris attacks by Islamic State; US- north Korean sanction in 2017 and US-Iran tensions in 2018. Figure 1 plots the state-change probabilities against the GPR index in Figure 1, where the dotted line indicates the state-change probabilities, and the solid line indicates the geopolitical risk index during our sample.

[Insert Figure 1 here]

From Figure 1, we observe that the GPR index switches to high states during the six major geopolitical risk events. Thus, based on these event dates, we identify *Post_event* that equals one for the three months after the significant geopolitical events and zero for the three months before the event. Next, we create a dummy variable to identify the treated and control firms based on the terciles from the previous month, β^{GPR}. *Treat* indicates treated firms, which is equal to one when β^{GPR} lies in the top tercile of the (year-) monthly distribution and zero when β^{GPR} lies in the bottom tercile of the (year-) monthly distribution. To ensure that our results are not driven by selection bias, we match the top and bottom tercile firms based on propensity score matching (PSM) using the nearest-neighbor approach using all the covariates from equation (2). Next, we employ the stacked difference-in-differences (DiD) regression to compare the average differences in bond excess returns between the treated and control firms before and after major events. Accordingly, we estimate the following model:

$$Ret_{i,t+1} = \alpha + \beta_{Trt}\, Treat_{i,t} + \beta_{post}\, Post_t + \beta_{TrtPost}\, Treat_{i,t} \times Post_t + \delta X_{i,t} + \varphi Y_{j,t} + \theta_i + \vartheta + \tau + \varepsilon_{i,t} \tag{3}$$

Table 4 reports the regression for Eq. (3). as shown in specifications (1) and (2), the coefficient on *Treat* is negative and is not significantly different from. The coefficient for *Post_event* × *Treat* ($\beta_{TrtPost}$) interaction coefficient is negative and significant at 1% significance (Coef. = -0.17, *t-statistics* = -5.48) for the full sample, and the corresponding coefficient for the PSM sample is -0.21 (*t-statistics* = -6.16). It indicates a stronger negative association between GPR-beta and bond returns when firms are exposed to geopolitical risk events. In other words, in response to the major geopolitical events, investors need to be compensated with significantly lower (higher) returns for bonds with high positive (negative)

GPR-beta – validating the hedging (or risk premium) hypothesis. In all specifications, we include cohort × bond to force identifications within each cohort (geopolitical event) and each bond. We also add cohort × year × month fixed effects to control for seasonal effects and aggregate trends within each cohort. Overall, we find that after major geopolitical events, the absolute value of the differential bond return is around 17 to 20 bps larger than that before the exposure to the events. The economic size of the coefficients in DiD specifications is also significant, given that the unconditional mean (standard deviation) for bond return is 0.56% (2.63%), the coefficient for the PSM sample translates into 0.207/0.56 = 37% (0.207/2.63 = 7.9%) reduction as compared to the mean (standard deviation) of monthly bond return.

[Insert Table 4 here]

As the (negative) differential returns between high GPR-beta and low GPR-beta bonds reflect investors' hedging demand or hedging cost for GPR, the results suggest that investors' hedging demand is amplified when they are stricken by major geopolitical events. The effect of GPR beta on bond returns is negative; hence, it clearly rejects the investor preference hypothesis.[14]

4.2. Parallel trend assumption

Furthermore, to examine whether the documented effects are subject to a non-parallel trend, we also examine the dynamic effect of such geopolitical events to identify the exact timing of the treatment effects. We estimate dynamic regressions and report the interaction coefficient estimates in Panel B of Table 4. Also, to provide a graphical presentation of the dynamic impact, we plot the coefficient estimates as well as their corresponding confidence

[14] Investor preference hypothesis implies a positive relationship between GPR beta and bond returns following shocks to the GPR factor that might influence investors' tastes.

interval in Figure 2. In Panel B of Table 4, we report the results from the dynamic DiD specification:

$$Ret_{I,t+1} = \sum_{n=-3}^{3} \beta_n [1\,(t=n) \times TREAT_i] + \beta^X X_{I,t} + \epsilon_{I,t+1} \quad (3)$$

where $1(t=n)$ indicates n years around the event. In line with the argument that our treatment effects are truly driven by the geopolitical events, we find that the coefficients for the interaction of $Before^3 \times Treat$ and $Before^2 \times Treat$ are statistically insignificant. However, the coefficients for the interaction of $After^0 \times Treat$, $After^1 \times Treat$, and $After^2 \times Treat$ are all negative and statistically significant. This finding indicates that the parallel assumption of the DiD estimates is satisfied. The results suggest no evidence of diverging pre-trends in bond returns between treated and control firms before the event, and the decrease in bond returns of the treated firms relative to the control firms becomes evident just after the event. Overall, using the major geopolitical events as a quasi-natural experiment and a difference-in-difference approach, we provide causal evidence that an exogenous shock to GPR enlarges the negative relation between bond return and its exposure to geopolitical risk.

[Insert Figure 2 here]

4.3. Placebo test

Having established that geopolitical risk negatively impacts the subsequent bond returns, we further investigate whether such a relationship is not driven by other macroeconomic shocks that can affect the overall financial markets. Additionally, we answer a potential concern that our findings could be driven by the potential systematic measurement error arising from the method to estimate GPR beta. Thus, we conduct falsification tests by first identifying significant events that can affect the bond markets but are not related to geopolitical events. To do so, we resort to the corporate bond distress index (CMDI) and identify the events that cause CMDI to surge but are unrelated to the GPR index. For example, we employ the events of the 2008-2009 global financial crisis (GFC) and the COVID-19 pandemic as our placebo events.

A preliminary examination of Figures 3a and 3b shows that the CMDI and the GPR index have a very low correlation (0.09), and during the GFC and COVID-19 window, CMDI seems to surge, but we do not observe a similar movement in the GPR index. Next, to formally examine that the negative relationship is not driven by the effects of CMDI, in Table 5, we repeat the differences-in-difference (DiD) regressions of Table 4. We estimate the one-month-ahead corporate bond excess returns (in percentage terms) for the entire sample (column 1) or the propensity-score matched (PSM) sample matched one period before the event using all control variables and bond returns as matching covariates (column 2). We estimate the effects surrounding our placebo events that cause the bond distress index (CMDI) to surge but are unrelated to geopolitical risk, namely, the events of the 2008-2009 global financial crisis and the COVID-19 pandemic. For the global financial crisis, *Post_PlaceboEvent* is equal to one from Aug 2007 to June 2009 and is equal to zero from January 2006 to July 2007. For the COVID-19 pandemic, *Post_PlaceboEvent* is equal to one from February 2020 to May 2020 and is equal to zero from November 2019 to January 2020. We combine both events in the regression to estimate a stacked DiD approach. *Treat* equals one (zero) when β^{GPR} is in the top (bottom) tercile of the (year-) monthly sample distribution. All regressions include control variables from column 3 of Table 3, cohort×bond fixed effects, cohort×year×month fixed effects similar to Table 4. The *t*-statistics based on robust standard errors are clustered at the bond level. In Table 5, we find that the coefficients for the *Post_PlaceboEvent* ×*Treat* are statistically insignificant under both the full sample and the PSM sample. This placebo result indicates that the observed effects in Table 4 are not driven by bond distress events and provides confidence in our inferences about the negative relationship between geopolitical risk and future bond returns.

[Insert Table 5 here]

5. Potential channels explaining the relationship between GPR betas and bond returns

So far, we have examined the effects of a bond's hedging ability on its future bond returns through various approaches. In this section, we identify the plausible underlying channels underlying the negative relationship between β^{GPR} and bond returns.

5.1. Risk prevalence

Risk-based theories (Bloom, 2009; Bekaert, Hoerova, and Lo Duca , 2013; and Bali et al., 2017) imply that the hedging demand can be time varying and stronger for high GPR-beta bonds when investor risk-aversion is elevated. In Table 6, Panel A, we conduct bivariate analysis by accounting for broader market-level risks by sorting bonds into quintiles based on their exposure to downside risk (measured as 5 percentile value at risk of bond returns), volatility (as measured by the VIX), and economic policy uncertainty (EPU). We then analyze the Q5–Q1 alphas within each group. We observe that alpha spreads are negative in all quintiles and are more pronounced among bonds that are highly sensitive to these sources of uncertainty. Specifically, alpha spreads in the top quintiles of downside risk, VIX, and EPU are -25, -32, and -29 basis points, respectively, all statistically significant. These findings suggest that the effect of geopolitical risk sensitivity on bond returns is not subsumed by conventional measures of market uncertainty, and the hedging effect of low GPR portfolios is significantly higher when underlying firms are also highly sensitive to underlying downside risk, market risk-aversion, and economic policy uncertainty. The bivariate evidence, therefore, favors the risk premium or hedging hypothesis.

[Insert Table 6, Panel A here]

In addition, Panel B of Table 6 provides the regression results. It shows that β^{GPR} has an even stronger negative effect on bond returns for elevated levels of downside risk, VIX, and EPU. We find that the interaction effect of β^{GPR} with *Downside risk*, the dummy variable that indicates high VIX or high EPU, is negative and significant; the coefficient for $\beta^{GPR} \times$ *Downside risk* is -4.10 (*t-statistics* = -4.7), $\beta^{GPR} \times$ *High VIX* is -0.033 (*t-statistics* = -5.3), and $\beta^{GPR} \times$ *High EPU* is -0.03 (*t-statistics* = -3.9). Overall, we find the negative relationship is prominent for firms with higher downside risk, and during higher volatility and economic uncertainty periods. The results, therefore, support the hedging hypothesis and rule out the underreaction interpretation.

[Insert Table 6, Panel B here]

5.2. The Effects of International Exposure

Generally, multinational companies (MNCs) operate in diverse political and economic environments, increasing their exposure to a wider range of geopolitical risks. Political instability, such as coups, revolutions, or civil wars, can disrupt operations, damage assets, and lead to the expropriation or nationalization of investments in a country. Such events can disrupt supply chains, increase costs, and limit access to markets. Firms with international exposure are also exposed to rising tensions between countries, such as military conflicts or cyberattacks, which can lead to disruptions in international trade and investment, as well as increased risks for MNCs operating in affected regions.[15] Previous studies have argued that political risks in host countries are associated with the lower performance of multinational corporations (MNCs) (Kesternich and Schnitzer 2010; Benischke, Guldiken, Doh, Martin & Zhang, 2022; Bussy & Zheng, 2023).[16] Accordingly, we hypothesize that demand for bonds with high hedging ability

[15] For example, during the Russian Ukrainian war many MNCs, including McDonald's, abandoned the Russian market, and Russia has seized assets of companies that left the country. Similarly, H&M (a global fashion and design company) suffered a decline in sales after being boycotted by Chinese consumers amid the labor rights controversy in Xinjiang.

[16] For example, Kesternich and Schnitzer (2010) show that MNCs adjust capital structure in response to host-country political risk, increasing leverage costs, and lowering performance. Similarly, Benischke, Guldiken, Doh, Martin & Zhang (2022) argue that high political risks prompt MNCs to favor greenfield investments over acquisitions to safeguard CEO equity wealth, reflecting behavioral responses to uncertainty. In a similar vein, Bussy & Zheng (2023) find that GPR has a negative impact on the foreign direct investment decisions of multinational firms.

against geopolitical risk rises with the underlying firms' international exposure. To do so, we classify the firms in our sample into international or domestic based on the firm's revenue from non-domestic segments and examine the relationship between the interaction of β^{GPR} and foreign sales and subsequent bond returns.

In Table 7, we formally test our hypothesis by re-estimating our baseline model but conditional upon the firm's international exposure. Specifically, we identify the total revenues from foreign sales of each firm in our sample and calculate the ratio of the sales revenues produced by the firms' nondomestic segments to their total sales (*ForeignSale*). In column 1, we interact *ForeignSale* with β^{GPR} estimated through equation (1). We find that the coefficient for the interaction is negative and significant at the 5% level. Similarly, in column 2, we replace ForeignSale with a dummy that takes the value of 1 when a firm has exposure to at least 1 non-domestic segment and zero otherwise (*D_ForeignSale*). We find the coefficient for the interaction between *D_ForeignSale* and β^{GPR} is negative and significant at the 5% level. These estimates indicate that hedging or risk premiums from low GPR-beta bonds are higher for firms with higher international exposure, as evident by the stronger effect of GPR beta on subsequent bond returns for those firms.

[Insert Table 7 here]

5.3. The Effects of Supply Chain Disruption

Increasing geopolitical tensions have placed supply chains in the spotlight, amplifying vulnerabilities as firms pursue more globalized networks prone to cascading disruptions in supply and demand. Events like COVID-19, the 2011 Tohoku earthquake, Hurricane Sandy (2012), the 2015 West Coast port strike, and the 2022 Russia-Ukraine war have inflicted severe operational losses and reputational damage, with prior studies documenting significant bottom-line impacts from stalled production, inventory buildup, and fulfillment delays (Blome &

Schoenherr, 2011; Chiu & Choi, 2016; Wu, 2024). These ripple effects underscore the need to quantify how such extreme shocks propagate through interconnected global networks. We therefore examine whether firms that have significant supply chain constraints are subject to higher hedging demands against geopolitical risks as opposed to firms with low supply chain risk. We argue that firms with higher supply chain risks are more vulnerable to increased geopolitical risks, and we hypothesize that investors have a stronger demand for hedging against these geopolitical risks for those firms. Thus, in Table 8, we formally test our hypothesis and examine whether firms with higher supply chain risks experience significantly lower bond returns during periods of high geopolitical risk. To identify these supply chain risks, we utilize two firm-level measures. Our first measure of supply chain risk considers the firm's sensitivity to changes in the logistics performance index (LPI) in the U.S., published by the World Bank (*LPI_US_Index*). LPI measures the country level trade logistics performance based on six core dimensions—customs, infrastructure, international shipments, logistics competence, tracking, and timeliness—on a scale from 1 (worst) to 5 (best). Our second measure employs a textual analysis approach based on the supply-chain-related words proposed by Wu (2024). We use the supply-chain-related wordlist from Wu (2024) along with the risk-related wordlist from Hassan et al. (2019) to capture the associated supply chain risks. Specifically, to measure firm-level supply chain risk, we count instances of supply-chain-related words that occur in the same sentence as risk-related words using the firm's 10-K filings. We take the natural logarithm of these counts before entering them into our regression.

In Table 8, we implement the baseline regressions, conditioning them on the firm's supply chain risk exposure. In column (1), we interact β^{GPR} with *ΔLPI_global_index*. We find that the coefficient for this interaction is negative and strongly significant at the 1% level, implying that premium for low GPR beta bonds is higher when supply chain stress is higher. Similarly, in column (2), we interact with the text-based measure of firm-level supply chain risk (SCR). We find that the coefficient for the interaction between SCR and β^{GPR} is negative and significant at the 1% level. These estimates suggest that supply chain risk enhances the effect of GPR-beta on expected bond returns, aligning with the argument that bond investors require a higher risk premium for firms with elevated supply chain risk.

[Insert Table 8 here]

5.4. The Effects of Default Risk

Given that default risk is a key driver for bond returns (Bharath and Shumway, 2008; Giesecke et al., 2011; Chen et al., 2018), we examine how firm's default risk influences negative relationship between GPR and bond returns. Bonds issued by a firm with higher default risk behave more like stocks, and their returns have a larger equity component. (Vassalou and Xing,2004; Campbell, Hilscher, and Szilagyi, 2008). For firms closer to the default boundary, the chance of default gets higher as macroeconomic and geopolitical factors increase. Therefore, the hedging demand against geopolitical risk is greater for those firms of high default risk. We test this hypothesis by examining the interaction effect of GPR with different levels of default probability. To do so, we use three different proxies for default risk: 1) the inverse of distance to default (*DTD*) (source: Risk Management Institute or RMI), 2) the loan spread (*Loan spread*) in bps, extracted from the Dealscan database, and a greater value indicates high distress risk. and 3) a dummy to identify whether CDS contracts protect the firm's debt, as a CDS contract can reduce a creditor's exposure to the firm's default risk, sourced from the Markit database. *NoCDS_protection* dummy is set to one if the firm has no CDS contract traded on it and zero otherwise. No CDS traded on a bond implies higher default risk exposure. Table 9 reports the coefficients from fixed effects regression examining the effects of firms' financial distress in moderating bond investors' hedging demand. Column 1 shows the results by interacting β^{GPR} with the inverse of distance to default (*Inv. DTD*). Column 2 presents the results by interacting β^{GPR} with loan spreads, and column 3 presents the results by interacting β^{GPR} with *NoCDS_protection*. From the regressions in Table 9, we find that firms that have higher default risk have significantly negative subsequent bond returns during heightened geopolitical risk. For example, the coefficient for the interaction between β^{GPR} × *Inv. DTD* is -0.252 (*t-statistic* = -1.96)[17]. Similarly, the coefficients for the interactions of β^{GPR} × *Loan spread* and β^{GPR} × *NoCDS_protection* are -0.016 (*t-statistics* = -3.23) and -2.967 (*t-statistics* = -3.86). The coefficients are statistically and economically significant at 5% or below, suggesting that default risk accentuates the negative relationship between β^{GPR} and bond returns.

[Insert Table 9 here]

5.5. Accounting for bond and equity characteristics

We next study the effect of different bond and equity characteristics on the observed relationship of GPR beta and bond returns. We first conduct bivariate portfolio sorts controlling for a range of bond characteristics, including ratings, maturity, illiquidity, and bond age; Panel A, Table 10 shows that these variables do not explain the observed relationship between bond returns and β^{GPR}. The negative association between average returns and geopolitical risk exposure remains statistically significant (except for non-investment-grade bonds). Even after controlling for bond characteristics, the Q5–Q1 return spreads remain mostly negative and statistically significant, with average alphas ranging from -7 to -40 basis points across characteristic-based quintiles. These results reinforce the conclusion that traditional bond characteristics do not account for the lower returns observed in high-β^{GPR} portfolios. Furthermore, we find significant evidence of the hedging effect (i.e., negative alpha spread) even for investment grade, longer-term, illiquid, and younger firms (with annualized alphas for

[17] Note that we multiply the variable Distance to default by -1 denoted as *DTD* for ease of interpretation.

high-low quintile portfolios ranging from -1.9% to -2.7%), indicating that the hedging effect dominates across several bond characteristics.

[Insert Table 10, Panel A here]

In Panel B we present cross-sectional regressions showing how the bond characteristics moderate the relationship between β^{GPR} and expected returns. We interact the β^{GPR} with the dummy variables that capture bonds with high/low bond features. For example, the dummy variables for ratings and maturity are based on median values in a given month, which takes the value of one when the variable is greater than the median and zero otherwise. Illiquidity dummy takes the value of one when the bond illiquidity is greater than the first quartile of illiquidity and zero otherwise. Table 10 reports the results. We find that the coefficient estimates for the interaction terms β^{GPR} × Ratings dummy and β^{GPR} × illiquidity dummy are all negative and statistically significant at the 1% level. This indicates that investors demand higher GPR risk premiums from bonds when the underlying firms experience higher idiosyncratic volatility or greater equity exposure to GPR. However, we find that the interaction for β^{GPR} × Maturity dummy is positive and significant, suggesting that investors holding short maturity bonds demand the GPR premium during times of a higher geopolitical risk environment.

[Insert Table 10, Panel B here]

Prior work also shows that equity risks affect bond returns; for e.g., Chung, Wang, and Wu (2019) document a positive idiosyncratic volatility effect, consistent with incomplete diversification from information limits, regulation, or frictions. Moreover, stock prices lead bond prices amplifying the negative β^{GPR} relation when equity risks rise, as investors shift to high-β^{GPR} bonds for hedging. Therefore, we hypothesize that this market segmentation accentuates the relationship between β^{GPR} and subsequent bond returns, as investors are more likely to shift to the bond market, and especially high GPR-beta bonds, for hedging purposes when equity risk is high. We present cross-sectional regressions in Table 10, Panel B by focusing on the two forms of equity risks: 1) idiosyncratic volatility (*IdioVol*), which is the standard deviation of the residuals from the rolling-window regression of 36-month monthly returns using a Fama-French three-factor model, and 2) return sensitivity to market factors (β^{Stock}) estimated using the Fama-French three-factor model. We standardize *IdioVol* and β^{Stock} before interacting them with β^{GPR}. reports the results for the interaction between β^{GPR} and the degree of equity idiosyncratic volatility, while column 2 presents the results for the interaction between β^{GPR} and equity risk. We find that the coefficient estimates for the interaction terms $\beta^{GPR} \times IdioVol$ and $\beta^{GPR} \times \beta^{Stock}$ are all negative and statistically significant at the 1% level. This indicates that investors demand higher GPR risk premiums from bonds when the underlying firms experience higher idiosyncratic volatility or greater equity exposure to GPR.

6. Robustness and Supplementary tests

In this section, we conduct a battery of tests to check the robustness of our findings.

6.1. Alternative measures of geopolitical risk

In our *first robustness check*, we employ an alternative geopolitical risk index to ensure our results are not dependent on the choice of geopolitical risk index. Therefore, inspired by the measure of Caldara & Iacoviello (2022), we construct an alternative measure of geopolitical risk index based on Google Trends. Specifically, to create our Google Trends geopolitical sentiment index (GSI), we follow the approach of Da, Engelberg, & Gao (2015) and Gao, Ren, & Zhang (2020). We follow the following six steps. (A) We begin by compiling a bag of words from Caldera and Iacoviello (2022). (B) Next, using the Google Trends API, we search for the top 25 queries related to each keyword in Caldera & Iacoviello's (2022) word list. This process yields 248 keywords after excluding unrelated search terms that might be from a bag of words but are unconnected to geopolitical risk. We manually review the queries and filter out unrelated terms. (C) Next, we download the weekly Search Volume Index (SVI) data, covering search volume from Sunday to Saturday for each term, spanning January 2004 to December 2020.[18] (C) We then calculate the changes in SVI, winsorize the observations at 2.5%, remove seasonality in SVI using monthly dummies, and standardize each time series to ensure comparability. (D) Following the methodology of Da, Engelberg, & Gao (2015) and Gao, Ren, & Zhang (2020), we identify the top 30 terms most closely related to market returns to construct our index. By running expanding backward rolling regressions of adjusted SVI changes (ΔASVI) on each S&P 500 weekly return every six months (every June and December), we identify the top 30 keywords that have the highest t-statistics. (E) Finally, we sum the weekly index in a given month to obtain the monthly index. Additionally, for thoroughness, we also construct an additional index where we restrict keywords that have at least 5 SVI values to ensure we pick the most relevant keywords. This approach, inspired by the GPR index, focuses on changes in search frequency to provide a more accurate measure of sentiment. We re-estimate our baseline regressions (i.e., Table 3) by first re-estimating equation (1) and calculating the GSI betas that essentially capture the bond sensitivity to geopolitical risk and repeat the fixed-effects regressions in Panel A1 of Table 3.[19]

Table 11 reports the coefficients from the fixed effects regressions of one-month-ahead corporate bond excess returns (in percent) on bond return sensitivity to geopolitical risk (β^{GPR}) measured based on Google Trends. Column (1) uses β^{GPR}_SVI based on the GSI constructed based on the top and bottom 30 keywords, and Column (2) uses β^{GPR}_SVI5 based on the GSI

[18] The main data source, Google Trends (https://www.google.com/trends/), provides the Search Volume Index (SVI) of any search item.

[19] Although we use similar keywords as Caldara & Iacoviello (2022), our measure of GSI has a correlation of 0.29 with the GPR index suggesting that the GSI could be capturing information that might not be subsumed in the GPR index. This could also be because we use both web searches and newspapers in our Google Trends search, whereas Caldara & Iacoviello (2022) mainly use newspaper articles to construct their index. However, we find that our sentiment index sufficiently captures the peaks of major geopolitical events and similarly tracks the GPR index.

that restricts the keywords to at least 5 SVI. Similar to our baseline regressions, we find that the coefficients for alternative measures of GPR betas are negative and significant at a 1% level (β^{GPR}*_SVI* = -0.36, *t-statistics* = -6.62 and β^{GPR}*_SVI5* = -0.25, *t-statistics* = -3.71). Thus, providing evidence that our main results hold even with the alternative geopolitical risk index.

[Insert Table 11 here]

We conduct *second robustness check* by using alternate GPR indices. So far, we have examined whether U.S. corporate bonds are sensitive to the U.S. GPR index. However, Caldara & Iacoviello (2022) document that the U.S. GPR is also closely related to global measures of geopolitical risk: the global GPR, geopolitical threats (GPT), and geopolitical acts (GPA). Therefore, to ensure our results are robust to global measures of geopolitical risk, we conduct second robustness check and re-estimate our baseline tests by replacing the U.S GPR index with Global GPR, GPT, and GPA in equation (1) and re-calculate the betas. In Table 12, we use these betas against next-month bond returns similar to Panel A1 of Table 3. From Table 12, we find that the coefficients for Global GPR (β^{GPR_global}), GPT (β^{GPRT}), and GPA (β^{GPRA}) are negative and statistically and economically significant. Thus, the supplementary tests support the risk premium hypothesis.

[Insert Table 12 here]

In our *third robustness test*, we examine our baseline tests with the firm's exposure to foreign-sales weighted geopolitical risk - i.e., the GPR index is weighted by the firm's geographical segment sales sourced from the Thomson Reuters Worldscope database. The purpose of this test is to appropriately identify the firm's international exposure to its segment of countries' GPR. Note that we use the U.S. GPR index for our main tests; however, one can argue that a firm headquartered in the U.S. might have operations in other countries, exposing them to those countries' geopolitical risks. Therefore, to ensure we assign the appropriate weights to domestic and international GPR of a firm, we re-estimate the β^{GPR} based on the GPR index weighted by i) the firm's segment sales and ii) the firm's non-U.S. segment sales. The intuition behind this test is that it ensures the β^{GPR} captures the firm's exposure to geopolitical risk located in foreign countries where its business segments operate. We weigh GPR in the firm's foreign segments by their sales revenues. In column 1 of Table 13, we focus on firm's each firm's segment, and β^{AllSeg_GPR} denotes bond return sensitivity to the all-segment-sales-weighted GPR. In column 2, we focus on firms' non-US segments and $\beta^{ForeignSeg\_GPR}$ bonds return sensitivity to the foreign-segment-sales-weighted GPR. We find that the coefficients for β^{AllSeg_GPR} and $\beta^{ForeignSeg\_GPR}$ are negative and statistically significant, consistent with those reported in Table 3. The results in Table 13 provide evidence that the use of a firm's international exposure to GPR does not change our main inferences, indicating that the geopolitical risk originating from non-US operations can also have a far-reaching impact on the bond market.

[Insert Table 13 here]

6.2. Controlling for the firm-level geopolitical risk, firm-level political risk index, and heterogeneity across industries

So far, we have established that corporate bond returns are sensitive to geopolitical risk, regardless of whether this risk is measured through various alternative methods. However, several studies have highlighted the importance of political risk and its effect on asset pricing, as shown by Pastor & Veronesi (2013), Bekaert, Harvey, Lundblad, and Siegel (2014, 2016), and Brogaard, Dai, Ngo, & Zhang (2020). Recently, Hassan, Hollander, van Lent, and Tahoun (2019) developed a new measure of political risk at the firm level, using textual analysis of the firm's quarterly earnings conference calls, in contrast to the aggregate measure used in earlier research. The firm-level risk measure has been applied to examine the impact of political risk on various areas, including the cross-section of equity returns (Gorbatikov, van Lent, Naik, Sharma & Tahoun, 2021), option markets (Ho, Kagkadis, & Wang, 2024), private and public credit markets (Gad, Nikolaev, Tahoun & van Lent, 2024; Ceballos, Piljak, and Swinkels, 2024), creditor control (Isakin & Pu, 2019), bank loan contracting (Saffar, Wang and John Wei, 2024), corporate investment (Choi, Chung & Wang, 2022; Boah & Ujah, 2024), corporate social responsibility (Chatjuthamard, Treepongkaruna, Jiraporn & Jiraporn, 2021), and the decision between public or private debt financing (Huang, Shen and Wu, 2023). Although geopolitical risk is distinct from political and economic risks and uncertainties (Baur & Smales, 2020), one can argue that the firm-level political risk measure could encompass our GPR beta. Gad, Nikolaev, Tahoun, and van Lent (2024) suggest that political risk can be a significant source of idiosyncratic risk rather than just an aggregate measure.

Recent literature recognizes geopolitical risk as a crucial factor influencing asset returns, in addition to economic policy uncertainty and political risk. However, Ceballos, Piljak, & Swinkels (2024), in their robustness checks, found no significant evidence that geopolitical risk affects corporate bond returns, contrasting the clear premium found for firm-level political risk. Thus, to ensure that the sensitivity of bond returns (i.e., β^{GPR}) is not influenced by any omission of important risk factors, including the firm-level geopolitical risk and firm-level political risk, we construct the firm-level geopolitical risk using the earnings call transcripts following the methodology by Caldara and Iacoviello (2022).[20] Furthermore, we utilize the firm-level political risk measure of Hassan et al. (2019) and re-estimate our baseline regressions as shown in Table 14.[21] Our models in Table 14 reveal that even after including the firm-level measures of geopolitical and political risk measures, the coefficients for GPR beta remain strongly significant, indicating that our results capture a unique risk distinct from those encompassed in political risk measures. Specifically, from (1), where we find the GPR_{firm} has a negative albeit

[20] Following Caldara and Iacoviello (2022), we conduct textual analysis on earnings call transcripts for firms in our sample—by applying their GPR dictionary of war, terror, and military terms (with threat/act modifiers)—to construct an aggregate firm-level quarterly GPR exposure measure.

[21] Though we use the political risk index in Table 13, we re-estimate with changes in the political risk index to account for marginal effect of increase in political risk and we find qualitatively similar signs and significance for β^{GPR}.

insignificant coefficient. In (2), we estimate our baseline specification, but with the inclusion of GPR_{firm} to examine if β^{GPR} continues to be significant. Subsequently, in (3), we control for the firm-level political risk (*PRI*) and finally in (4), we include *PRI* and GPR_{firm}, in our baseline model. In Table 14, we continue to find that β^{GPR} is strongly significant even after the inclusion of firm-level geopolitical and political risk measures.

[Insert Table 14 here]

Next, we examine whether the effect of GPR beta on expected bond returns is heterogeneous across different industries. To do so, we examine the effect of β^{GPR} on expected bond returns for each of the Fama-French 12 industry classifications across the firms in our sample. Specifically, we estimate the fixed effects and Fama-MacBeth regressions for the 12 industry portfolios in Table 15, where we include all the controls and the fixed effects as in our baseline regressions. We find that the effect of GPR-beta on future returns is strongly negative in the technology (-7.3 bps per month, *t-statistic* = -3.94), oil and gas (-5.29 bps per month, *t-statistic* = -3.48), consumer non-durables & durables sector (-4.53 bps per month, *t-statistic* = -2.08), real estate (-3.45 bps per month, *t-statistic* = -4.65) and healthcare (-3.09 bps per month, *t-statistic* = -2.69), showing that the hedging evidence is more prevalent in downstream industries where investors are more exposed to GPR risk. Overall, from the industry-level analyses, we find that β^{GPR} has a significantly negative effect in sectors that are vulnerable to downstream risks such as supply chain risk, economic risk, or policy-related risks. On the other hand, firms in industries such as services and manufacturing do not display any significant effect of GPR on bond returns.

[Insert Table 15 here]

6.3. *Beta estimation using additional factors*

To further ensure that the information from the β^{GPR} is not subsumed by other factors, we re-estimate the GPR beta using alternative models reported in Tables A2.1 and A2.2 of the appendix. In model (1) of Table A2.1, we re-estimate the β^{GPR} with just the bond-market factor (*BMKT*) following Dickerson, Mueller, and Robotti (2023).[22] Second stage baseline fixed effects regression shows that β^{GPR} is negative and statistically significant. Similarly, in models 2-5, we re-estimate β^{GPR} by augmenting our original model (Eq. 1) with BMKT, shocks in economic uncertainty (UNC), downside risk, and shocks in VIX. Next, we re-estimate the fixed-effect regressions of Table 3. From A2.1, we find that the estimates for β^{GPR} are negative and statistically significant, similar to our baseline results.

In A2.2 we augment the original model from equation (1) with stock momentum and stock liquidity factors in Model 1, whereas in Models 2 and 3 we include changes in the economic policy uncertainty index (UNC) and the firm distress risk factor, respectively, because Bali, Subrahmanyam & Wen (2019) document that UNC has a significant premium in the cross-section of bond returns. Finally, to confirm whether β^{GPR} remains significant after adding β^{UNC} we include β^{UNC} as an additional control in our baseline regression. Therefore, the augmented models control other macroeconomic factors that could affect bond returns. Next, we re-estimate the quintile portfolios of Table 2 and calculate the average excess returns and alphas for each of the quintile portfolios. The results from Table A2 show that even with the augmented models, the alphas and the average portfolio return spread between the low β^{GPR} and high β^{GPR} are economically and statistically significant, in the range of -10 bps to -19 bps, and significant at the 1% level. Overall, we find that using alternative geopolitical risk indexes or a stricter model does not change the inferences and significance of our baseline results.

[22] Dickerson et al. (2023) re-examine the evidence for multifactor models in the corporate bond market and show that incremental information in previously proposed corporate bond factors—such as downside risk, credit risk, and liquidity risk— disappear once value-weighted corporate bond market factor is included.

6.4. Testing the nonlinearity of the GPR Premium

Our hypothesis posits that the influence of the GPR beta on future bond returns varies over time and becomes more significant during periods of elevated climate change news risk. Therefore, we provide an empirical test to identify if there is a non-linearity in the GPR premium. To do so, we examine whether the joint relationship between β^{GPR} and GPR significantly affects the expected corporate bond returns. We begin by augmenting our baseline specification with an interaction term of standardized GPR index values × β^{GPR}, incorporating both the interaction term (GPR index × β^{GPR}) and GPR index individually. We argue that if the marginal effect of the GPR index has any bearing on the relationship between the β^{GPR} and expected bond returns, then the interaction should be negative and significant when the GPR index surges. Additionally, we determine each month whether the current month's GPR exceeds the past 36-month median value. Based on this criterion, we create a dummy variable, *HIGH_GPR*, which equals 1 for months with a GPR index above the past 36 months' median GPR index and 0 for others. We then interact *HIGH_GPR* with β^{GPR} and revisit our baseline regressions, incorporating both the interaction term (*HIGH_GPR* × β^{GPR}) and *HIGH_GPR* individually. The estimation results are presented in Table A3. Supporting the prediction of the main hypothesis, Table A3 reveals that the coefficients on the interactions between GPR index × β^{GPR} and *HIGH_GPR* × β^{GPR} are negative and statistically significant. This indicates that when geopolitical risk is elevated, the impact of the GPR beta on future bond returns is notably stronger than during periods of lower geopolitical risk. From Table A3, we find that the coefficients for the interactions are statistically and economically significant GPR index × β^{GPR} = -1.65, *t-statistics* = -3.98; *HIGH_GPR* × β^{GPR} = -1.3, *t-statistics* = -1.95). The results from Table A3 indicate that as GPR increases, the relationship between β^{GPR} and expected returns strengthens, thus reinforcing our main results.

6.5. Impact of Geopolitical risk (GPR) Beta on credit default swap (CDS) spreads

We additionally examine whether the CDS markets reflect the GPR hedging premium. We obtain the 5-year CDS data for the firms in our sample from Markit and re-estimate our baseline regression, replacing bond expected returns with CDS spreads. The hypothesis is that the β^{GPR} should be negatively related to CDS spreads because firms facing higher default risk typically have greater hedging demand against geopolitical risk. We filter the CDS data following prior studies such as Duong, Kalev, Kalimipalli, and Trivedi (2025), Bai and Wu (2016), Griffin, Hong, and Kim (2016), and Ericsson, Jacobs, and Oviedo (2009): (1) keep only US dollar-denominated CDS; (2) focus on senior unsecured obligations for liquidity and those with a 5-year tenor; (3) include CDS with modified restructuring clauses before April 2009 and exclude those with later restructuring clauses; (4) remove CDS with spreads exceeding 10,000 basis points to avoid illiquidity errors; (5) exclude CDS without spread observations across tenors. Next, we merge the monthly CDS data with our monthly GPR beta dataset. We exclude firms with missing or nonpositive asset values. The final sample consists of 175 firms with monthly data from February 2006 to June 2020. Table A4 in the appendix presents the regression estimates from Fama-MacBeth (FM) and fixed effect (FE) regressions. Consistent with our hypothesis, we find that the coefficient estimate for β^{GPR} is negative and significant at the 5% level (FM = -0.038; FE = -0.068), indicating that higher geopolitical risk correlates with higher CDS spreads.

6.6. GPR beta and equity markets

We finally examine whether the GPR effect is captured in equity markets. We first obtain equity GPR beta by regressing stock returns on geopolitical risk, controlling for the Fama-French three stock market factors (i.e., excess stock market return, the size factor, and the book-to-market factor), the momentum factor, Pastor-Stambaugh liquidity factor, and the investment and profitability factors from Hou, Xue, and Zhang (2016). We then conduct quintile portfolio sorts by the pre-ranking equity GPR beta estimated over a 36-month rolling window. We also conduct Fama Macbeth (1973) regressions of one-month-ahead stock excess returns on equity GPR beta and other control variables from Table 3. Results are reported in Table A5 in the Internet Appendix. We find no significant difference in high minus low quintile portfolio returns; we also find no significance for equity GPR beta. Our findings, therefore, do not support the hedging effect for equities

7. Summary & Conclusions

In this paper, we investigate how corporate bond investors respond to GPR by analyzing the relationship between firms' sensitivity to GPR and subsequent bond returns. By exploring how bond markets price geopolitical risk, this paper offers new insights into the pricing mechanisms in corporate debt markets under heightened geopolitical uncertainty.

We document significant negative relationship between GPR beta and bond returns. The difference-in-differences analysis using major geopolitical conflicts as quasi-natural experiments further supports the hedging hypothesis, showing that low GPR-beta firms experience larger subsequent bond returns following the major geopolitical conflicts. Additional cross-sectional analyses find that this negative relationship is larger for firms with high downside risk, greater international exposure, more supply chain disruptions, and higher credit risk, and during times of elevated volatility and economic uncertainty. Robustness checks using Google GPR indices and alternative beta measures and controlling for firm-level political and GPR risks, confirm that the negative relation between GPR-beta and return persists. Industry-level analysis shows that hedging evidence is more prevalent in downstream industries where investors are more exposed to GPR risk. While CDS markets show evidence of GPR hedging risk, no such evidence is found in equities. Our findings provide robust empirical evidence supporting the hedging or risk premium hypothesis, demonstrating that corporate bonds with high GPR-beta (bonds that pay off well in a high GPR environment) can offer lower returns, reflecting the hedging premium for bearing downside geopolitical risk.

This study makes two key contributions. First, it extends the corporate bond pricing literature by isolating the impact of GPR from other macroeconomic factors such as liquidity, volatility, and credit risk. While previous work has focused on economic uncertainty, political and climate risks, this paper emphasizes GPR as an independent and material driver of bond pricing. Second, it contributes to the growing literature on geopolitical risk in financial markets, which has primarily focused on equity returns, exchange rates, and exchange-traded funds (ETFs). By focusing on the corporate bond market, the paper addresses an important but underexplored area, providing new insights into how institutional investors factor geopolitical dynamics into risk assessment and asset pricing.

References

Addoum, J. M., Delikouras, S., Korniotis, G. M., & Kumar, A. (2019). Income hedging, dynamic style preferences, and return predictability. Journal of Finance, 74(4), 2055–2106.

Alqahtani, A., Bouri, E., & Vo, X. V. (2020). Predictability of GCC stock returns: The role of geopolitical risk and crude oil returns. Economic Analysis and Policy, 68, 239–249.

Ambrocio, G., & Hasan, I. (2021). Quid Pro Quo? Political Ties and Sovereign Borrowing. Journal of International Economics, 133, 103523. https://doi.org/10.1016/j.jinteco.2021.103523

Ambrocio, G., Hasan, I., & Li, X. (2024). Global Political Ties and the Global Financial Cycle. https://doi.org/10.2139/ssrn.4948739

Atilgan, Y., Demirtas, K. O., Edmans, A., & Gunaydin, A. D. (2024). Does the Carbon Premium Reflect Risk or Outperformance?. *FEB-RN Research Paper*, (03).

Augustin, P., Cong, L. W., Lopez A, R., & Tédongap, R. (2025, August). Downside Risk and the Cross-Section of Corporate Bond Returns. Paris December 2020 Finance Meeting EUROFIDAI-ESSEC.

Augustin, P., & Tédongap, R. (2021). Disappointment aversion, term structure, and predictability puzzles in bond markets. Management Science, 67(10), 6266–6293.

Aysan, A. F., Demir, E., Gozgor, G., & Lau, C. K. M. (2019). Effects of the geopolitical risks on Bitcoin returns and volatility. Research in International Business and Finance, 47, 511–518.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. Quarterly Journal of Economics, 131(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Bakshi, G., & Kapadia, N. (2003). Delta-hedged gains and the negative market volatility risk premium. Review of Financial Studies, 16(2), 527–566.

Balcilar, M., Bonato, M., Demirer, R., & Gupta, R. (2018). Geopolitical risks and stock market dynamics of the BRICS. Economic Systems, 42(2), 295–306.

Bali, T. G., Brown, S. J., & Tang, Y. (2017). Is economic uncertainty priced in the cross-section of stock returns? Journal of Financial Economics, 126(3), 471–489.

Bali, T. G., & Cakici, N. (2008). Idiosyncratic volatility and the cross section of expected returns. Journal of Financial and Quantitative Analysis, 43(1), 29–58.

Bali, T. G., Subrahmanyam, A., & Wen, Q. (2021). The macroeconomic uncertainty premium in the corporate bond market. Journal of Financial and Quantitative Analysis, 56(5), 1653–1678.

Bao, J., Pan, J., & Wang, J. (2011). The illiquidity of corporate bonds. Journal of Finance, 66(3), 911–946.

Baur, D. G., & Smales, L. A. (2020). Hedging geopolitical risk with precious metals. Journal of Banking & Finance, 117, 105823.

Bekaert, G., Harvey, C. R., Lundblad, C. T., & Siegel, S. (2014). Political Risk Spreads. Journal of International Business Studies, 471–493.

Bekaert, G., Harvey, C. R., Lundblad, C. T., & Siegel, S. (2016). Political risk and international valuation. Journal of Corporate Finance, 37, 1–23.

Bekaert, G., Hoerova, M., & Duca, M. L. (2013). Risk, uncertainty and monetary policy. Journal of Monetary Economics, 60(7), 771–788.

Benischke, M. H., Guldiken, O., Doh, J. P., Martin, G., & Zhang, Y. (2022). Towards a behavioral theory of MNC response to political risk and uncertainty: The role of CEO wealth at risk. Journal of World Business, 57(1), 101265.

Ben-Rephael, A., Carlin, B. I., Da, Z., & Israelsen, R. D. (2021). Information consumption and asset pricing. Journal of Finance, 76(1), 357–394.

Bessembinder, H., Kahle, K. M., Maxwell, W. F., & Xu, D. (2008). Measuring abnormal bond performance. Review of Financial Studies, 22(10), 4219–4258.

Bhandari, L. C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. Journal of Finance, 43(2), 507–528.

Bharath, S. T., & Shumway, T. (2008). Forecasting default with the Merton distance to default model. Review of Financial Studies, 21(3), 1339–1369.

Blome, C., & Schoenherr, T. (2011). Supply chain risk management in financial crises—A multiple case-study approach. International Journal of Production Economics, 134(1), 43–57.

Bloom, N. (2009). The impact of uncertainty shocks. Econometrica, 77(3), 623–685.

Boah, E., & Ujah, N. U. (2024). Firm-level political risk and corporate R&D investment. Journal of Empirical Finance, 78, 101513.
Bongaerts, D., & Schoenmaker, D. (2024). Liquidity and clientele effects in green debt markets. Journal of Corporate Finance, 86, 102582.
Brogaard, J., Dai, L., Ngo, P. T., & Zhang, B. (2020). Global political uncertainty and asset prices. Review of Financial Studies, 33(4), 1737–1780.
Bussy, A., & Zheng, H. (2023). Responses of FDI to geopolitical risks: The role of governance, information, and technology. International Business Review, 32(4), 102136.
Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. American Economic Review, 112(4), 1194–1225.
Campbell, J. Y. (1993). Intertemporal asset pricing without consumption data. American Economic Review, 83, 487–512.
Campbell, J. Y. (1996). Understanding risk and return. Journal of Political Economy, 104(2), 298–345.
Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. Journal of Finance, 63(6), 2899–2939.
Campbell, J. Y., Ramadorai, T., & Ranish, B. (2014). Getting Better or Feeling Better? How Equity Investors Respond to Investment Experience (No. W20000). National Bureau of Economic Research.
Ceballos, L., Piljak, V., & Swinkels, L. (2024). Is firm-level political risk priced in the corporate bond market? Journal of Empirical Finance, 79, 101562.
Çelik, S., Demirtaş, G., & Isaksson, M. (2020). Corporate Bond Market Trends, Emerging Risks and Monetary Policy (OECD Capital Market Series). OECD.
Chatjuthamard, P., Treepongkaruna, S., Jiraporn, P., & Jiraporn, N. (2021). Does firm-level political risk influence corporate social responsibility (CSR)? Evidence from earnings conference calls. Financial Review, 56(4), 721–741.
Chen, B., Gan, Q., & Vasquez, A. (2025). Does the options market underreact to firms' left-tail risk? Journal of Financial and Quantitative Analysis, 60(4), 1827–1858.
Chen, H., Cui, R., He, Z., & Milbradt, K. (2018). Quantifying liquidity and default risks of corporate bonds over the business cycle. Review of Financial Studies, 31(3), 852–897.
Chen, J., Hong, H., & Stein, J. C. (2002). Breadth of ownership and stock returns. Journal of Financial Economics, 66(2–3), 171–205.
Chen, X., Huang, J. Z., Sun, Z., Yao, T., & Yu, T. (2020). Liquidity premium in the eye of the beholder: An analysis of the clientele effect in the corporate bond market. Management Science, 66(2), 932–957.
Chesney, M., Reshetar, G., & Karaman, M. (2011). The impact of terrorism on financial markets: An empirical study. Journal of Banking & Finance, 35(2), 253–267.
Chiu, C. H., & Choi, T. M. (2016). Supply chain risk analysis with mean-variance models: A technical review. Annals of Operations Research, 240(2), 489–507.
Choi, W., Chung, C. Y., & Wang, K. (2022). Firm-level political risk and corporate investment. Finance Research Letters, 46, 102307.
Chung, K. H., Wang, J., & Wu, C. (2019). Volatility and the cross-section of corporate bond returns. Journal of Financial Economics, 133(2), 397–417.
Cochrane, J. H. (2000). Asset Pricing. Princeton University Press.
Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. Review of Financial Studies, 28(1), 1–32.
Daniel, K. D., Hirshleifer, D., & Subrahmanyam, A. (2001). Overconfidence, arbitrage, and equilibrium asset pricing. Journal of Finance, 56(3), 921–965.
Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance, 52(3), 1035–1058.
Demir, E., & Danisman, G. O. (2021). The impact of economic uncertainty and geopolitical risks on bank credit. North American Journal of Economics and Finance, 57, 101444.
Dick-Nielsen, J. (2009). Liquidity Biases in TRACE. Journal of Fixed Income, 19(2), 43.
Dick-Nielsen, J. (2014). How to Clean Enhanced TRACE Data.
Dick-Nielsen, J., Feldhütter, P., & Lando, D. (2012). Corporate bond liquidity before and after the onset of the subprime crisis. Journal of Financial Economics, 103(3), 471–492.

Duan, T., Li, F. W., & Wen, Q. (2025). Is carbon risk priced in the cross section of corporate bond returns? Journal of Financial and Quantitative Analysis, 60(1), 1–35.
Elton, E. J., Gruber, M. J., Agrawal, D., & Mann, C. (2001). Explaining the rate spread on corporate bonds. Journal of Finance, 56(1), 247–277.
Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. Journal of Finance, 47(2), 427–465.
Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5
Fisher, L., & Weil, R. L. (1971). Coping with the Risk of Interest-Rate Fluctuations: Returns to Bondholders from Naive and Optimal Strategies. Journal of Business, 408–431.
Gad, M., Nikolaev, V., Tahoun, A., & van Lent, L. (2024). Firm-level political risk and credit markets. Journal of Accounting and Economics, 77(2–3), 101642.
Gao, Z., Ren, H., & Zhang, B. (2020). Googling investor sentiment around the world. Journal of Financial and Quantitative Analysis, 55(2), 549–580.
Ge, S., & Weisbach, M. S. (2021). The role of financial conditions in portfolio choices: The case of insurers. Journal of Financial Economics, 142(2), 803–830.
Gebhardt, W. R., Hvidkjaer, S., & Swaminathan, B. (2005). The cross-section of expected corporate bond returns: Betas or characteristics? Journal of Financial Economics, 75(1), 85–114.
Giesecke, K., Longstaff, F. A., Schaefer, S., & Strebulaev, I. (2011). Corporate bond default risk: A 150-year perspective. Journal of Financial Economics, 102(2), 233–250.
Goldsmith-Pinkham, P., Gustafson, M. T., Lewis, R. C., & Schwert, M. (2020). Sea Level Rise Exposure and Municipal Bond Yields [Unpublished manuscript].
Goldstein, I., Jiang, H., & Ng, D. T. (2017). Investor flows and fragility in corporate bond funds. Journal of Financial Economics, 126(3), 592–613.
Gorbatikov, E., van Lent, L., Naik, N. Y., Sharma, V., & Tahoun, A. (2019). Is Firm-Level Political Exposure Priced?
Greenwood, R., & Hanson, S. G. (2013). Issuer quality and corporate bond returns. Review of Financial Studies, 26(6), 1483–1525.
Gul, F. (1991). A Theory of Disappointment Aversion. Econometrica, 667–686.
Hailemariam, A., & Ivanovski, K. (2021). The impact of geopolitical risk on tourism. Current Issues in Tourism, 24(22), 3134–3140.
Harvey, C. R., Liu, Y., & Zhu, H. (2016). … and the cross-section of expected returns. Review of Financial Studies, 29(1), 5–68.
Hassan, T. A., Hollander, S., Van Lent, L., & Tahoun, A. (2019). Firm-level political risk: Measurement and effects. Quarterly Journal of Economics, 134(4), 2135–2202.
Heath, D., Jarrow, R., & Morton, A. (1990). Bond pricing and the term structure of interest rates: A discrete time approximation. Journal of Financial and Quantitative Analysis, 25(4), 419–440.
Henderson, B. J., Jegadeesh, N., & Weisbach, M. S. (2006). World Markets for Raising New Capital. Journal of Financial Economics, 82(1), 63–101. https://doi.org/10.1016/j.jfineco.2005.08.004
Ho, T., Kagkadis, A., & Wang, G. (2024). Is Firm-Level Political Risk Priced in the Equity Option Market? Review of Asset Pricing Studies, 14(1), 153–195.
Hong, H., & Sraer, D. (2013). Quiet bubbles. Journal of Financial Economics, 110(3), 596–606.
Hsu, J. C., Saa-Requejo, J., & Santa-Clara, P. (2003). Bond Pricing with Default Risk (Qt5bb1j39q). Anderson Graduate School of Management, UCLA.
Huang, A., Kalimipalli, M., N, S., & Ramchand, L. (2019). Risk Mitigation by Institutional Participants in the Secondary Market: Evidence from Foreign Rule 144A Debt Market. Journal of Banking & Finance, 99, 202–221.
Huang, G. Y., Shen, C. H. H., & Wu, Z. X. (2023). Firm-level political risk and debt choice. Journal of Corporate Finance, 78, 102332.
Huynh, N., & Le, Q. N. (2025). From chain to capital: Supply chain risks and working capital management. Economics Letters, 247, 112100.
Huynh, T. D., & Xia, Y. (2021a). Climate change news risk and corporate bond returns. Journal of Financial and Quantitative Analysis, 56(6), 1985–2009.
Huynh, T. D., & Xia, Y. (2021b). Panic Selling When Disaster Strikes: Evidence in the Bond and Stock Markets. Management Science.

Iacoviello, M., Caldara, D., Penn, M., & Conlisk, S. (2024). Do Geopolitical Risks Raise or Lower Inflation?
Isakin, M., & Pu, X. (2019). The impact of firm-level political risk on creditor control. Journal of Fixed Income, 29(1), 44–54.
Iyke, B. N., Phan, D. H. B., & Narayan, P. K. (2022). Exchange rate return predictability in times of geopolitical risk. International Review of Financial Analysis, 81, 102099.
Jiang, H., Li, Y., Sun, Z., & Wang, A. (2022). Does mutual fund illiquidity introduce fragility into asset prices? Evidence from the corporate bond market. Journal of Financial Economics, 143(1), 277–302.
Jung, S., Lee, J., & Lee, S. (2021). The Impact of Geopolitical Risk on Stock Returns: Evidence from Inter-Korea Geopolitics. University Library of Munich.
Kesternich, I., & Schnitzer, M. (2010). Who is afraid of political risk? Multinational firms and their choice of capital structure. Journal of International Economics, 82(2), 208–218.
Koijen, R. S., Lustig, H., & Van Nieuwerburgh, S. (2017). The cross-section and time series of stock and bond returns. Journal of Monetary Economics, 88, 50–69.
Lee, C.-C., & Chen, M.-P. (2020). Do natural disasters and geopolitical risks matter for cross-border country exchange-traded fund returns? North American Journal of Economics and Finance, 51, 101054.
Lin, H., Wang, J., & Wu, C. (2011). Liquidity risk and expected corporate bond returns. Journal of Financial Economics, 99(3), 628–650.
Liu, J., Ma, F., Tang, Y., & Zhang, Y. (2019). Geopolitical risk and oil volatility: A new insight. Energy Economics, 84, 104548.
Lochstoer, L. A., & Muir, T. (2022). Volatility expectations and returns. Journal of Finance, 77(2), 1055–1096.
Ma, F., Lu, F., & Tao, Y. (2022). Geopolitical risk and excess stock returns predictability: New evidence from a century of data. Finance Research Letters, 50, 103211.
Malkiel, B. G. (1962). Expectations, bond prices, and the term structure of interest rates. Quarterly Journal of Economics, 76(2), 197–218.
Massa, M., & Zhang, L. (2021). The spillover effects of Hurricane Katrina on corporate bonds and the choice between bank and bond financing. Journal of Financial and Quantitative Analysis, 56(3), 885–913.
Merton, R. C. (1973). An Intertemporal Capital Asset Pricing Model. Econometrica, 867–887.
Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance, 29(2), 449–470.
Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. Journal of Financial Economics, 142(2), 550–571.
Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns. Journal of Financial Economics, 146(2), 403–424.
Pástor, Ľ., & Veronesi, P. (2013). Political uncertainty and risk premia. Journal of Financial Economics, 110(3), 520–545.
Patton, A. J., & Verardo, M. (2012). Does beta move with news? Firm-specific information flows and learning about profitability. Review of Financial Studies, 25(9), 2789–2839.
Petersen, M. A. (2008). Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies, 22(1), 435–480.
Routledge, B. R., & Zin, S. E. (2010). Generalized disappointment aversion and asset prices. Journal of Finance, 65(4), 1303–1332.
Saffar, W., Wang, Y., & Wei, K. J. (2024). Firm-level political risk and bank loan contracting. Contemporary Accounting Research, 41(3), 1577–1607.
Salisu, A. A., Lasisi, L., & Tchankam, J. P. (2022). Historical geopolitical risk and the behaviour of stock returns in advanced economies. European Journal of Finance, 28(9), 889–906.
Singleton, K. J. (2021). Presidential Address: How Much "Rationality" Is There in Bond-Market Risk Premiums? Journal of Finance, 76(4), 1611–1654.
Smales, L. A. (2021). Geopolitical risk and volatility spillovers in oil and stock markets. Quarterly Review of Economics and Finance, 80, 358–366.

Strebulaev, I. A., & Yang, B. (2013). The Mystery of Zero-Leverage Firms. Journal of Financial Economics, 109(1), 1–23. https://doi.org/10.1016/j.jfineco.2013.02.001

Su, C.-W., Qin, M., Tao, R., Shao, X.-F., Albu, L. L., & Umar, M. (2020). Can Bitcoin hedge the risks of geopolitical events? Technological Forecasting and Social Change, 159, 120182.

Umar, Z., Bossman, A., Choi, S. Y., & Teplova, T. (2022). Does geopolitical risk matter for global asset returns? Evidence from quantile-on-quantile regression. Finance Research Letters, 48, 102991.

Vassalou, M., & Xing, Y. (2004). Default risk in equity returns. Journal of Finance, 59(2), 831–868.

Wang, K. H., Su, C. W., & Umar, M. (2021). Geopolitical risk and crude oil security: A Chinese perspective. Energy, 219, 119555.

Wang, X., Wu, Y., & Xu, W. (2024). Geopolitical Risk and Investment. Journal of Money, Credit and Banking, 56(8), 2023–2059.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies, 21(4), 1455–1508.

Wu, D. (2024). Text-based measure of supply chain risk exposure. Management Science, 70(7), 4781–4801.

Zaremba, A., Cakici, N., Demir, E., & Long, H. (2022). When bad news is good news: Geopolitical risk and the cross-section of emerging market stock returns. Journal of Financial Stability, 58, 100964.

Zhang, Y., He, J., He, M., & Li, S. (2023). Geopolitical risk and stock market volatility: A global perspective. Finance Research Letters, 53, 103620.

Figure 1: Markov-switching estimations for high/low states in GPR.
The dotted line indicates the state-change probabilities, and the solid line indicates the geopolitical risk index during our sample. The vertical dotted lines indicate the Russia-Ukraine and US–Iran conflicts.

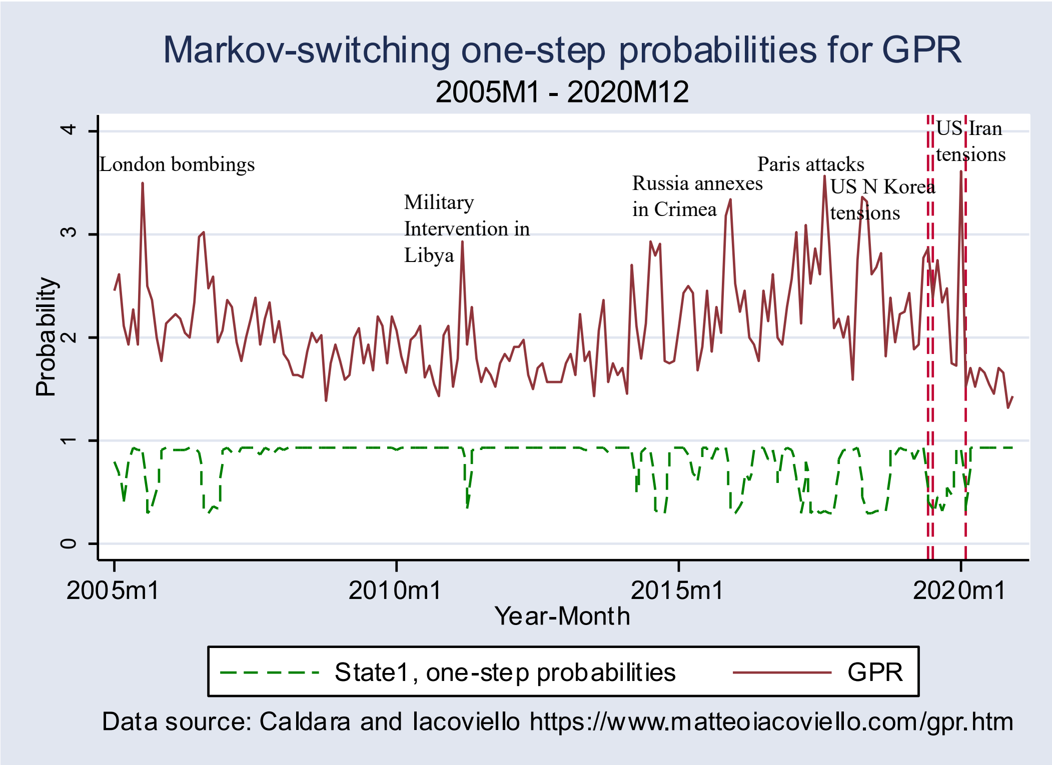

Figure 2: Coefficient estimates of dynamic analysis
The graph depicts the coefficient estimates and 95% confidence interval of the dynamic impact of the treated firm on future bond returns around the geopolitical event time. *t-j* (*t+j*) indicates *j* months before (after) the event, and the month before the event date (*t-1*) is regarded as the reference period and thereby omitted.

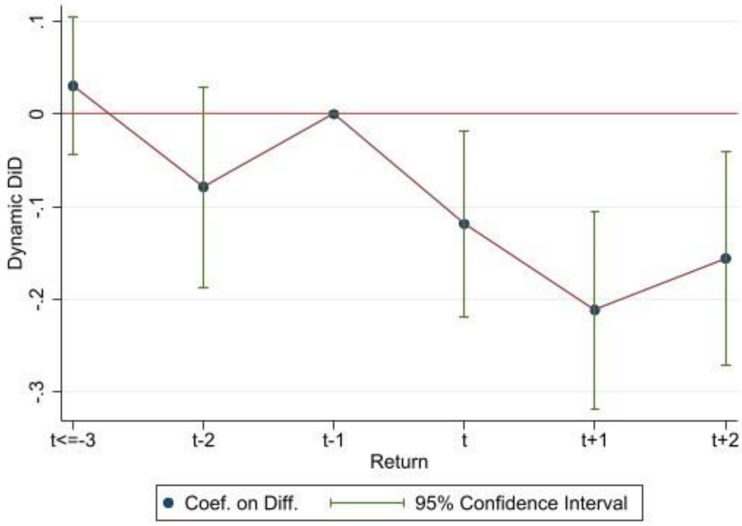

Figure 3a: Geo-political risk (GPR) index against corporate bond market distress indicator (CMDI)

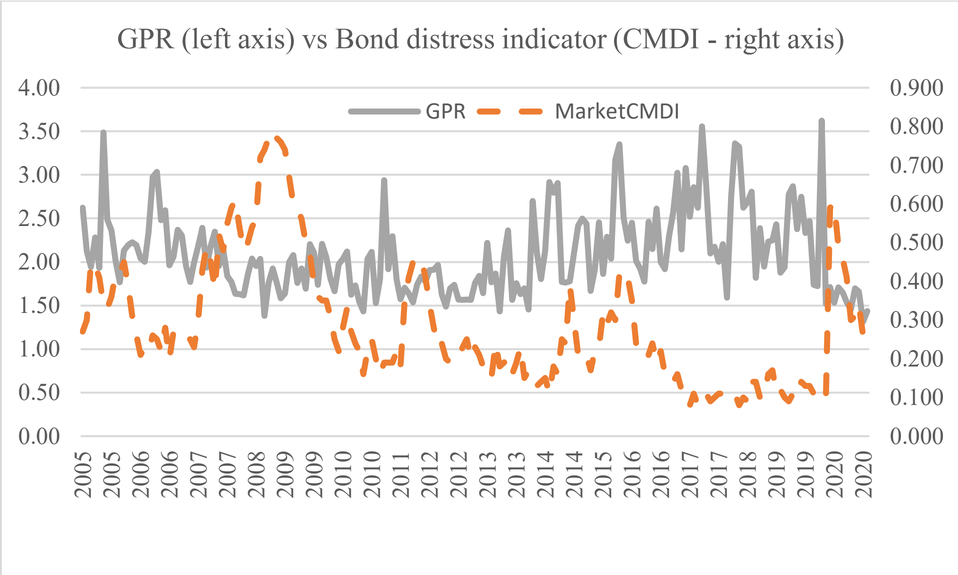

Figure 3b: Scatterplot of GPR index against corporate bond market distress indicator (CMDI)

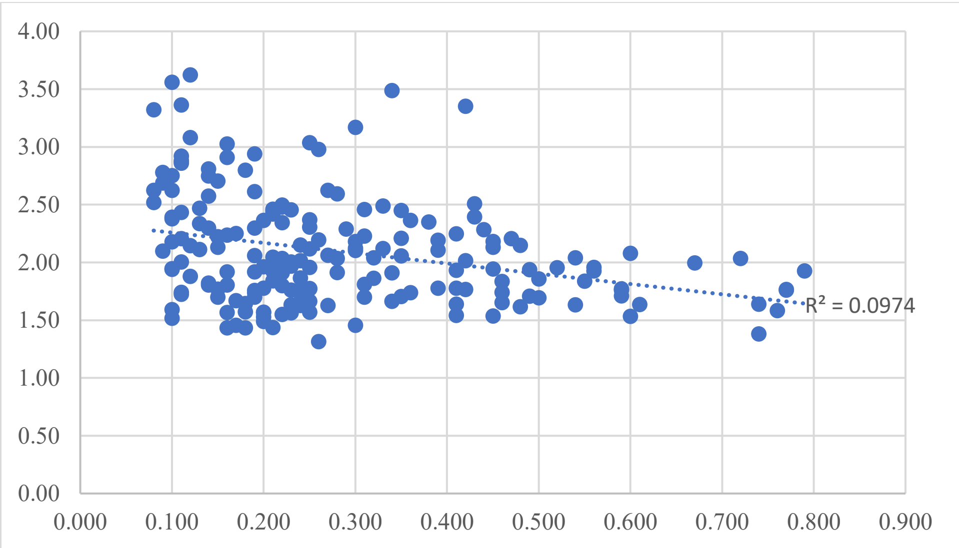

Table 1 – Summary Statistics and Correlation

Panel A shows the number of observations after removing those with missing values in our baseline regression from Table 3, along with the mean, 1%, 25%, 50%, 75%, and 90% percentiles of the key variables used over the sample period from January 2005 to December 2020. Panel B presents the overall pairwise correlation of bond characteristics within our panel data set, including beta on GPR (β^{GPR}) (geopolitical risk), illiquidity (measured in percentage terms), the logarithm of amounts outstanding (denoted as *Size*), bond credit ratings, bond age, maturity, downside risk measured as 5% VAR of bond returns, CAPM beta of bond returns (denoted as β^{BMKT}), beta on the term spread (denoted as β^{TERM}), and beta on the default premium (denoted as β^{DEF}). *ROE* is calculated as income before extraordinary items (IB) divided by the book value of common equity (CEQ). *Log_MV* represents the natural logarithm of a firm's market value of common equity (*PRC* x *SHROUT*) at the end of each month, with the market value measured in thousands. ∗ indicates statistical significance at the 5% level or below.

Panel A: Descriptive statistics over the period of Jan 2005 to Dec 2020

Variable	N	Mean	p1	p50	p25	p75	p99	SD
Bond returns (%)	578,751	0.559	-8.581	0.394	-0.336	1.432	10.218	2.631
β^{GPR}	578,751	-0.001	-0.043	-0.001	-0.005	0.003	0.041	0.013
β^{TERM}	578,751	0.979	-0.028	0.857	0.514	1.334	2.731	0.37
β^{DEF}	578,751	0.481	-0.307	0.415	0.223	0.690	1.456	0.491
β^{BMKT}	578,751	0.510	-0.441	0.400	0.186	0.742	2.094	0.617
Illiquidity (%)	578,751	0.013	-0.012	0.002	0.000	0.009	0.236	0.04
Size	578,751	13.103	10.127	13.122	12.612	13.634	14.914	0.862
Rating	578,751	8.425	1.000	8.000	6.000	10.000	17.000	3.179
Age	578,751	5.618	1.164	4.142	2.483	7.108	22.922	4.567
Time to Maturity	578,751	9.454	1.186	6.131	3.428	12.344	29.261	8.422
Downside Risk	578,751	0.038	0.004	0.028	0.016	0.046	0.211	0.036
Leverage	578,751	0.366	0.035	0.350	0.235	0.476	0.898	0.181
ROE	578,751	0.119	-1.995	0.113	0.057	0.193	1.992	0.408
Log_MV	578,751	16.684	12.155	16.806	15.687	17.809	19.700	1.636

Panel B: Pairwise correlation of panel data

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Bond returns (%) $_{t+1}$	1													
(2) β^{GPR}	-0.005*	1												
(3) β^{TERM}	0.022*	-0.076*	1											
(4) β^{DEF}	0.033*	-0.018*	0.623*	1										
(5) β^{BMKT}	0.047*	-0.010*	0.750*	0.712*	1									
(6) Illiquidity (%)	0.103*	-0.014*	0.009*	0.057*	0.053*	1								
(7) Bond Size	-0.003*	-0.024*	0.174*	0.098*	0.141*	-0.210*	1							
(8) Rating	0.032*	0.012*	-0.174*	0.156*	0.118*	0.102*	-0.207*	1						
(9) Age	0.014*	-0.002	-0.042*	-0.039*	-0.045*	0.145*	-0.347*	-0.026*	1					
(10) Time to Maturity	0.058*	0.041*	0.702*	0.453*	0.604*	0.120*	0.013*	-0.133*	0.082*	1				
(11) Downside Risk	0.134*	-0.001	0.176*	0.360*	0.404*	0.314*	-0.161*	0.315*	0.103*	0.308*	1			
(12) Leverage	0.007*	-0.011*	-0.052*	0.070*	0.070*	0.010*	-0.012*	0.344*	-0.057*	-0.061*	0.081*	1		
(13) ROE	-0.007*	0.007*	0.031*	-0.050*	-0.030*	-0.047*	0.030*	-0.121*	0.009*	0.025*	-0.087*	-0.060*	1	
(14) Log_MV	-0.029*	-0.013*	0.196*	-0.059*	-0.007*	-0.134*	0.267*	-0.631*	0.096*	0.159*	-0.246*	-0.162*	0.139*	1

Table 2 – Univariate Statistics of Portfolio Analysis – sorted by GPR beta

This table reports the average beta on GPR for each quintile portfolio sorted by the pre-ranking GPR beta estimated over a 36-month rolling window for each bond return, controlling for the bond market factors (default spread, term spread), and Fama-French three stock market factors (i.e., excess stock market return SMKT, the size factor SMB, and the book-to-market factor HML) specified by equation (1)). Low-1 (High-5) is the portfolio with the lowest (highest) GPR beta in the previous month. The portfolio is value-weighted, using the outstanding bond size as weights. This table shows the average excess return (over the risk-free rate), the characteristics-adjusted return (adjusted for bond ratings and maturities) consistent with Chung, Wang, and Wu (2019), the 3-factor alpha (estimated using a 3-factor model comprising only bond market factors: market illiquidity index BLIQ, default spread DEF, and term spread TERM), and the 6-factor alpha (estimated with a 6-factor model that includes both bond and stock market factors: BLIQ, DEF, TERM, SMKT, SMB, and HML) for each portfolio. Returns and alphas are expressed in percentage terms. "High-Low" represents the difference between "High-5" and "Low-1," with the corresponding t-statistics, based on Newey-West standard errors adjusted for autocorrelation up to four lags, shown in parentheses. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Quintiles	β^{GPR}	Excess Return	Adjusted Return	3-factor alpha	6-factor alpha
Low-Q1	-0.018	0.509***	0.003	0.668***	0.647***
		(3.42)	(0.10)	(6.15)	(6.79)
2	-0.005	0.396***	-0.024**	0.569***	0.554***
		(3.68)	(-2.01)	(6.87)	(6.81)
3	-0.001	0.342***	-0.035**	0.509***	0.489***
		(3.47)	(-2.39)	(6.06)	(5.95)
4	0.004	0.392***	-0.028*	0.568***	0.542***
		(3.28)	(-1.94)	(6.58)	(6.66)
High-Q5	0.017	0.403**	-0.083***	0.499***	0.459***
		(2.52)	(-2.82)	(4.44)	(4.63)
High-Low (Q5–Q1)		-0.106**	-0.086***	-0.169***	-0.187***
		(-2.18)	(-2.73)	(-3.28)	(-3.65)

Table 3 – Geopolitical risk and expected bond returns

This table reports the multivariate regressions of one-month-ahead corporate bond excess returns (in percentage terms) on β^{GPR} and other control variables. Panel A1 (Columns (1), (2), and (3)) of the table reports the coefficients from the fixed effects panel regressions, and Panel A2 (Columns (4), (5), and (6)) reports the Fama and MacBeth (1973). Panel B reports the fixed effects regressions of β^{GPR} on *t+2*, *t+3*, and *t+4* months' bond returns. All variables are within-transformed to remove bond-level characteristics. The *t*-statistics based on Newey-West standard errors adjusted for autocorrelation of up to lag 4 are shown in parentheses. The *t-statistics* based on robust standard errors are clustered at the bond level and are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Regressions of GPR betas on *t*+1 bond returns.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A1: Fixed Effect (FE)			Panel A2: Fama-Macbeth (FM)		
$\boldsymbol{\beta^{GPR}}$	**-4.033*** **	**-3.627*** **	**-3.637*** **	**-3.272** **	**-2.830** **	**-3.008** **
	(-10.89)	**(-10.01)**	**(-10.03)**	**(-2.49)**	**(-2.28)**	**(-2.43)**
β^{BMKT}	0.525***	0.271***	0.271***	0.288**	0.086	0.088
	(27.60)	(13.93)	(13.96)	(2.54)	(0.84)	(0.89)
β^{TERM}	-0.508***	-0.217***	-0.219***	-0.502***	-0.083	-0.103
	(-16.77)	(-7.24)	(-7.30)	(-3.61)	(-0.70)	(-0.89)
β^{DEF}	-0.072***	-0.132***	-0.129***	0.011	-0.094	-0.092
	(-3.87)	(-7.25)	(-7.10)	(0.18)	(-1.50)	(-1.56)
Illiquidity (%)		2.378***	2.392***		1.333***	1.388***
		(11.20)	(11.25)		(2.95)	(3.29)
Size		0.089***	0.091***		0.008	0.022
		(4.08)	(4.14)		(0.12)	(0.35)
Rating		0.072***	0.074***		0.069***	0.068***
		(10.59)	(10.61)		(4.92)	(4.62)
AGE		0.031*	0.031*		0.116***	0.117***
		(1.75)	(1.75)		(3.68)	(3.93)
Maturity		0.136***	0.137***		0.082***	0.079***
		(5.48)	(5.56)		(2.83)	(2.84)
Downside Risk		9.312***	9.377***		9.357***	9.617***
		(30.14)	(30.48)		(7.13)	(7.15)
Leverage			-0.262***			-0.320
			(-2.99)			(-1.35)
ROE			0.035**			0.026
			(2.53)			(0.93)
Log_MV			0.005			-0.021
			(0.28)			(-0.32)
Constant	0.240***	-3.237***	-3.281***	-0.005	-0.002	0.006
	(17.03)	(-8.12)	(-6.57)	(-0.04)	(-0.02)	(0.07)
Bond FE	Yes	Yes	Yes	-	-	-
Year-Month FE	Yes	Yes	Yes	-	-	-
Obs.	578,751	578,751	578,751	578,751	578,751	578,751
Ave./Adj. R-squared	0.052	0.107	0.119	0.269	0.276	0.276

Panel B: Fixed effects regressions of GPR betas on *t+2* through *t+4* bond returns.

	(1)	(2)	(3)
	Fixed Effect (FE)		
	t+2	***t+3***	***t+4***
β^{GPR}	-2.344***	-2.076***	-2.043***
	(-6.27)	(-5.56)	(-5.58)
Controls	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Obs.	534,399	518,868	504,937
$Adj.R^2$	0.281	0.280	0.279

Table 4 – Investor preference tests: Difference-in-Difference (DiD) approach

Panel A of the table presents the coefficients from the differences-in-difference regressions of one-month-ahead corporate bond excess returns (in percentage terms) for the entire sample (Column (1)) or the propensity-score matched (PSM) sample that is matched one period before the event using all control variables and bond returns matching covariates (Column (2)). "Treat" indicates treated firms, which equals one when β^{GPR} lies in the top tercile of the (year-)monthly distribution and zero when β^{GPR} lies in the bottom tercile of the (year-)monthly distribution. "*Post_event*" equals one for the three months after the significant geopolitical events and zero for the three months before the event and is absorbed by year×month fixed effects. Panel B shows the results from the following dynamic DiD specification by extending the event period to five years before, where "n" indicates n years after the event. "$Before^{\leq 3}$" indicates more than 2 months before the event, and "$Before^{2}$" indicates 2 months before the event. The reference year is one year before the event. "$After^{0}$" is the event month, and "$After^{1(2)}$" indicates 1 (2) month after the event. All regressions include control variables from column (3) of Table 3, cohort×bond fixed effects, and cohort×year×month fixed effects. The *t-statistics*, based on robust standard errors, are clustered at the bond level and are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. DiD regression		
	(1)	**(2)**
	Full sample	PSM matched sample
Treat	-0.187**	-0.151
	(-2.13)	(-1.41)
Post_event × Treat	-0.166***	-0.207***
	(-5.48)	(-6.16)
Controls	Yes	Yes
Cohort × Bond FE	Yes	Yes
Cohort ×Year × Month FE	Yes	Yes
Obs.	82,781	56,174
Adj.R^2	0.124	0.135

Panel B. Parallel trend assumption: Dynamic DiD	
	PSM matched sample
Treat	-0.054
	(-0.61)
$Before^{\leq 3}$ x Treat	0.030
	(0.79)
$Before^{2}$ x Treat	-0.079
	(-1.43)
$After^{0}$ x Treat	-0.119***
	(-2.32)
$After^{1}$ x Treat	-0.218***
	(-3.89)
$After^{2}$ x Treat	-0.156***
	(-2.66)
Control Variables	Yes
Cohort × Bond FE	Yes
Cohort ×Year × Month FE	Yes
Obs.	72,213
Adj.R^2	0.187

Table 5 – Placebo tests with the Global Financial Crisis and COVID-19

The table presents the coefficients from the differences-in-difference regressions of one-month-ahead corporate bond excess returns (in percentage terms) for the entire sample (column 1), and the propensity-score matched (PSM) sample, matched one period before the event, using all control variables and bond returns as matching covariates (column 2). We estimate the effects surrounding our placebo events that cause the bond distress index (CMDI) to surge but are unrelated to geopolitical uncertainty. We employ the events of the 2008-2009 global financial crisis and the COVID-19 pandemic as our placebo events. For the global financial crisis, *Post_PlaceboEvent* equals one from August 2007 to June 2009 and equals zero from January 2006 to July 2007. For the COVID-19 pandemic, *Post_PlaceboEvent* is equal to one from February 2020 to May 2020 and is equal to zero from November 2019 to January 2020. We combine both events in the regression. *Treat* equals one (zero) when β^{GPR} is in the top (bottom) tercile of the (year-)monthly sample distribution. Column (3) of the table uses a continuous treatment variable by interacting β^{GPR} with *Post_ PlaceboEvent*. All regressions include control variables from column (3) of Table 3, cohort×bond fixed effects, and cohort×year×month fixed effects. The *t-statistics* based on robust standard errors are clustered at the bond level and are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Full sample	(2) PSM matched sample
Treat	-0.056	-0.186
	(-1.06)	(-1.38)
Post_PlaceboEvent ×Treat	0.018	0.048
	(0.31)	(0.38)
Controls	Yes	Yes
Cohort × Bond FE	Yes	Yes
Cohort ×Year × Month FE	Yes	Yes
Obs.	66,366	11,473
$Adj.R^2$	0.337	0.433

Table 6 – Risk prevalence

The table presents the fixed-effects regressions of the interactions of β^{GPR} with downside risk (column 1), the high volatility index (VIX) dummy (column 2), and the high economic uncertainty index (EPU) dummy (column 3). VIX is derived from data provided by the Chicago Board of Options Exchange (CBOE), and EPU is sourced from Baker, Bloom, and Davis (2016). Each regression incorporates all the controls from Table 3, as well as bond-level fixed effects and year-level fixed effects. The *t-statistics*, calculated using robust standard errors clustered at the bond level, are presented in parentheses. $***$, $**$ and $*$ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Double sorting based on beta of downside risk, VIX, and EPU.

	Sorted by beta on Downside Risk				
	Low (1)	2	3	4	High (5)
High-Low (Q5–Q1) portfolio based on β^{GPR}	-0.06	-0.14**	-0.17*	-0.17***	-0.25**
	(-0.89)	(-2.43)	(-1.68)	(-2.66)	(-2.53)
	Sorted by beta on VIX				
High-Low (Q5–Q1) portfolio based on β^{GPR}	-0.26***	-0.05	-0.15***	-0.22***	-0.32***
	(-3.62)	(-0.76)	(-2.70)	(-3.72)	(-4.13)
	Sorted by beta on Economic Policy Uncertainty (EPU)				
High-Low (Q5–Q1) portfolio based on β^{GPR}	-0.28***	-0.10*	-0.03	-0.10*	-0.29***
	(-2.64)	(-1.70)	(-0.62)	(-1.89)	(-4.00)

Panel B:

	(1)	(2)	(3)
β^{GPR} × Downside risk	-40.93***		
	(-4.728)		
β^{GPR} × High *VIX*		-2.96***	
		(-5.256)	
β^{GPR} × High EPU			-3.3***
			(-3.955)
β^{GPR}	-0.55	-1.85***	0.494
	(-0.855)	(-4.435)	(0.832)
Downside risk	12.266***		
	(35.035)		
High VIX		0.371***	
		(46.831)	
High EPU			0.402***
			(55.684)
Controls	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	578,751	578,751	578,751
Adj.R^2	0.06	0.054	0.051

Table 7 – The Effects of International Exposure

The table shows the coefficients from fixed effects regression examining the relationship between β^{GPR} and future bond returns (%) conditional on the firm's international exposure. Column (1) *ForeignSale* is defined as the ratio of the sales revenues produced by the firms' nondomestic segments to their total sales (domestic plus nondomestic sales), and column (2) presents the results by interacting β^{GPR} with *D_ ForeignSale*, which is the dummy variable indicating that *ForeignSale*>0. Each regression includes controls from column 6 of Table 5, bond-level fixed effects, and year-month-level fixed effects. The *t-statistics* based on robust standard errors clustered at the bond level are shown in the parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
β^{GPR} × *ForeignSale*	-2.450**	
	(-2.17)	
β^{GPR} × *D_ForeignSale*		-1.605**
		(-2.16)
β^{GPR}	-2.978***	-2.724***
	(-6.49)	(-4.90)
ForeignSale	-0.065*	
	(-1.91)	
D_ ForeignSale		-0.023
		(-1.52)
Controls	Yes	Yes
Bond FE	Yes	Yes
Year-Month FE	Yes	Yes
Obs.	578,751	578,751
Adj.R^2	0.276	0.276

Table 8 - The effects of supply chain disruption

The table shows the coefficients from fixed effects regression examining whether supply chain disruption alters investors' hedging demand. Column (1) shows the results by interacting β^{GPR} with the logistics performance index (LPI) in the US, published by the World Bank (*LPI_US_Index*). Column (2) presents the results by interacting β^{GPR} with firm-level text-based measures of supply chain risk estimated using firms' 10-K filings (SCR). In particular, we count the total instances of words in the supply-chain-related word list extracted from Wu (2023), provided that a risk word from the risk word list extracted from Hassan et al. (2019) also occurs in the same sentence. For firms with missing values, we replace them with the average value of supply chain risk in the same SIC industry. We then take the natural logarithm of the counts to construct *SCR*. Each regression includes controls from column 6 of Table 5, bond-level fixed effects, and year-month-level fixed effects. The *t-statistics* based on robust standard errors clustered at the bond level are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
β^{GPR}	-6.094***	-1.241*
	(-11.11)	(-1.65)
β^{GPR} × ΔLPI_global_index	0.87***	
	(4.69)	
β^{GPR} × SCR		-0.125***
		(-2.63)
SCR		0.0002
		(0.34)
Controls	Yes	Yes
Bond FE	Yes	Yes
Year-Month FE	Yes	Yes
Obs.	519,572	268,038
Adj.R^2	0.286	0.298

Table 9 - The effects of default risk

The table shows the coefficients from fixed effects regression examining the effects of firms' financial distress in moderating bond investors' hedging demand. Column (1) shows the results by interacting β^{GPR} with the inverse of distance to default (*Inv. DTD*). Column (2) presents the results by interacting β^{GPR} with loan spread (in basis points, and a greater value indicates high distress risk). Column (3) presents the results by interacting β^{GPR} with whether CDS contracts protect the firm's debt, denoted as *NoCDS_protection*, which is set to one if the firm has no CDS traded on it. Each regression includes controls from column 3 of Table 3, bond fixed effects, and year-month level fixed effects. The *t-statistics* based on robust standard errors clustered at the bond level are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
β^{GPR}	-4.219***	-2.992***	-5.578***
	(-5.23)	(-2.60)	(-8.38)
β^{GPR} × *Inv. DTD*	-0.252**		
	(1.96)		
β^{GPR} × Loan spread		-0.016***	
		(-3.23)	
β^{GPR} × *NoCDS_protection*			-2.967***
			(-3.86)
Inv. DTD	-0.018***		
	(-8.80)		
Loan spread		0.000	
		(0.36)	
NoCDS_protection			-0.068**
			(-2.41)
Controls	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Obs.	480,112	306,515	578,751
$Adj.R^2$	0.279	0.293	0.276

Table 10 - Accounting for equity and bond characteristics

The table shows the reports the results of bivariate portfolio analysis in Panel A and coefficients from OLS fixed effects regression conditioning on the degree of equity idiosyncratic volatility (column 1), equity market risk (column 2), bond ratings (column 3), bond maturity (column 4), and bond illiquidity (column 5) in Panel B. In Panel A, at the end of each month, we first sort all bonds into two groups based on whether they are rated as investment grade (BBB or above) or non-investment grade (the rest), and sort the bonds into high versus low maturity, illiquidity versus liquid, and young versus old using their median as the breakpoint. Then, within each group, we further sort them into quintiles based on the GPR beta (β^{GPR}). In Panel B, we sort all bonds into quintile portfolios based on betas of downside risk, VIX (CBOE volatility index), and beta on economic policy uncertainty (EPU) at the end of every month, and then within each portfolio, we further sort them into quintiles based on the GPR beta (β^{GPR}). The alphas are presented in percentage terms. The portfolio Low-1 (High-5) stands for the portfolio with the lowest (highest) GPR beta, and "High-Low" is the difference between "High-5" and "Low-1"; the corresponding *t-statistics* based on Newey-West standard errors adjusted for autocorrelation of up to four lags are shown in the parentheses. Equity idiosyncratic volatility (*IdioVol*) and equity market risk (β^{Stock}) are all standardized before entering into the regression. The dummy variables ratings and maturity are based on median values in a given month, which takes the value of one when the variable is greater than the median and zero otherwise. The illiquidity dummy takes the value of one when the bond illiquidity is greater than the first quartile of illiquidity and zero otherwise. Each regression includes bond-level fixed effects and year-month-level fixed effects. The *t-statistics* based on robust standard errors clustered at the bond level are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A : Bi-variate sorts

	Low (1)	2	3	4	High (5)	High-Low (Q5–Q1)
Investment grade	0.61***	0.48***	0.46***	0.38**	0.23	**-0.39*** **
	(3.21)	(2.80)	(2.92)	(2.58)	(1.25)	**(-4.73)**
Non-investment grade	0.67***	0.56***	0.50***	0.56***	0.60***	-0.07
	(7.89)	(7.76)	(7.30)	(7.88)	(6.97)	(-1.61)
Low Maturity	0.80***	0.82***	0.82***	0.80***	0.66***	**-0.14** **
	(6.32)	(6.79)	(7.13)	(6.43)	(5.24)	**(-2.05)**
High Maturity	0.58***	0.63***	0.58***	0.50***	0.40***	**-0.19*** **
	(5.13)	(6.25)	(4.64)	(4.90)	(3.70)	**(-2.98)**
Liquid	0.49***	0.41***	0.39***	0.42***	0.38***	**-0.12** **
	(5.49)	(5.59)	(5.61)	(5.61)	(3.85)	**(-2.49)**
Illiquid	0.75***	0.72***	0.69***	0.64***	0.51***	**-0.23*** **
	(7.19)	(7.72)	(7.45)	(7.21)	(5.10)	**(-3.77)**
Young	0.64***	0.53***	0.49***	0.52***	0.48***	**-0.16*** **
	(6.02)	(4.69)	(4.77)	(5.86)	(5.63)	**(-2.71)**
Old	0.66***	0.56***	0.50***	0.52***	0.45***	**-0.21*** **
	(8.58)	(7.58)	(6.76)	(7.21)	(3.73)	**(-2.71)**

Panel B: Fixed effect regressions

	(1)	(2)	(3)	(4)	(5)
β^{GPR} × IdioVol	-1.645***				
	(-4.72)				
β^{GPR} × β^{Stock}		-1.671***			
		(-4.62)			
β^{GPR} × Ratings dummy			-1.713**		
			(-2.227)		
β^{GPR} × Maturity dummy				2.683***	
				(3.227)	
β^{GPR} × illiquidity dummy					-2.574***
					(-3.030)
β^{GPR}	-2.487***	-2.986***	-1.895***	-4.826***	-2.149***
	(-7.20)	(-8.62)	(-3.501)	(-6.959)	(-4.553)
IdioVol	0.068***				
	(5.22)				
β^{Stock}		-0.003			
		(-0.42)			
Ratings dummy			0.038***		
			(4.921)		
Maturity dummy				0.164***	
				(13.837)	
illiquidity dummy					0.096***
					(8.623)
Controls	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Obs.	495,596	493,744	578,751	578,751	578,751
$Adj.R^2$	0.228	0.228	0.051	0.051	0.047

Table 11 - Robustness Check I: the use of Google trends to capture geopolitical risk

This table presents the coefficients from fixed effects regressions of one-month-ahead corporate bond excess returns (in percent) on bond return sensitivity to geopolitical risk (β^{GPR}). This sensitivity is measured based on Google Trends' most relevant 25 queries related to each keyword used in Caldara and Iacoviello (2022), resulting in a total of 248 keywords. Next, we obtain weekly Search Volume Index (SVI) data for each of the keywords and calculate the changes in SVI, winsorize the observations at 2.5%, remove seasonality in SVI using monthly dummies, and standardize each time series to ensure comparability, following the methodologies of Da, Engelberg, and Gao (2015) and Gao, Ren, and Zhang (2020). We identify the top 30 terms most closely related to market returns (based on *t-statistics* from a forward rolling regression) to construct the GPR index. For thoroughness, we also construct an additional index restricting keywords to those that have at least 5 SVI values to ensure relevance. Column (1) uses β^{GPR}*_SVI*, while Column (2) uses β^{GPR}*_SVI5* as the main explanatory variable. This approach, inspired by the GPR index, focuses on changes in search frequency to provide a more accurate measure of sentiment. All regressions include control variables from column (3) of Table 3, along with bond fixed effects and year-month fixed effects. The *t-statistics*, based on robust standard errors, are clustered at the bond level and are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
β^{GPR}*_SVI*	-0.357***	
	(-6.62)	
β^{GPR}*_SVI5*		-0.251***
		(-3.71)
Controls	Yes	Yes
Bond FE	Yes	Yes
Year-Month FE	Yes	Yes
Obs.	551,741	571,556
$Adj.R^2$	0.279	0.277

Table 12 - Robustness Check II: the use of the global geopolitical risk index

The table reports the coefficients from the fixed effects regressions of one-month-ahead corporate bond excess returns (in percent) on bond return sensitivity to the global geopolitical risk index (β^{GPR_global}) (normalized to average a value of 1 between 1985 and 2019) in column (1), global geopolitical risk threat index (β^{GPRT}) in column (2) and global geopolitical risk act index (β^{GPRA}) in column (3). All regressions include control variables from column (3) of Table 3, bond fixed effects, and year-month fixed effects. The *t-statistics* based on robust standard errors are clustered at the bond level and are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
β^{GPR_global}	-129.970***		
	(-7.69)		
β^{GPRT}		-170.341***	
		(-7.88)	
β^{GPRA}			-64.385***
			(-2.69)
Controls	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Obs.	578,751	578,751	578,751
$Adj.R^2$	0.276	0.276	0.276

Table 13 - Exposure to international-sales weighted GPR index

The table reports the coefficients from the fixed effects regressions of one-month-ahead corporate bond excess returns (in percentage terms) on bond return sensitivity to firms' international exposure to geopolitical risk, weighted by the firm's geographical segment sales provided by the Thomson Reuters Worldscope database. We employ the firm's all-segment sales in column (1) and the firm's non-US segment sales in column (2). β^{AllSeg_GPR} bonds return sensitivity to the sales-weighted GPR $\beta^{ForeignSeg\_GPR}$ is bond return sensitivity to the sales-weighted GPR index, and the weight is computed as the *firm's non-US geographical segment sales.* All regressions include control variables from column (3) of Table 3, bond fixed effects, and year-month fixed effects. The *t-statistics* based on robust standard errors are clustered at the bond level and are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
β^{AllSeg_GPR}	-3.292***	
	(-10.06)	
$\beta^{ForeignSeg\_GPR}$		-0.746***
		(-8.94)
Controls	Yes	Yes
Bond FE	Yes	Yes
Year-Month FE	Yes	Yes
Obs.	578,751	578,751
$Adj.R^2$	0.276	0.276

Table 14 – Firm-level geo-political risk and political risk measures

The table shows the coefficients from the fixed effect regressions of one-month-ahead corporate bond excess returns (in percent) on bond return sensitivity to the geopolitical risk index (β^{GPR}), after controlling for the firm-level geopolitical risk (GPR_{firm}) constructed using earnings call transcripts, and the firm-level political risk index (*PRI*) from Hassan et al. (2019). All regressions except for Column (3) incorporate all the controls from the baseline specification in Table 3. The *t-statistics*, based on robust standard errors clustered at the bond level, are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
β^{GPR}		-3.351***	-3.384***	-3.757***	-3.608***
		(-7.240)	(-8.681)	(-9.972)	(-7.655)
GPR_{firm}	-0.002	-0.002			-0.006
	(-0.554)	(-0.476)			(-1.477)
PRI			0.043**	0.04**	0.005**
			(2.297)	(2.228)	(2.097)
Controls	Yes	Yes	No	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Obs.	351,179	351,179	539,604	539,604	351,179
$Adj.R^2$	0.237	0.237	0.27	0.28	0.238

Table 15 – GPR beta and bond returns for industry classifications

The table reports the coefficients from the regressions of one-month-ahead corporate bond excess returns (in percent) on bond return sensitivity to the geopolitical risk index (β^{GPR}) for each of the 12 Fama-French industry classifications. All regressions include the controls from the baseline specification in Table 3. Fixed effects regressions include bond and year-month fixed effects. The *t-statistics* based on robust standard errors are clustered at the bond level and are shown adjacent to the coefficients. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	Fixed effect regressions			Fama-Macbeth regressions		Controls
	Coefficient (β^{GPR})	*t-statistics*	*Adj.*R^2	Coefficient (β^{GPR})	*t-statistics*	
Consumer Nondurables	-4.926***	-3.702	0.297	-4.011**	-2.074	Yes
Consumer Durables	-4.532**	-2.084	0.431	-4.265	-0.928	Yes
Manufacturing	-0.919	-0.833	0.264	1.442	0.583	Yes
Oil & Gas	-5.292***	-3.484	0.381	-4.140	-1.536	Yes
Chemicals and Allied Products	-0.143	-0.068	0.269	-1.208	-0.240	Yes
Technology	-7.297***	-3.941	0.291	-5.256	-1.538	Yes
Telecommunications	-2.793**	-2.461	0.335	-0.387	-0.166	Yes
Utilities	-2.798***	-3.569	0.342	-2.474**	-1.984	Yes
Services	-1.018	-0.738	0.272	-0.773	-0.383	Yes
Healthcare	-3.091***	-2.686	0.324	1.174	0.468	Yes
Real Estate	-3.453***	-4.651	0.299	-4.773***	-2.941	Yes
Others	-4.642***	-5.131	0.314	-3.635**	-2.246	Yes

Appendix A

Table A1. Variable definitions and sources

Variables	Definition	Data Source
Bond returns (%)	Next month's bond returns	TRACE
β^{GPR}	Estimated over a 36-month rolling window for each bond returns bond market factors (default spread, term spread), and Fama-French three stock market factors (i.e., excess stock market return *SMKT*, the size factor *SMB* and the book-to-market factor *HML*) specified by equation (1)	
β^{TERM}	The term spread beta is estimated from equation (2). The term spread is computed as the difference between the monthly return on the Ibbotson U.S. long-term government bond index and the 1-month T-bill return.	TRACE, Mergent FISD, Welch and Goyal (2014)
β^{DEF}	The default spread beta is estimated from equation (2). The default spread is computed as the difference between BAA-rated and AAA- rated corporate bond monthly yields.	TRACE, Mergent FISD, Welch and Goyal (2014)
β^{BMKT}	The bond market beta is estimated from the monthly rolling regressions of individual bond excess returns on the excess bond market return over a 36-month window. The excess bond market return is proxied through the value-weighted monthly returns of all the bonds in our sample over the monthly risk-free rate.	TRACE
Illiquidity (%)	Using transaction-based data from TRACE, illiquidity is computed at the end of each month *t* for each bond as the autocovariance of the daily price changes within each month consistent with Chung, Wang and Wu (2019).	TRACE
Size	The natural logarithm of a bond's amount outstanding.	Mergent FISD
Rating	A bond's credit rating as a numerical score, where 1 refers to an AAA rating and 22 refers to a D rating. Investment-grade bonds have ratings from 1 (AAA) to 10 (BBB). Non-investment-grade bonds have ratings above 10. A larger number indicates higher credit risk or lower credit quality.	Mergent FISD
Age	Bond age	Mergent FISD
Time to Maturity	bond's time to maturity.	Mergent FISD
Downside Risk	downside risk measured as 5% VAR of bond returns	TRACE
Leverage	The sum of long-term debt (DLTT), short-term debt (DLC), minority interests (MIBT), and preferred stock (PSTK), divided by total assets (AT).	Compustat
ROE	Income before extraordinary items (IB) divided by the book value of common equity (CEQ).	CRSP
Log_MV	The natural logarithm of the market value of a firm's common equity (PRC SHROUT) at the end of each month. The market value of equity is measured in thousands.	Compustat, CRSP
Foreign Sales	Total non-US revenue for each firm in a given year	Compustat Segment data
LPI_US_Index	Logistics performance index is from the World Bank website	World Bank data is available in this URL:
Distance to default	Distance to default metric	Risk Management Institute (RMI) and National University of Singapore.
Loan spread		Dealscan
IdioVol	Standard deviation of the residuals from the rolling-window regression of 36-month monthly bond returns using the Fama-French three-factor model	Kenneth French's website.
No CDS_protection	A dummy variable that indicates whether CDS contracts protect the firm's debt, which is set to one if the firm has no CDS traded on it.	Markit

Table A2.1: Estimations of beta-GPR using alternative models

This table re-estimates the baseline multivariate regressions of Table 3, where one-month-ahead corporate bond excess returns (in percentage terms) are regressed on β^{GPR} and other control variables. β^{GPR} is estimated with the following models:

(1) $R_{it}=\alpha_{it}+\beta^{GPR}\Delta GPR+\boldsymbol{\beta^{BMKT}BMKT}+\epsilon_{it}$

(2) $R_{it}=\alpha_{it}+\beta^{GPR}\Delta GPR+\beta^{DEF}DEF+\beta_{TERM}TERM+\beta_{BLIQ}BLIQ+\beta_{SMKT}SMKT+\beta_{SMB}SMB+\beta_{HML}HML+\boldsymbol{\beta^{BMKT}BMKT}+\epsilon_{it}$

(3) $R_{it}=\alpha_{it}+\beta^{GPR}\Delta GPR+\beta^{DEF}DEF+\beta_{TERM}TERM+\beta_{BLIQ}BLIQ+\beta_{SMKT}SMKT+\beta_{SMB}SMB+\beta_{HML}HML+\boldsymbol{\beta_{UNC}\Delta UNC}+\epsilon_{it}$

(4) $R_{it}=\alpha_{it}+\beta^{GPR}\Delta GPR+\beta^{DEF}DEF+\beta_{TERM}TERM+\beta_{BLIQ}BLIQ+\beta_{SMKT}SMKT+\beta_{SMB}SMB+\beta_{HML}HML+\boldsymbol{\beta_{DFR}Downside\ Risk}+\epsilon_{it}$

(5) $R_{it}=\alpha_{it}+\beta^{GPR}\Delta GPR+\beta^{DEF}DEF+\beta_{TERM}TERM+\beta_{BLIQ}BLIQ+\beta_{SMKT}SMKT+\beta_{SMB}SMB+\beta_{HML}HML+\boldsymbol{\beta_{VIX}\Delta VIX}+\epsilon_{it}$

	(1)	(2)	(3a)	(3b)	(4)	(5)
β^{GPR}	-1.460***	-1.304***	-1.741***	-1.730***	-1.299***	-1.971***
	(-3.08)	(-3.60)	(-5.39)	(-5.46)	(-4.18)	(-5.76)
β^{UNC}				-0.026**		
				(2.31)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	564,903	564,903	564,903	564903	469,062	564,903
$Adj.R^2$	0.276	0.276	0.276	0.269	0.269	0.276

Table A2.2 GPR portfolios using additional factors.

This table reports the average beta on GPR for each quintile portfolio sorted by the pre-ranking GPR beta estimated over a 36-month rolling window with the following models:

(6) $R_{it}=\alpha_{it}+\beta^{GPR}\Delta GPR+\beta^{DEF}DEF+\beta_{TERM}TERM+\beta_{BLIQ}BLIQ+\beta_{SMKT}SMKT+\beta_{SMB}SMB+\beta_{HML}HML+\beta_{SMOM}MOM+\beta_{SLIQ}SLIQ+\epsilon_{it}$

(7) $R_{it}=\alpha_{it}+\beta^{GPR}\Delta GPR+\beta^{DEF}DEF+\beta_{TERM}TERM+\beta_{BLIQ}BLIQ+\beta_{SMKT}SMKT+\beta_{SMB}SMB+\beta_{HML}HML+\beta_{UNC}\Delta UNC+\epsilon_{it}$

(8) $R_{it}=\alpha_{it}+\beta^{GPR}\Delta GPR+\beta^{DEF}DEF+\beta_{TERM}TERM+\beta_{BLIQ}BLIQ+\beta_{SMKT}SMKT+\beta_{SMB}SMB+\beta_{HML}HML+\beta_{DRF}DRF+\epsilon_{it}$

This table then reports the average excess return (over the risk-free rate) and 6-factor alpha for each portfolio. Returns and alphas are presented in percentage terms. Low (1) (High (5)) is the portfolio with the lowest (highest) GPR beta in the previous month. "High-Low" is the difference between "High-5" and "Low (1)", and the corresponding *t-statistics* based on Newey-West standard errors adjusted for autocorrelation of up to lag 4 are shown in the parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)			(2)			(3)		
Quintiles	β^{GPR}	Excess Return	9-factor alpha	β^{GPR}	Excess Return	8-factor alpha	β^{GPR}	Excess Return	8-factor alpha
Low-Q1	-0.021	0.619***	0.737***	-0.018	0.613***	0.729***	-0.020	0.628***	0.731***
		(4.29)	(6.92)		(4.30)	(7.32)		(4.41)	(7.03)
2	-0.006	0.505***	0.659***	-0.005	0.500***	0.632***	-0.006	0.503***	0.644***
		(4.79)	(7.10)		(4.77)	(6.90)		(5.01)	(7.85)
3	-0.001	0.436***	0.553***	-0.001	0.443***	0.572***	-0.001	0.451***	0.584***
		(4.75)	(6.81)		(4.80)	(6.64)		(5.02)	(7.18)
4	0.004	0.488***	0.597***	0.004	0.489***	0.625***	0.004	0.488***	0.626***
		(4.40)	(7.05)		(4.31)	(6.95)		(4.26)	(6.45)
High-Q5	0.018	0.510***	0.563***	0.017	0.509***	0.548***	0.020	0.507***	0.541***
		(3.31)	(5.35)		(3.26)	(5.13)		(3.15)	(4.79)
High-Low		-0.109**	-0.174***		-0.104**	-0.181***		-0.122***	-0.190***
(Q5–Q1)		(-2.31)	(-3.75)		(-2.33)	(-3.61)		(-2.64)	(-4.11)

Table A3 – Nonlinearity of the GPR premium

The table displays the interactions of β^{GPR} with the standardized GPR index (column 1) and *HIGH_GPR* (column 2). *HIGH_GPR* equals 1 for months when GPR index values exceed the past 36-month median and 0 otherwise. Each regression includes all controls from Table 3, bond-level fixed effects, and year fixed effects. The *t-statistics* calculated using robust standard errors clustered at the bond level are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
GPR index x β^{GPR}	-1.653***	
	-3.977	
HIGH_GPR x β^{GPR}		-1.3*
		-1.954
β^{GPR}	-3.385***	-0.021***
	-7.857	-4.494
GPR index	0.047***	
	14.480	
HIGH_GPR		0.292***
		42.512
Controls	Yes	Yes
Bond FE	Yes	Yes
Year FE	Yes	Yes
Obs.	578,751	578,751
Adj.R^2	0.052	0.054

Table A4 –*Geopolitical risk (GPR) Beta on credit default swap (CDS) spreads*

This table reports the multivariate regressions of credit default swap (CDS) spreads on β^{GPR} and other control variables. Columns (1) of the table report the coefficients Fama and MacBeth (1973) regressions. Column (2) reports the fixed effects panel regressions. All variables are within-transformed to remove bond-level characteristics. The *t*-statistics based on Newey-West standard errors adjusted for autocorrelation of up to lag 4 are shown in parentheses. The *t-statistics* based on robust standard errors are clustered at the firm level and are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	Fama-MacBeth	Fixed Effects
	(1)	(2)
β^{GPR}	-0.038**	-0.068**
	-2.594	-2.547
Controls	Yes	Yes
Firm FE	-	Yes
Year-Month FE	-	Yes
Obs.	111,106	111,106
Adj.R^2		0.54

Table A5 – GPR premium in equity markets

This table reports the average beta on stock (SGPR) for each quintile portfolio, sorted by the pre-ranking SGPR beta estimated over a 36-month rolling window using the following models:

$R_{it}=\alpha_{it}+\beta^{SGPR}{}_{it}\Delta SGPR_t+\beta^{MKT}{}_{it}MKT_t+\beta^{SMB}{}_{it}SMB_t+\beta^{HML}{}_{it}HML_t+\beta^{UMD}{}_{it}UMD_t+\beta^{LIQ}{}_{it}LIQ_t+\beta^{RI/A}{}_{it}RI/A_t+\beta^{R\,roe}{}_{it}Rroe_t+\epsilon_{it})$.

Where R_{it} is the excess stock monthly returns over the risk-free rate, β^{SGPR} is the stock-level beta on geopolitical risk controlling for the Fama-French three stock market factors (i.e., excess stock market return MKT, the size factor SMB, and the book-to-market factor HML), and the momentum factor (UMD), Pastor-Stambaugh liquidity factor (LIQ), and the investment and profitability factors from Hou, Xue, and Zhang (2016) ($R_{I/A}$, R_{ROE}). Low-1 (High-5) is the portfolio with the lowest (highest) SGPR beta in the previous month. The portfolio is value-weighted, using the market value as weights.

Panel A reports the value-weighted quintile portfolio alphas for each of the SGPR beta (β^{SGPR}) quintiles. The monthly 3-factor alpha controls MKT, SMB, HML, whereas the 5-factor alpha augments the 3-factors with $R_{I/A}$ and R_{ROE}. All the alphas are presented in monthly percentage terms. Low (1) and High (5) portfolios include the stocks with the lowest (highest) SGPR beta in the previous month. "High-Low" is the difference between "High-5" and "Low (1)", and the corresponding *t-statistics* based on Newey-West standard errors adjusted for autocorrelation of up to lag 2 are shown in the parentheses.

Panel B reports the multivariate regressions of one-month-ahead stock excess returns (in percentage terms) on β^{SGPR} and other control variables from Table 3. Columns (1) and (2) of Panel B report the coefficients from the fixed effects panel regressions, and Fama and MacBeth (1973) regression coefficients respectively. All variables are within-transformed to remove stock-level characteristics. The *t*-statistics based on Newey-West standard errors adjusted for autocorrelation of up to lag 4 are shown in the parentheses. The *t-statistics* based on robust standard errors are clustered at the firm level and are shown in parentheses. ∗∗∗, ∗∗ and ∗ denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Univariate Statistics of Portfolio Analysis – sorted by stock GPR (SGPR) beta

Quintiles	β^{SGPR}	3-factor alpha	5-factor alpha
Low-Q1	-0.14	0.187***	0.196***
		(5.19)	(5.61)
2	-0.05	0.153***	0.153***
		(7.52)	(7.57)
3	0.002	0.130***	0.129***
		(7.37)	(7.40)
4	0.054	0.142***	0.140***
		(6.38)	(6.22)
High-Q5	0.16	0.263***	0.270***
		(5.83)	(6.12)
High-Low		0.076	0.074
(Q5–Q1)		(1.49)	(1.45)

Panel B: Regressions of GPR betas on *t*+1 stock returns.

	(1)	(2)
$\boldsymbol{\beta^{SGPR}}$	-0.674	-0.158
	(-1.53)	(-0.15)
β^{BMKT}	0.971***	0.497**
	(8.09)	(2.11)
β^{TERM}	-0.976***	-1.038**
	(-4.93)	(-2.54)
β^{DEF}	0.064	0.203
	(0.65)	(1.01)
Illiquidity (%)	4.332***	0.905
	(3.26)	(0.65)
Size	-0.260*	-0.272
	(-1.95)	(-1.43)
Rating	0.987***	0.836***
	(16.12)	(11.17)
AGE	0.142	0.155*
	(1.32)	(1.86)
Maturity	0.173**	0.286***
	(1.99)	(3.28)
Downside Risk	17.830***	20.953***
	(8.68)	(4.86)
Leverage	3.033***	2.373***
	(4.96)	(2.61)
ROE	0.074	0.185
	(1.08)	(1.36)
Log_MV	4.524***	3.959***
	(34.98)	(10.60)
Constant	0.000***	0.048
	(21.21)	(0.15)
Firm FE	Yes	-
Year-Month FE	Yes	-
Obs.	236,381	236,381
Ave./Adj. R-squared	0.28	