

The Impact of Geopolitical Risk on Firm Behavior and Stock Returns

VIGGO V. OLOFSSON

ALEXANDER GEORGI

Bachelor Thesis

Stockholm School of Economics

2025



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Abstract:

We adopt established textual analysis methods to create the first validated firm level measure of geopolitical risk. We analyze the distribution of geopolitical risk across firms and the impacts of geopolitical risk exposure on firm actions and stock prices. We find evidence that, although firms are concerned about aggregate geopolitical risk, they may be more concerned about firm-specific geopolitical risk exposure. Further, we find evidence for the conclusion that geopolitical risk is negatively associated with capital expenditures and sales growth, and positively associated with stock price volatility. Finally, we find that portfolios consisting of firms with high geopolitical risks outperform portfolios of other firms in terms of abnormal returns.

Keywords:

Asset pricing, Finance, Geopolitics, Textual analysis

Authors:

Viggo V. Olofsson (25804)

Alexander Georgi (25711)

Tutors:

Mustafa Bulut, Postdoctoral Fellow, Swedish House of Finance

Examiner:

Ramin P Baghai, Associate Professor, Department of Finance, SSE

Acknowledgement:

We extend our heartfelt gratitude to Mustafa Bulut for his unwavering dedication, invaluable guidance, and inspiring presence throughout the entirety of our research journey.

Bachelor Thesis

Bachelor Program in Business & Economics

Stockholm School of Economics

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I. Introduction

Geopolitical risks have grown increasingly complex and interconnected, with recent events underscoring their far-reaching implications on global security and trade policies. Events like Russia's invasion of Ukraine demonstrate how geopolitical shocks in one region can ripple across the global economy, impacting firms worldwide. Despite widespread speculation on how geopolitical shocks propagate through the world economy, the size of their impact on firm behavior and stock returns remains largely unknown. Measuring these effects has been difficult due to a paucity of data on firm-level exposure to geopolitical risks.

In this paper, we construct a firm-level measure of geopolitical risk. We define geopolitical risk broadly, encompassing not only risks of violence and territorial competition, but also indirect threats such as economic sanctions. The methodology we use closely resembles the method developed by Hassan, Hollander, Van Lent, and Tahoun (2019). We use our measure to study the distribution of geopolitical risk across firms and its effect on firm actions and stock returns.

In pursuit of these goals, we first construct our firm-level measure by analyzing quarterly earnings call transcripts from S&P 500 constituents. We score a firm's exposure to geopolitical risk at a given point in time based on the share of its earnings call dedicated to discussions of geopolitical risks. We use a similar methodology to construct a measure of geopolitical sentiment. News about geopolitical shock exposure is likely not independent of news about these shocks' conditional mean. While our measure of geopolitical risk captures news of firm-level *variance* of geopolitical shocks, constructing a proxy for geopolitical sentiment allows us to measure news about their *mean* and, in principle, separate information about first and second moment impacts (Hassan et al., 2019, 2023, 2024).

We strengthen the interpretation of our measure as a proxy of geopolitical risk by showing that passages from the highest rated transcripts correctly identify discussions on geopolitical risk. Further, from manual reading of 200 transcripts, we show that our measure indeed captures discussions on geopolitical risk across its distribution. Moreover, our measure captures major known changes in geopolitical risk, spiking in association with geopolitical events like Brexit, the major tariffs in the US-China trade war, and Russia's invasion of Ukraine.

When looking at the properties of our measure, we find that just 2.52% of the variation in our measure is explained by time fixed effects, and that only 1.41% of the variation is accounted for by permanent differences between sectors. Strikingly, just 8.73% is accounted for at the sector level and the economy as a whole. 91.27% of the variation in our measure plays out at the "firm level," with 15.77% being accounted for by permanent differences across firms. In our sample of large U.S. firms, we find that 75.50% of the variation in geopolitical risk plays out across same-sectored firms over time. This large variation suggests that, within a given industry, although firms are concerned about broad-reaching geopolitical events, they are also concerned about geopolitical risk specific to them at a given time. At the firm level, we argue that firms exhibit heterogeneous exposure to aggregate geopolitical risk,

while also facing distinct firm-specific geopolitical challenges (e.g., risk of expropriation, rather than risk of conflict escalation in the Middle East).

Moving on, we study whether firm level geopolitical risks have an impact on firm actions and stock prices. Traditional models of uncertainty predict that increased risk exposure decreases firm investments and employment growth, while simultaneously driving greater stock price volatility (e.g., Pindyck, 1988; Bloom, Bond, and Van Reenen, 2007). We show evidence that firms with greater geopolitical risk reduce capital expenditures. Further, we show that there is a negative association between geopolitical risk and sales growth, and a positive association between geopolitical risk and stock price volatility. The strongest result is the association with capital expenditures, which remains at least marginally significant even when adequately adding controls to assess robustness. The association with sales and stock price volatility becomes insignificant when controlling for systematic time and firm level differences.

We do not find a statistically significant association between our measure of firm-level geopolitical risk and employment growth. This could suggest that firm-level exposure to geopolitical risks has no impact on employment growth. However, it may also reflect insufficient statistical power to detect what are likely small effect sizes.

Finally, we study whether geopolitical risk is priced in stock returns. We perform quarterly portfolio sorts with our measure of geopolitical risk as the sorting variable. We find evidence that portfolios with higher geopolitical risk outperform other firms in terms of generating higher abnormal returns, although our findings are only significant at the 10% level.

We would like to highlight two important considerations to address in our results. First, our measures of geopolitical risk show signs of containing substantial measurement error. Second, measuring the share of discussions on geopolitical risk is only an approximation of actual exposure to geopolitical risk. Our measure is more accurately described as measuring geopolitical risk as experienced by firm managers. For these reasons, one should be careful when handling our measures and interpreting our findings.

1.1 Literature

Our research builds upon recent developments in the textual analysis literature. Traditionally, many researchers have relied on pre-defined dictionaries to analyze documents and quantify the prevalence of specific themes, such as economic policy uncertainty, within the text (Baker, Bloom, and Davis, 2016). However, we instead rely on the methodology outlined by Hassan et al. (2019) which avoids exogenously defining dictionaries. Hassan et al. (2019) use their methodology to construct a measure of firm-level political risk. They extensively validate their measure and find it captures meaningful economic information at the firm level.

The general methodology developed by Hassan et al. (2019) has been applied to measure a wide range of risks at the firm-level. For example, Ersahin, Gianetti, and Huang (2024) study firm-level supply chain risks. Sautner, Van Lent, Vilkov, and Zhang (2023) use a slightly

altered methodology to analyze firm-level climate change exposure. They find significant heterogeneity in how different firms are exposed to climate change, even within sectors. In our research, we apply the same methodology as Hassan et al. (2019) to study firm-level geopolitical risk, particularly its impact on firm behavior and stock returns. We also propose some improvements in the construction of the training libraries of the Hassan et al. (2019) method. Notably, we filter out specific unwanted topics.

To date, there is already a significant amount of research on political and geopolitical risks. For example, Kelly, Pastor, and Veronesi (2016) look at the relationship between government policy and stock price volatility. They find that, on average, stock prices fall at the announcement of a policy change. Further, Caldara and Iacoviello (2020) study trade policy uncertainty. They show that increases in trade policy uncertainty is associated with reduced investments.

Moreover, several studies have specifically examined geopolitical risks. Caldara and Iacoviello (2022) create an aggregate measure of geopolitical risk by analyzing newspaper articles. They find that higher geopolitical risk leads to periods of lower investment and employment. Additionally, they build a firm-level measure of geopolitical risk following Hassan et al. (2019) and briefly study the impacts of geopolitical risk on investments at the firm level. However, their paper does not include validation of the firm-level measure of geopolitical risk. In our research, we validate that the methodology outlined in Hassan et al. (2019) is applicable for measuring geopolitical risk at the firm-level, providing the first validated measure of firm-level geopolitical risk in the literature.

We use our measure to further extend the research by studying how geopolitical risk is distributed across firms and subsequently what impact geopolitical risk has on a wider set of firm actions. In doing so, we also test the predictions of the real options literature, i.e., that heightened exposure to any form of risk should have a greater impact on hard-to-reverse investments than short term output growth (Pindyck, 1988). Finally, we examine the relationship between firm-level geopolitical risk and stock price volatility, as well as its asset pricing implications.

II. Data

We gather quarterly earnings calls for S&P 500 companies from Refinitiv Eikon “Advanced Events.” Firms generally host one earnings call in each quarter, generating 4 observations per firm per year. 19077 transcripts are initially collected, spanning the 10-year period from 2014 through 2023.

Moving on, we include companies that were part of the S&P 500 index at any point during our period of study, even if they later dropped out. This is to prevent survivorship bias in our sample. We collect all available transcripts for these firms for the entire period of study. Finally, we exclude 135 transcripts with incorrectly formatted file names, as we cannot

accurately match these with the correct company and date. After these steps, our final sample consists of 23 486 transcripts.¹

The earnings calls predominantly share the same general structure; They start with a management presentation followed up with a Q&A session where analysts and other market participants are invited to ask questions. We construct our measure of firm-level geopolitical risk using the entire conference call.

We use Center for Stock Price Returns (CRSP) to obtain both monthly and daily stock price data. We obtain U.S. equity factor returns (market excess return, SMB, HML and UMD) from the Fama-French Data Library. Finally, we use Compustat data for balance sheet and income statement items. Table 1 provides summary statistics for the variables used, and Appendix Table 1 provides further detail of the variables used.

III. Constructing a Measure of Geopolitical Risk at the Firm Level

In this section, we first define geopolitical risk. Next, we develop a measure for geopolitical risk, and finally, we validate the measure to ensure it accurately reflects what it is intended to capture.

Definitions of geopolitics range from very narrow to broadly inclusive (Caldara and Iacoviello, 2022). For example, when the media refer to geopolitics, they are often referring to international violence and crises (Rogers, Castree, and Kitchin, 2013). Formally, geopolitics is concerned with how geographical factors including territory, population, and natural resource endowments, as modified by economies and technology, affect relations between states (Foster, 2006). We adopt this formal definition of geopolitics in our paper.

Acts of violence and territorial competition, e.g., the Russo-Ukrainian War, are captured in this definition of geopolitics. We also consider power struggles that occur without necessarily involving violence, e.g., tensions between North Korea and the United States (U.S.), in our definition. Furthermore, in line with recent global developments, we also include trade wars, tariffs, and economic sanctions in our definition, as restrictions are increasingly being used as tools of political leverage. We define geopolitical risk as the uncertainty stemming from any aspect of our comprehensive definition of geopolitics.

3.1 Measure Construction

To construct our proxy of geopolitical risk, we first define a measure of the share of quarterly earnings call discussions centered around geopolitical risks. We argue that the geopolitical

¹ On rare occasions, firms have 2 available earnings call transcripts in one quarter. If the two observations are at most 1 day from each other, we merge these observations into one.

risks covered during earnings calls are likely to reflect actual concerns of firm managers and analysts on average. We assume their concern reflects actual exposure to geopolitical risk.²

We distinguish geopolitical and non-geopolitical topics by comparing language patterns used in earnings calls to that of geopolitical text, e.g., a textbook on geopolitics. To identify association with risk, we check that these language patterns of geopolitical risk topics are used together with synonyms of *risk* and *uncertainty*. This pattern-based sequence classification closely resembles the method used by Hassan et al. (2019).

To construct our measure of geopolitical risk we first compile a training library of text archetypical of geopolitical topics ($\mathbb{G}$) and another library with text that is archetypical of neutral, non-geopolitical topics ($\mathbb{N}$). The libraries are decomposed into the set of its composite bigrams, i.e., all adjacent two-word combinations the text contains. We define *geopolitical bigrams* as $\mathbb{G} \setminus \mathbb{N}$, i.e., the set of bigrams that are unique to the training library of archetypical geopolitical text. Congruently, we also decompose each earnings call transcript for firm i at time t into the list of bigrams it contains $b = 1, 2, \dots, B_{i,t}$.

We then define our measure of geopolitical risk for firm i at time t by counting the number of geopolitical bigrams contained within the 10-word window surrounding a synonym of *risk* or *uncertainty* in the transcript of firm i 's earnings call held at time t . To normalize for the length of the transcript, we multiply by a factor of $\frac{1}{B_{i,t}}$. The formal definition is as follows (Hassan et al., 2019):

$$GPRisk_{i,t} = \frac{1}{B_{i,t}} \sum_b^{B_{i,t}} \left(I[b \in \mathbb{G} \setminus \mathbb{N}] \times I[|b - r| < 10] \times \frac{f_{b,\mathbb{G}}}{B_{\mathbb{G}}} \right) \quad (1)$$

where $I[*]$ is the indicator function,³ r is the position of the nearest synonyms of risk or uncertainty, $f_{b,\mathbb{G}}$ is the frequency of bigram b in the library of geopolitical texts $\mathbb{G}$, and $B_{\mathbb{G}}$ is the total number of bigrams in $\mathbb{G}$. In (1), we weight each bigram according to its *term frequency* $\frac{f_{b,\mathbb{G}}}{B_{\mathbb{G}}}$, i.e., its relative frequency in the geopolitical training library. Clearly, geopolitical bigrams will be assigned a greater weight if they occur more often in $\mathbb{G}$. Weighting by $\frac{f_{b,\mathbb{G}}}{B_{\mathbb{G}}}$ enables us to score the extent to which passages are related to geopolitical risks. Despite weighting bigrams, we interpret $GPRisk_{i,t}$ simply as the share of earnings calls dedicated to risks associated with geopolitical topics.⁴

Variance shocks may be correlated to shocks to their conditional mean. For example, a U.S. aluminum exporter may be concerned about potential tariffs on its Chinese exports and expect less cash flow in the future (i.e., lowering of the conditional mean), while

² Obviously, this will likely not hold perfectly in practice. However, we believe it to be a good approximation.

³ $I[*] = 1$ if the condition inside is fulfilled, otherwise, $I[*] = 0$.

⁴ See, e.g., Hassan et al. (2019) for a similar interpretation.

simultaneously expecting higher variance due to uncertainty surrounding the imposition of the trade restrictions. To differentiate between first- and second-moment impacts, we define $GPSentiment_{i,t}$. Following Hassan et al. (2019), we use the same procedure as when constructing (1), but instead of conditioning on nearness of geopolitical bigrams, we condition the measure on proximity to words with positive or negative sentiment:

$$GPSentiment_{i,t} = \frac{1}{B_{i,t}} \sum_b^{B_{i,t}} \left(I[b \in \mathbb{G} \setminus \mathbb{N}] \times \frac{f_{b,\mathbb{G}}}{B_{\mathbb{G}}} \times \sum_{c=b-1}^{b+10} S(c) \right),$$

where $S(c) = 1$ if bigram c is associated with positive sentiment and $S(c) = -1$ if bigram c is associated with negative sentiment; $S(c) = 0$ otherwise.

Following Hassan et al. (2019), we also create a firm-level measure of overall sentiment to use as a control:

$$Sentiment_{i,t} = \frac{1}{B_{i,t}} \sum_b^{B_{i,t}} S(b).$$

With this method, we can construct a firm level measure of geopolitical risk, and by validating it, it is the first validated firm-level measure of geopolitical risk in the literature.

3.2 Training Libraries

In our specification, we define our library of topics archetypical of geopolitical topics with four texts on different geopolitical topics. This is different from previous approaches in the literature which have used one textbook in the library archetypical of the type of the risk of interest. We believe that constructing the geopolitical library with several books improves the measure in two main ways. First, it reduces the risk that common bigrams in the geopolitical library are prevalent due to the author's writing style rather than the actual subject matter. Second, it allows us to cover the topics associated with our definition of geopolitics; we found that different textbooks on geopolitics generated bigrams with vastly different weights, i.e., term frequency $\frac{f_{b,\mathbb{G}}}{B_{\mathbb{G}}}$. For example, some textbooks might not mention sanctions at all, while others focus on them as a central topic. To capture all aspects of our definition of geopolitics, we inevitably included more than one book in our geopolitical library.

For our library of discussion archetypical of non-geopolitical topics, we include an undergraduate textbook on financial accounting to compensate for the fact that earnings calls tend to focus on financial information. In this library we also include the bigrams from the Santa Barbara Corpus of Spoken American English (2000) to filter out bigrams that are specifically related to spoken language, such as “next question.” Furthermore, we include an

undergraduate textbook on differential equations and technical portions from the COVID-19 Wikipedia page to filter out bigrams specifically associated with mathematics and the COVID-19 pandemic respectively. Using the neutral library to filter our specific topics is an innovation in the field of using textual analysis to measure risk.

To improve accuracy, we exclude from the final specification bigrams among the top 1000 contributors to $GPRisk_{i,t}$ in the penultimate specification that are not explicitly linked to geopolitical risk. The bigrams removed were of the character: “focused on,” “coupled with,” and “information on.”

The sentiment of words was categorized using Loughran and McDonald’s (2011) sentiment dictionary. Common positive sentiment classified words include, e.g., “good,” “strong,” and “great,” while negative-sentiment words include, e.g., “loss,” “slowdown,” and “difficult.”

Finally, we create the set of synonyms of *risk* and *uncertainty* from the Oxford dictionary (see Appendix Table 1). We exclude “question,” “questions,” and “venture” in accordance with the previous literature because they are likely to often have a meaning separate from referencing risk in the context of earnings calls.

3.3 Validation and Properties

In this section, we explore whether our measure of firm-level geopolitical risk captures actual discussions of risks associated with geopolitics. In Table 2, we show the geopolitical bigrams most strongly associated with geopolitical discussions – i.e., the elements of $\mathbb{G} \setminus \mathbb{N}$ with the highest assigned weight in the construction of $GPRisk_{i,t}$. The highest weighted bigrams have a strong geopolitical connotation. The top bigrams are almost exclusively geopolitical in nature; “trade policy,” “of sanctions,” and “war in.” However, the top bigrams also contain a few bigrams that are less exclusively connected to geopolitics, e.g., “the Russian,” “Europe and,” and “influence in.” Bigrams of this character may cause our measure to misidentify conversations as centering around geopolitical risk when they contain discussions on international non-geopolitical risks (e.g., unfavorable local fashion trends). However, from manual reading of transcripts, we found the frequency of such misidentifications to be very low. The distribution of all bigrams in $\mathbb{G} \setminus \mathbb{N}$ by their term-frequency is plotted in Figure 1. The term-frequency exhibits a strong right skew, which is in-line with previous literature (Hassan et al., 2019).⁵

Table 3 shows the highest rated passages from the 10 transcripts with the highest $GPRisk_{i,t}$. It is reassuring that the passages which contribute most to the highest rated transcripts clearly address geopolitical risk. The only exception is the transcript from Monster Beverage Corp, where call participants discuss risks associated with the global supply chain environment at the time. Although geopolitical factors do influence the global supply chain

⁵ The median term-frequency is $0.955 \cdot 10^{-5}$, in line with the order of magnitude of term frequency in the previous literature (Hassan et al., 2019).

environment, the supply chain environment is distinct from geopolitics and can be affected by non-geopolitical factors. Accordingly, we classify the discussion as a false positive.

Although our approach is intended to identify the share of the transcript which centers around discussions of geopolitical risk, the fact that the passages which contribute the most to $GPRisk_{i,t}$ contain discussions on geopolitical risk further validates our measure as capturing the share of discussions centering around geopolitical risk. As additional validation, we plot the share of true positives at a given average level of $GPRisk_{i,t}$ in Figure 2. The figure shows a positive, possibly linear, relationship between the share of true positives and $GPRisk_{i,t}$. This result indicates that the assigned value of $GPRisk_{i,t}$ contains information of discussions on geopolitical risk across its distribution, not just for the highest rated observations.

Of the top-rated transcripts, most receive their greatest contribution from discussions on trade policy and tariffs. Moreover, many of the bigrams with the highest weight seem to be associated with international trade-related topics. These facts suggest that our measure is more sensitive to trade-related risks, compared to other geopolitical risks. Importantly, from manual reading of transcripts, we note that our measure captures additional integral components of geopolitical risk well, such as the shock in geopolitical uncertainty associated with Russia’s invasion of Ukraine (without the mention of any trade-related concerns). Further, many of the highest weighted bigrams capture other aspects of geopolitics, e.g., “of geopolitical,” “war in,” and “invasion of.” Although the measure is quite sensitive toward international trade related discussions, the measure captures the other facets of our definition of geopolitical risk, with its biggest spike occurring when Russia invades Ukraine.

We now explore the properties of the measures generated. Figure 3 plots a times series of the mean $GPRisk_{i,t}$ ⁶ across all firms in each quarter. Quarterly aggregate $GPRisk_{i,t}$ varies intuitively with geopolitical events. For example, it spikes in 2016 Q2 in association with the Brexit referendum and the following announcement of the results. Furthermore, aggregate $GPRisk_{i,t}$ spikes in the same quarter as the announcement of the first major tariffs imposed by the U.S. on China in 2018 Q2 and drops in 2019 Q4 when the U.S. and China agree to the Phase One trade deal to prevent further escalation of the trade conflict. Aggregate $GPRisk_{i,t}$

⁶ We lead $GPRisk_{i,t}$ when constructing Figure 3, such that the risk in quarter t is constructed from the transcripts of quarter $t+1$. The earnings calls in our sample are concentrated towards the beginning of the quarter as shown in Appendix Figure 1, with half of earnings calls occurring within the first 31 days of the quarter on average. Assuming relevant geopolitical risks are uniformly distributed and limited to each quarter, the average firm is discussing almost two-thirds of total geopolitical risks which became apparent in quarter $t-1$ in quarter t . Leading the risk measure as we do above has not been discussed in the textual-analysis literature. For example, Hassan et al. (2019) investigate association of Brexit and political risk by searching for “brexit” in 2016 Q3 without discussing why they do not search for “brexit” in the previous quarter – i.e., the quarter in which the referendum was held. Leading quarterly measures of geopolitical risk does not solve the timing issues, but it may ameliorate them, and should be considered when constructing quarterly measures from earnings calls.

spikes in the beginning of 2020 in relation to the global COVID-19 pandemic spreading. Our measure also responds as expected to Russia's invasion of Ukraine in Q1 2022.

Figure 4 compares $GPRisk_{i,t}$ with Caldara and Iacoviello's (2022) GPR index. Whereas our measure is constructed using discussions from decision makers and analysts on large U.S. companies, the GPR index is constructed by analyzing newspapers published in the U.S., United Kingdom, and Canada. $GPRisk_{i,t}$ measures risk at the firm-level, while the GPR index measures geopolitical risk at the aggregate level. The two series have a low but positive Pearson correlation coefficient of 0.234.⁷ Reassuringly, the two series behave similarly around the time when Russia invades Ukraine in 2022 Q1. However, the GPR index focuses on wars and terrorism, while we have a much broader definition of geopolitics, including other geopolitical uncertainties such as trade regulations. For example, their measure is visually silent on Brexit, while the mean of $GPRisk_{i,t}$ spikes in the quarter of the referendum. The low correlation between the two series suggests that risks other than those associated with war and terrorism (e.g., trade policy) account for a large share of the variation in the aggregate concerns of firms and analysts about geopolitical events. The divergence might also reflect the distinct perspectives of media outlets versus corporate decision-makers, suggesting that the GPR index cannot be interpreted as a comparable benchmark of geopolitical risk. The fact that Caldara and Iacoviello's (2022) firm level measure of geopolitical risk using Hassan et al.'s (2019) method and their newspaper-based method have a similarly low correlation coefficient of 0.19 supports the latter interpretation.

In total, our results reassure us that we measure geopolitical risk. Importantly, the transcripts with the highest $GPRisk_{i,t}$ contain discussions centering around geopolitical risk, $GPRisk_{i,t}$ appears to be informative across its distribution, and the time series of aggregate $GPRisk_{i,t}$ spikes as expected in response to known geopolitical shocks.

Next, we investigate the decomposition of the variance of $GPRisk_{i,t}$. We look at the share of variation explained by select sets of fixed effects (Table 4). Time fixed effects account for just 2.52% of the variation. Permanent differences across sectors explain just 1.41% of the variation. Moreover, 8.73% of the variation in $GPRisk_{i,t}$ is accounted for by time fixed effects, sector fixed effects, and the interaction of time and sector fixed effects together. An interpretation of these results is that only a small portion of the variation in geopolitical risk is explained at the sector level or at the level of the broader economy.⁸ That is, the overwhelming majority (91.27%) of the variation in $GPRisk_{i,t}$ is not explained by economy-wide shocks or shocks to individual industries.

We decompose the remaining firm level variation and note that 15.77% of the total $GPRisk_{i,t}$ variation is accounted for by time-invariant differences between firms, while the substantial residual (75.50% of total variation in $GPRisk_{i,t}$) is explained by fluctuations in $GPRisk_{i,t}$ over time across same-sectored firms.

⁷ The Pearson correlation weakens between the two series to 0.067 when we do not lead $GPRisk_{i,t}$ as explained in Footnote 6.

⁸ See Hassan et al. (2019) for a similar interpretation of this set of fixed effects.

The large share of firm level variance not explained by fixed effects suggests that geopolitical events have disparate effects across firms even within the same sector. Our results are quite striking, as one might expect geopolitical risks to affect firms in a relatively consistent manner, particularly when the firms are members of the same industry. One might, for instance, reason that firms in the same sector, e.g., oil and gas companies, would be similarly impacted by rising tensions in the Middle East. However, our data does not support this view.

One potential explanation for the large residual is that same-sectored firms have vastly different exposures to aggregate geopolitical risk. For example, terrorist threats may concern commercial airline firms to varying degrees, depending on the regions they service.⁹ However, we argue that it is unlikely that the heterogeneity is sufficiently large (as large U.S. airlines generally service similar regions) to explain the large residual. Firms being concerned about risks specific to them at a given point in time (e.g., risk of expropriation) would also explain the large residual. Taken together, our results suggest that, although firms are worried about major geopolitical risks to which their industry or the wider economy is exposed (e.g., rising tensions in the Middle East, escalation of Russo-Ukraine War), they are not uniformly impacted by these risks and may be just as worried about risks specific to their firm.

Hassan et al. (2019) similarly find that 91.69% variation in *political* risk played out at the firm level.¹⁰ Time fixed effects explain more than three times the variation in $GPRisk_{i,t}$ (2.52%) than Hassan et al.'s (2019) political risk (0.81%). Comparison of our results could suggest that geopolitical risk is more systemic than political risk. However, we want to caution against such interpretations because, although we both study U.S. firms, the firms in our sample are on average larger and studied in a different time period. Hassan et al. (2019) study U.S. listed firms between 2002 and 2016, while we are limited to firms in the S&P 500 index from 2014 to the end of 2023. For example, it is plausible that larger firms are more exposed to aggregate shocks. As firm size is not controlled for, this possibility would confound our results. Furthermore, it is also plausible that firms in more recent periods are exposed to a greater proportion of common geopolitical risk in accordance with rising global geopolitical tensions.

⁹ The granularity of our sector definitions likely does not allow for classifications of narrow industries like the commercial airline industry. The examples are to convince the reader of plausibility of heterogeneous exposure to aggregate geopolitical risk in principle and that this heterogeneity is likely not the only explanation of the unaccounted firm level variation.

¹⁰ Hassan et al. defined sectors at the 2-digit SIC level, while we define sectors using the Fama & French 12 industry classification. When we define sectors with the same level of granularity, we still find that the great majority (78.23%) of the variation is explained at the firm level. We prefer the Fama & French 12 industry classification as we find their classification more informative. We do not think that we populate the sectors at the 2-digit SIC level sufficiently; we have ten times fewer firms than Hassan et al. (2019). Furthermore, although less variation is explained by the residual with the more granular sector definition, the decrease is not enough to challenge the arguments presented in the main text. As sector granularity increases, the residual will approach zero, as each sector becomes more narrowly defined, eventually containing only a single firm.

IV. Main Results

Having established that our measure of firm-level geopolitical risk captures discussions on geopolitical topics in company earnings calls, we next explore the effects of exposure to geopolitical risk on firm behavior, stock price volatility, and stock returns. We standardize $GPRisk_{i,t}$ by its standard deviation to aid interpretation. $GPRisk_{i,t}$, a proxy for the variance of geopolitical shocks, is likely correlated with news about the mean of geopolitical shocks, proxied by $GPSentiment_{i,t}$. Hence, by including $GPSentiment_{i,t}$ in our regressions, we reduce omitted variable bias and are more confidently able to interpret the effect of $GPRisk_{i,t}$. The correlation between $GPRisk_{i,t}$ and $GPSentiment_{i,t}$ is negative (-0.13), suggesting that increased geopolitical risk is indeed correlated with bad geopolitical news. Where applicable, we also control for overall $Sentiment_{i,t}$. We group industries based on the Fama-French 12 industry classification.

4.1 Stock Price Volatility

We now move on to study whether there is an association between geopolitical risk and stock price volatility. We expect heightened exposure to any risk, including geopolitical risk, to be associated with increased stock price volatility, as greater uncertainty about future cash flows leads to more variable asset prices. We test if this relationship holds true for $GPRisk_{i,t}$ and report our results in Table 5.

We control for the logarithm of firm total assets and cluster standard errors at the firm level in all specifications. Realized volatility is the volatility of daily stock returns in the window between day $t+1$ up until and including day $t+90$, where t is the day of the earnings call.

The first column reports the results of a simple OLS regression of realized volatility on our measure of geopolitical risk. The coefficient is positive and statistically significant; one standard deviation increase in $GPRisk_{i,t}$ is associated with 0.0315 (s.e. = 0.0069) increase in the standard deviation of stock price returns for the next 90 days. In the second column, we check if the result is robust to adding $GPSentiment_{i,t}$ and $Sentiment_{i,t}$ as controls. The coefficient (0.0232, s.e. = 0.0068) is noticeably smaller than in Column 1, implying that our initial specification suffered from omitted variable bias, suggesting that we were able to tease out the effect of changes in the variance of geopolitical shocks from the effects of variation in their conditional mean. Nevertheless, the coefficient is still significant at the 1% level and continues to support the hypothesis that higher $GPRisk_{i,t}$ is associated with increased stock price volatility. In Columns 3-5, we add various combinations of fixed effects to the specifications to test the robustness of our results. The relationship is robust to time fixed effects at the 5% significance level, with reduced coefficient (0.0206, s.e. = 0.0088). The coefficient is rendered insignificant when both controlling for time and industry fixed effects (Column 4) and time and firm fixed effects (Column 5).

To summarize, we initially find a positive association between $GPRisk_{i,t}$ and stock price volatility. However, the association is not robust to adding appropriate controls, e.g., controlling for time and firm fixed effects. The reduction in both the magnitude and

significance of the $GPRisk_{i,t}$ coefficient when adding time fixed effects implies that the relationship we observe in Columns 1 and 2 is partly driven by market-wide variation over time rather than firm-specific differences. Specifically, while Columns 1 and 2 show that higher $GPRisk_{i,t}$ is associated with higher stock price volatility, the results in Column 3 reveal that this relationship is partly explained by periods of high $GPRisk_{i,t}$ coinciding with periods of increased market-wide volatility, rather than firms with higher individual $GPRisk_{i,t}$ exposure consistently experiencing higher volatility relative to their peers.

Moreover, the decline in significance and magnitude of the $GPRisk_{i,t}$ coefficient when adding industry fixed effects suggests that the cross-sectional relationship between geopolitical risk and volatility is primarily driven by industry-level differences. Industries that tend to have higher stock price volatility also tend to have higher exposure to geopolitical risk, but within any given industry, there isn't a strong relationship between $GPRisk_{i,t}$ and stock price volatility. In other words, industries with greater geopolitical risk have permanent unobserved characteristics that are associated with higher stock price volatility. When these characteristics are controlled for, the relationship between $GPRisk_{i,t}$ and volatility disappears. Replacing industry fixed effects with firm fixed effects produces very similar results – insignificant coefficient of 0.0070 (s.e. = 0.0059).

Taken together, our results do not support the hypothesis that increased geopolitical risk exposure is associated with increased stock price volatility. Specifically, we cannot conclude that there is a within-firm effect over time of heightened $GPRisk_{i,t}$ on realized volatility, i.e., that a given firm would exhibit higher realized stock price volatility following an increase in geopolitical risk exposure.

4.2 Impact on Firm Actions

Next, we investigate how geopolitical risk affects capital expenditures, hiring, and sales. Table 6 reports the associations of $GPRisk_{i,t}$ with capital expenditures and firm hiring and sales. The term $100 \times \Delta Capex_{i,t+1} / Capex_{i,t}$ represents the percentage growth in capital expenditures from quarter t to quarter $t+1$. Similarly, $100 \times \Delta Emp_{i,t+1} / Emp_{i,t}$ represents the percentage growth in the number of employees from year t to year $t+1$.¹¹ For instance, if $GPRisk_{i,t}$ is measured in Q1, then $100 \times \Delta Capex_{i,t+1} / Capex_{i,t}$ reflects the percentage growth in capital expenditures from Q1 to Q2. We include $GPSentiment_{i,t}$ to disentangle first-moment effects from second-moment effects. This control is advised to include since changes $GPRisk_{i,t}$ is likely associated with news relating to geopolitical events. All specifications include the logarithm of firm total assets as a control for firm size. Standard errors are clustered at the firm level throughout all models.

The first, second, and third columns report the results of the association between our measure $GPRisk_{i,t}$ and capital expenditures. In Column 1, we regress the change in capital

¹¹ Data on capital expenditures and employment can be noisy. We therefore winsorize both of these variables at the 1st and 99th percentile.

expenditures on $GPRisk_{i,t}$ and include time and industry fixed effects. The coefficient in Column 1 is statistically significant and suggests that one standard deviation increase in $GPRisk_{i,t}$ is associated with a 0.564 (s.e. = 0.274) percentage point decrease in capital expenditures in the following quarter. In Column 2, we introduce $GPSentiment_{i,t}$ as control. The resulting coefficient is virtually unaffected with an effect size of -0.550 (s.e. = 0.273). Columns 1 and 2 show that cross-sectional differences in $GPRisk_{i,t}$ between firms in the same sector explain differences in capital expenditure growth. We find that the relationship holds when we control for geopolitical sentiment. In Column 3, we replace industry fixed effects with firm fixed effects. The coefficient maintains similar magnitude (now -0.519 vs -0.550), but it is only significant at the 10% level rather than the generally accepted 5% level.

Moving on, the fourth, fifth, and sixth columns report associations between $GPRisk_{i,t}$ and employment growth. Notably, none of the coefficients on $GPRisk_{i,t}$ are statistically significant in any of the regressions. These results therefore do not provide evidence of a significant relationship between firms' exposure to geopolitical risk and their employment decisions. We must note, however, that our data for employment is available only on a yearly basis. It is possible that we do not have enough statistical power to detect an association between $GPRisk_{i,t}$ and employment. The firms in our sample are large, and they may be unable to make substantial year-to-year employment adjustments. Accordingly, the effect of $GPRisk_{i,t}$ on employment levels may be too small to detect at a significant level without a larger sample.

Finally, we now move on to look at the association between $GPRisk_{i,t}$ and sales growth. While a firm cannot directly control sales to the same extent as capital expenditures or employment, it still retains some discretion over important decisions that indirectly affect sales. For example, it can choose to reduce its operations in geographically risky areas, indirectly reducing sales. The results of regressing sales growth on $GPRisk_{i,t}$ and various controls are shown in Table 6, Columns 7-9. The coefficient in Column 7 suggests that a one standard deviation increase in $GPRisk_{i,t}$ is associated with a 0.166 (s.e. = 0.083) percentage point decrease in sales growth. However, when we control for $GPSentiment_{i,t}$, the coefficient is no longer significant at the 5% level, implying that news to variation of geopolitical shocks was indeed entangled with news to the mean of these shocks. Furthermore, the coefficient is even smaller when controlling for firm fixed effects; We do not see a significant association between within-firm variation of $GPRisk_{i,t}$ and sales growth.

According to traditional models of uncertainty and investments, an increase in risk exposure should decrease firm investments and employment growth (Pindyck, 1988). We find support that firms react to increases in geopolitical risk exposure by decreasing capital expenditures. The results, although only marginally significant when adding necessary controls, suggest that one standard deviation increase in geopolitical risk exposure leads to roughly half a percent decrease in firm capital expenditures. However, we do not find evidence that increased exposure to geopolitical risk is associated with decreased employment growth or sales growth.

4.3 Impact on Stock Returns

We now move on to study whether portfolios with higher $GPRisk_{i,t}$ exhibit higher returns. Conventional finance theory tells us that securities with higher risk should earn a higher expected return to compensate for this risk (Markowitz, 1952). We study whether this holds true for our measure of firm-level geopolitical risk. We construct equally weighted portfolios at the end of each quarter with $GPRisk_{i,t}$ as the sorting variable. We keep the firms in the portfolios for the next quarter until we rebalance again. Portfolio 1 contains the tercile of firms with the lowest levels of $GPRisk_{i,t}$, while Portfolio 3 contains the tercile of firms with the highest levels of $GPRisk_{i,t}$. We analyze the performance of the portfolios. We report portfolio alphas adjusted for market risk (CAPM alphas), alphas adjusted for the Fama-French three factors (1992), and alphas adjusted for the Fama-French-Carhart factors (1997).

We further report the Newey-West standard errors for the respective alphas and report the difference in alphas in Portfolio 3 and Portfolio 1 under the respective models. The condensed results are shown in Table 7 while the full results from the regressions are outlined in Appendix Table 3.

Controlling only for the market factor, we find that the alpha of Portfolio 3 (high $GPRisk_{i,t}$) is higher than the alpha of Portfolio 1 (low $GPRisk_{i,t}$). However, the difference is not statistically significant. The same overarching pattern of higher alpha for the high $GPRisk_{i,t}$ portfolio is repeated when controlling for the factors in the Fama-French three-factor model and the Fama-French-Carhart four-factor model. Interestingly, when controlling for the Fama French's three factors and Fama-French-Carhart's four factors, we observe a difference in alphas that is statistically significant at the 10% level. Taken together, although the results are not significant at the generally accepted 5% level, we find some evidence that portfolios with higher $GPRisk_{i,t}$ earn higher abnormal returns over time.

4.4 Measurement Error

It is likely that our measure of geopolitical risk contains substantial measurement error. The large residual from the variance decomposition (Table 4) could be interpreted as the result of measurement error. Obviously, it is more difficult to pick up firm-level variation than at the levels of the sector or the wider economy. Very likely, much of the residual in the variance composition is due to measurement error, but we do not know how much. Hassan et al. (2019) found that 52.8% of their firm level variation could be attributed to measurement error, but that the rest contained information of economic significance. So far in this paper we have brazenly assumed that our data is of equivalent quality. However, barring an explanation of investor irrationality, the fact that we lose significance in the relationship between realized volatility and $GPRisk_{i,t}$ in Table 5 when controlling for time (2.52% of total variation) and sector (1.41% of total variation) could suggest that we have substantially more measurement error than Hassan et al. (2019). After controlling for these fixed effects, the overwhelming majority of the variation in $GPRisk_{i,t}$ remains, but we do not see the

expected relationship: that an increase in (geopolitical) risk as measured by $GPRisk_{i,t}$ increases realized volatility. It suggests that only a very small part of the variation in our measure is informative. And, if the residual from our firm level variance decomposition is overwhelmingly the result of measurement error, our interpretation that much of the variation is explained by changes in geopolitical risk exposure across same-sectored firms over time would be challenged. In light of this, our measures and results, particularly the variance decomposition, should be interpreted with care.

V. Conclusion

In this paper, we construct the first validated measure of firm-level geopolitical risk. We find evidence that firms in the same industry are concerned about both aggregate geopolitical risk, as well as distinct, firm-specific geopolitical risk. Furthermore, we use our measure to study firm actions and market responses to changes in geopolitical risk. We find support that firms respond to increases in geopolitical risk by decreasing capital expenditures. We also find weak support that increased geopolitical risk is associated with increased stock price volatility, but this result is not robust to adding all necessary controls. Finally, we find evidence that portfolios exposed to more geopolitical risk are compensated with higher abnormal returns, however, this result is only significant at the 10% level.

We would like to highlight two important limitations and considerations to address in our results. First, we find signs that our measures likely contain substantial measurement error. Second, in constructing our measure of geopolitical risk, we argue that firm's discussions centering around risks associated with geopolitics is equivalent to their actual exposure to geopolitical risk. Obviously, this is an approximation. We measure the geopolitical risk exposure of firms as perceived by senior managers (and analysts), but we do not know how well their perception reflects actual exposure to geopolitical risk. For these reasons, one should be careful when handling our measures and interpreting our findings.

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Figure 1: Distribution of bigram weights

This figure shows a histogram of $\frac{f_{b,G}}{B_G} \cdot 10^5$ for the geopolitical bigrams in $(G \setminus N)$. The mean of $\frac{f_{b,G}}{B_G} \cdot 10^5$ is 1.966.

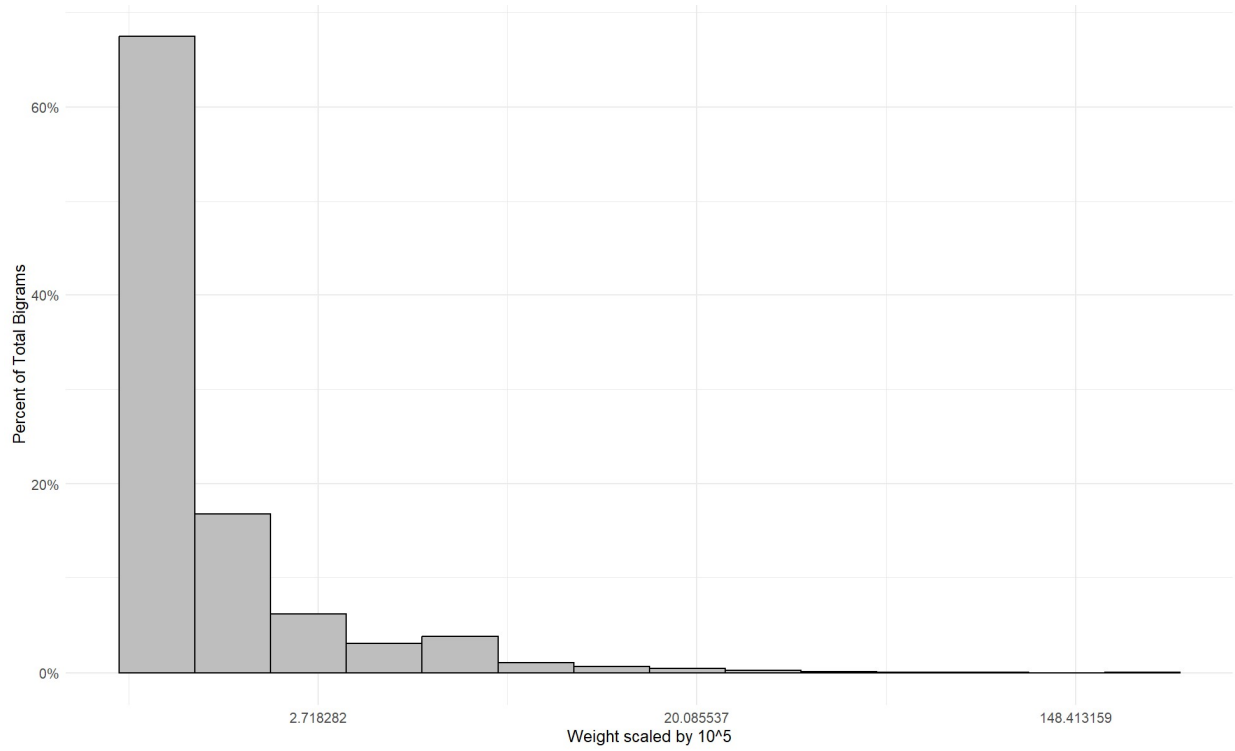


Figure 2: Correctly identified positives over $GPRisk_{i,t}$

This figure plots the results from an additional validation exercise. We manually read excerpts from 200 transcripts at various points of the distribution $GPRisk_{i,t}$. We select the 10 transcripts with the greatest $GPRisk_{i,t}$ at the 5th, 10th, 15th, ..., 100th percentiles and read windows of the adjacent 10 words to a synonym of *risk* or *uncertainty* which contributed to $GPRisk_{i,t}$. We count the number of true positives, i.e., the number of transcripts which contain a window of discussion obviously centered around geopolitical risk. The figure plots the number of true positives on the vertical axis over the median of $GPRisk_{i,t}$ for a given set at a given percentile. The median score is capped at the 97.5th percentile. The line of best fit is plotted.

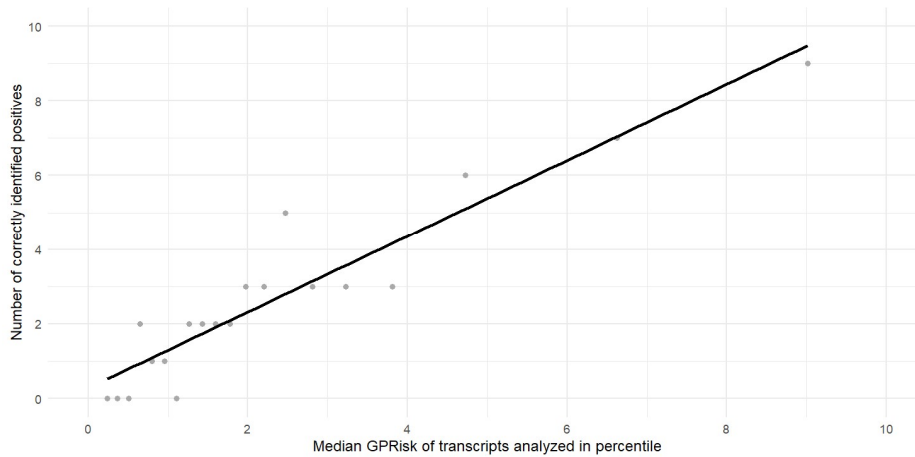


Figure 3: Variation in mean $GPRisk_{i,t}$ over time

This figure plots the quarterly mean of $GPRisk_{i,t}$ scaled by a factor of 10^8 . Key geopolitical events are indicated. We lead $GPRisk_{i,t}$ such that the value plotted in quarter t was generated from transcripts from quarter $t+1$. For more details, see Footnote 6.

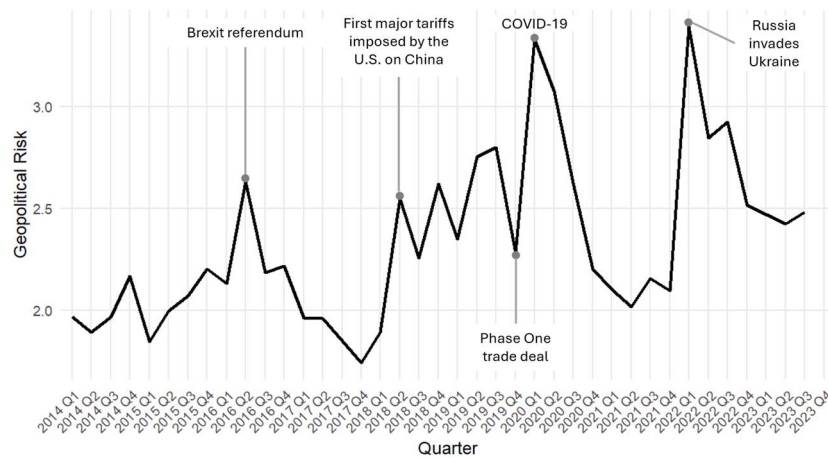


Figure 4: Variation in mean $GPRisk_{i,t}$ and GPR index over time

This figure plots the quarterly mean of $GPRisk_{i,t}$ and the news-based Geopolitical Risk (GPR) index developed by Caldara, D., and M. Iacoviello (2022). $GPRisk_{i,t}$ is scaled by a factor of 10^8 and the GPR index is scaled by a factor of $1/45$. The correlation between the two series is 0.234. We lead $GPRisk_{i,t}$ such that the value plotted in quarter t was generated from transcripts from quarter $t+1$. For more details, see Footnote 6.

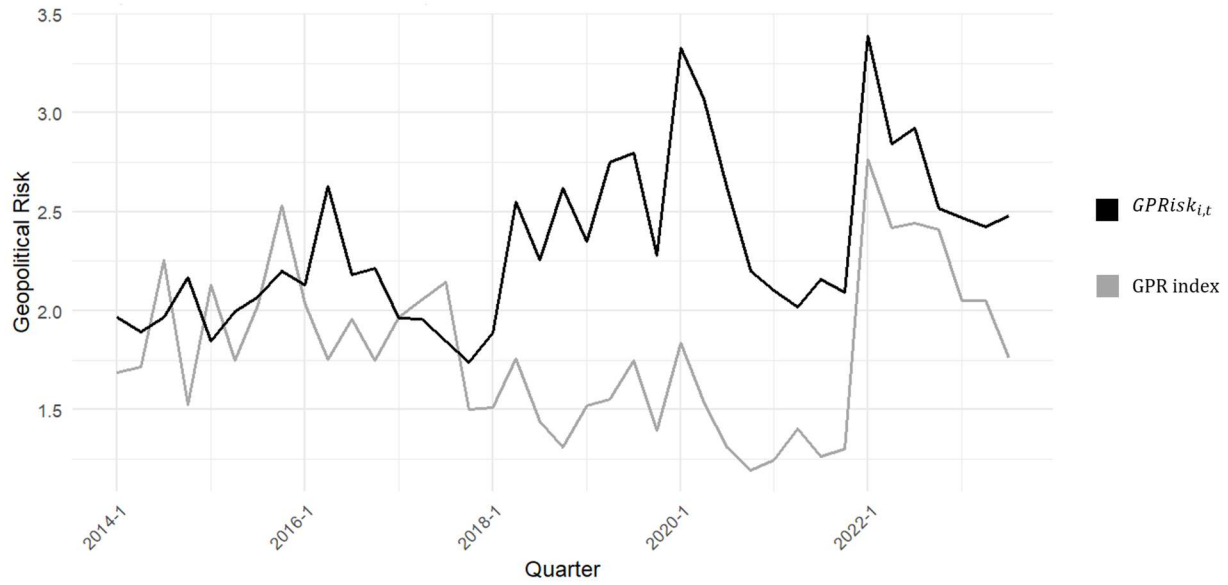


Table 1: Summary statistics

The table outlines summary statistics used for the variables. $GPRisk_{i,t}$ is the transcript-based score of geopolitical risk. $GPSentiment_{i,t}$ is the transcript-based score of geopolitical sentiment, while $Sentiment_{i,t}$ is the transcript-based score of overall sentiment. $GPRisk_{i,t}$, $GPSentiment_{i,t}$ and $Sentiment_{i,t}$ are all standardized by their standard deviation. 90 day realized stock price volatility is the standard deviation of stock price returns for a 90 day window. It is winsorized at the first and last percentile. $100 * \Delta Capex_{t+1} / Capex_t$ is the percentage growth in capital expenditures from quarter t until quarter $t+1$, $100 * \Delta Sales_{t+1} / Sales_t$ is the percentage growth in sales from quarter t until quarter $t+1$, and $100 * \Delta Emp_{t+1} / Emp_t$ is the percentage growth in employees from year t until year $t+1$. $100 * \Delta Capex_{t+1} / Capex_t$, $100 * \Delta Sales_{t+1} / Sales_t$, and $100 * \Delta Emp_{t+1} / Emp_t$ are all winsorized at the first and last percentile.

Variable	N	Mean	St. Dev.	Min	Max
$GPRisk_{i,t}$ (<i>Standardized</i>)	23,174	0.826	1.000	0.042	25.903
$GPSentiment_{i,t}$ (<i>Standardized</i>)	23,174	0.679	1.000	-14.736	11.244
$Sentiment_{i,t}$ (<i>Standardized</i>)	23,174	0.942	1.000	-3.417	5.075
Monthly Stock price return	21,904	0.001	0.049	-0.374	1.189
90 day realized volatility	21,290	1.983	1.153	0.421	27.094
Total Assets (millions)	21,288	44,999	131,700	13.635	2,455,113
$100 * \Delta Capex_{t+1} / Capex_t$	20,616	10.136	49.936	-76.891	259.319
$100 * \Delta Sales_{t+1} / Sales_t$	20,617	2.744	15.824	-43.784	76.391
$100 * \Delta Emp_{t+1} / Emp_t$	4,595	4.65	14.83	-37.500	73.51

Table 2: Top 100 highest weighted bigrams used in construction of $GPRisk_{i,t}$

This table lists the top 100 bigrams with the highest weight or term frequency $\left(\frac{f_{b,G}}{B_G}\right)$. The third column shows the contribution of a bigram to $GPRisk_{i,t}$ across all transcripts in promille (one thousandth of whole).

	Bigram	Weight	%o of $\sum GPRisk_{i,t}$		Bigram	Weight	%o of $\sum GPRisk_{i,t}$
1	('trade', 'policy')	251.22	10.92	51	('in', 'international')	26.75	1.07
2	('the', 'eu')	189.13	7.31	52	('and', 'imports')	26.75	0.95
3	('of', 'trade')	186.27	12.33	53	('imports', 'from')	26.75	1.08
4	('the', 'tariff')	113.67	6.18	54	('in', 'trade')	25.79	0.71
5	('trade', 'flows')	88.84	4.55	55	('the', 'wto')	25.79	0.89
6	('trade', 'and')	78.33	2.87	56	('the', 'uruguay')	25.79	1.19
7	('exchange', 'rate')	70.69	3.23	57	('world', 'price')	23.88	0.96
8	('and', 'russia')	68.78	3.41	58	('the', 'elasticity')	23.88	1.01
9	('europe', 'and')	66.87	2.39	59	('the', 'countrys')	23.88	1.05
10	('the', 'european')	62.09	3.53	60	('of', 'ukraine')	23.88	0.91
11	('the', 'western')	60.18	2.57	61	('russia', 'is')	22.93	1.16
12	('russia', 'on')	59.22	1.91	62	('trade', 'agreements')	22.93	0.88
13	('international', 'trade')	55.40	3.58	63	('imports', 'of')	22.93	0.99
14	('foreign', 'policy')	54.45	1.71	64	('imports', 'and')	22.93	0.65
15	('on', 'trade')	51.58	2.09	65	('of', 'export')	21.97	1.00
16	('and', 'foreign')	47.76	1.84	66	('of', 'imports')	21.97	1.08
17	('trade', 'policies')	45.85	1.95	67	('on', 'foreign')	21.97	0.93
18	('of', 'international')	44.90	2.59	68	('market', 'access')	21.97	0.61
19	('tariffs', 'and')	44.90	1.62	69	('russia', 'in')	21.97	1.37
20	('world', 'bank')	44.90	1.62	70	('and', 'political')	21.01	0.85
21	('of', 'foreign')	42.98	1.73	71	('with', 'russia')	21.01	0.86
22	('of', 'sanctions')	42.98	2.67	72	('tariff', 'on')	21.01	0.74
23	('war', 'in')	42.98	1.57	73	('tariffs', 'are')	21.01	0.87
24	('two', 'countries')	42.03	1.43	74	('invasion', 'of')	21.01	0.94
25	('the', 'eus')	41.07	1.71	75	('trading', 'partners')	21.01	0.71
26	('country', 'is')	40.12	1.62	76	('a', 'trade')	20.06	0.70
27	('in', 'ukraine')	37.25	1.37	77	('geography', 'and')	20.06	0.73
28	('a', 'tariff')	36.30	1.65	78	('of', 'geopolitical')	20.06	0.75
29	('russia', 'and')	35.34	1.47	79	('the', 'dialogue')	20.06	0.78
30	('european', 'union')	35.34	0.92	80	('exports', 'to')	20.06	0.78
31	('geopolitics', 'and')	34.39	1.71	81	('from', 'trade')	20.06	0.83
32	('trade', 'in')	34.39	1.43	82	('each', 'country')	20.06	0.59
33	('influence', 'in')	34.39	2.73	83	('of', 'war')	19.10	0.69
34	('in', 'foreign')	33.43	0.82	84	('sanctions', 'against')	19.10	0.82
35	('of', 'tariff')	33.43	1.17	85	('survey', 'data')	19.10	0.78
36	('geography', 'of')	33.43	1.18	86	('of', 'tariffs')	19.10	0.75
37	('russia', 'has')	32.48	0.86	87	('of', 'substitution')	19.10	0.55
38	('of', 'economic')	31.52	1.15	88	('of', 'economics')	19.10	0.71
39	('countries', 'in')	31.52	1.18	89	('cold', 'war')	19.10	0.76
40	('for', 'trade')	31.52	1.19	90	('of', 'import')	19.10	0.72
41	('united', 'nations')	31.52	1.13	91	('and', 'gas')	18.15	1.21
42	('gas', 'price')	30.57	1.19	92	('exports', 'and')	18.15	0.72
43	('the', 'hs')	30.57	1.21	93	('geopolitics', 'of')	18.15	0.92
44	('the', 'import')	30.57	1.15	94	('countries', 'are')	18.15	0.73
45	('the', 'export')	29.61	1.27	95	('policy', 'and')	18.15	0.51
46	('the', 'foreign')	29.61	1.15	96	('and', 'security')	18.15	0.87
47	('eu', 'and')	29.61	1.14	97	('the', 'union')	17.19	0.66
48	('dc', 'the')	28.66	0.89	98	('a', 'global')	17.19	0.67
49	('tariff', 'and')	28.66	1.70	99	('a', 'policy')	17.19	0.68
50	('of', 'exports')	28.66	1.18	100	('trade', 'between')	17.19	0.50

Table 3: Transcript experts with the highest $GPRisk_{i,t}$

This panel shows the 10 transcripts with the highest $GPRisk_{i,t}$ together with the corresponding firm name, date of the earnings call, the geopolitical score of the transcript along with the passage with the greatest contribution to this score. Geopolitical bigrams (elements of $\mathbb{G} \setminus \mathbb{N}$) are bolded and synonyms of *risk* and *uncertainty* are capitalized and italicized. $GPRisk_{i,t}$ is scaled by a factor of 10^7 .

Firm name	Call date	$GPRisk_{i,t} \cdot 10^7$	Passage with greatest contribution to $GPRisk_{i,t}$
Bunge Global SA	August 1, 2018	7.26	Bunge remains on course for a very good year despite changes in trade policy and the significant UNCERTAINTY in both commodity and financial markets that we saw during the second quarter.
Deere & Company	August 16, 2019	5.91	In the EU, the macroeconomic outlook remains clouded by ongoing UNCERTAINTY regarding Brexit and whether a deal will be reached between the U.K. and the EU before the October 31 deadline.
Franklin Resources, Inc.	August 1, 2018	5.64	The June quarter was challenging for the industry as the introduction of new regulations by the Department of Labor and the United Kingdom's vote to exit the European Union led to increased UNCERTAINTY .
Trimble Inc.	May 1, 2019	5.55	Although the Brexit effect is hard to pinpoint in what was a generally upbeat quarter for us in Europe, the UNCERTAINTY is impacting the appetite for investment to some degree .
Trimble Inc.	February 6, 2019	5.18	China is a significant 3-year question, <i>PENDING</i> improved clarification of trade policy and rules of engagement.
STERIS plc	February 11, 2020	4.49	We started out with UNCERTAINTIES in device tax, UNCERTAINTIES in labor rates, UNCERTAINTIES in trade. And for us, trade is North America, more than China.
FedEx Corporation	December 17, 2019	4.46	We remain optimistic on Chinese demand for Western logs despite near-term volatility caused by UNCERTAINTY with tariffs and trade policy .
Norwegian Cruise Line Holdings	February 21, 2019	4.08	Turning to consumers and despite stock market volatility, FEAR of trade wars , Brexit UNCERTAINTY and other short-term disruptions, such as the recent government shutdown, our indications are that consumers remain confident.
Monster Beverage Corp	May 5, 2022	3.83	The company continued to address the challenges in its supply chain as it navigates through the UNCERTAINTY of the current global supply chain environment.
Trimble Inc.	July 31, 2019	3.79	The first is broadly geopolitical. U.S. trade policy continues to create significant UNCERTAINTY for U.S. farmers and are resulting in reluctance to invest.

Table 4: Variance decomposition of $GPRisk_{i,t}$

This table reports the resulting total variance explained from regressing $GPRisk_{i,t}$ on various fixed effects. We regress $GPRisk_{i,t}$ individually on time fixed effects and sector fixed effects. We then regress $GPRisk_{i,t}$ on time and sector fixed effects, as well as their interaction term. The resulting residual variation is the “firm level” variation. Finally, we regress this firm level variation on firm fixed effects. The share of *total* variation in $GPRisk_{i,t}$ is reported. We classify sectors using the Fama-French 12 industry classification.

Fixed Effect		R^2
Time FE	2.52%	
Sector FE		1.41%
Sector $\times$ time FE		8.73%
'Firm-Level'		91.27%
Firm FE		15.77%
Residual		75.50%

Table 5: Stock price volatility

The table shows regressions of realized stock price volatility on $GPRisk_{i,t}$ and controls. Realized volatility is the 90-day stock price volatility calculated as the standard deviation of stock price returns between the date $t+1$ and $t+90$, if the observation of $GPRisk_{i,t}$ occurs at time t . Time fixed effects, where included, are at the year-month level. All specifications control the logarithm of total firm assets. Standard errors are clustered at the firm level in all regressions and ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Within R^2 is reported.

	<i>Dependent variable:</i>				
	Realized Volatility				
	<i>OLS</i>			<i>panel linear</i>	
	(1)	(2)	(3)	(4)	(5)
$GPRisk_{i,t}$ (<i>Standardized</i>)	0.0315*** (0.0069)	0.0232*** (0.0068)	0.0206** (0.0088)	0.0038 (0.0113)	0.0070 (0.0059)
$GPSentiment_{i,t}$ (<i>Standardized</i>)		-0.0307*** (0.0095)	-0.0338** (0.0147)	0.0023 (0.0106)	0.0116 (0.0073)
$Sentiment_{i,t}$ (<i>Standardized</i>)		-0.0486*** (0.0099)	-0.0536* (0.0321)	-0.0336 (0.0277)	-0.0814*** (0.0094)
Clustered SE	Firm	Firm	Firm	Firm	Firm
Time FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes	n/a
Firm FE	No	No	No	No	Yes
Observations	21,278	21,278	21,278	21,278	21,278
R^2	0.0301	0.0342	0.0218	0.0535	0.0093

Note:

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6: $GPRisk_{i,t}$ effect on capital expenditure, employment, and sales

The table shows regressions of capital expenditure growth, sales growth and employment growth on $GPRisk_{i,t}$. Capital expenditure and sales growth is from quarter t to quarter $t+1$. Employment growth is from year t to year $t+1$. Capital expenditure growth, employment growth and sales growth are winsorized at the first and last percentile. $GPRisk_{i,t}$ and $GPSentiment_{i,t}$ are all standardized by their respective standard deviations. All specifications include the logarithm of total firm assets as a control. Time fixed effects are at the year-month level. Standard errors are clustered at the firm level in all three regressions and ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively. The table reports total R^2 .

	<i>Dependent variable:</i>								
	100 * $\Delta Cape_{t+1}/Cape_t$			100 * $\Delta Emp_{t+1}/Emp_t$			100 * $\Delta Sales_{t+1}/Sales_t$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$GPRisk_{i,t}$ (Standardized)	-0.564** (0.274)	-0.550** (0.273)	-0.519* (0.291)	-0.166 (0.233)	-0.106 (0.232)	-0.218 (0.221)	-0.166** (0.083)	-0.149* (0.085)	-0.089 (0.090)
$GPSentiment_{i,t}$ (Standardized)		0.169 (0.314)	0.428 (0.341)		0.540** (0.217)	0.416* (0.231)		0.200* (0.118)	0.221* (0.131)
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	20,616	20,616	20,616	4,595	4,595	4,595	20,617	20,617	20,617
R^2	0.073	0.073	0.106	0.103	0.104	0.358	0.072	0.072	0.104

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 7: Portfolio alphas

This table reports CAPM, FF3 and FFC monthly alpha in percent for three portfolios. The portfolios are constructed at the end of each quarter based on $GPRisk_{i,t}$ as the sorting variable. The firms in each portfolio are kept until the end of the next quarter when portfolios are rebalanced again. The difference in alpha between the high and low $GPRisk_{i,t}$ portfolio is also shown. The table reports associated Newey-West-corrected t-statistics for each of the alphas in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	[P1 - Low GPRisk]	[P2 - Middle Group]	[P3 - High GPRisk]	[P3] - [P1]
CAPM alpha	0.031 [0.218]	0.145 [0.887]	0.250 [1.731]	0.219 [0.942]
FF3 alpha	0.115 [1.072]	0.277** [2.453]	0.349*** [3.693]	0.234* [1.701]
FFC alpha	0.123 [1.14]	0.281** [2.474]	0.362*** [3.847]	0.239* [1.721]

Appendix

Appendix A: A Note on AI

AI tools ChatGPT and Claude were used to debug code in R and Python. ChatGPT was also used to format output tables and figures in R and LaTeX.

Appendix B: Other Model Specifications

We experimented with novel specifications in which bigrams closer to synonyms of *risk* and *uncertainty* carried greater weight.

$$GPRisk_{i,t} = \frac{1}{B_{i,t}} \sum_b^{B_{i,t}} \left(I[b \in \mathbb{G} \setminus \mathbb{N}] \times I[|b - r| < 20] \times \frac{f_{b,G}}{B_G} \times \frac{20 - |b - r|}{20} \right) \quad (2)$$

Here, the window size is increased to 20, and the weight of the bigram decreases linearly with distance from the risk synonym due to the addition of the factor $\frac{20 - |b - r|}{20}$. We also experimented with augmenting the Hassan et al. method such that it would exhibit the behavior of bigrams associated with (2), i.e. bigrams closer to the risk synonym would be weighted higher:

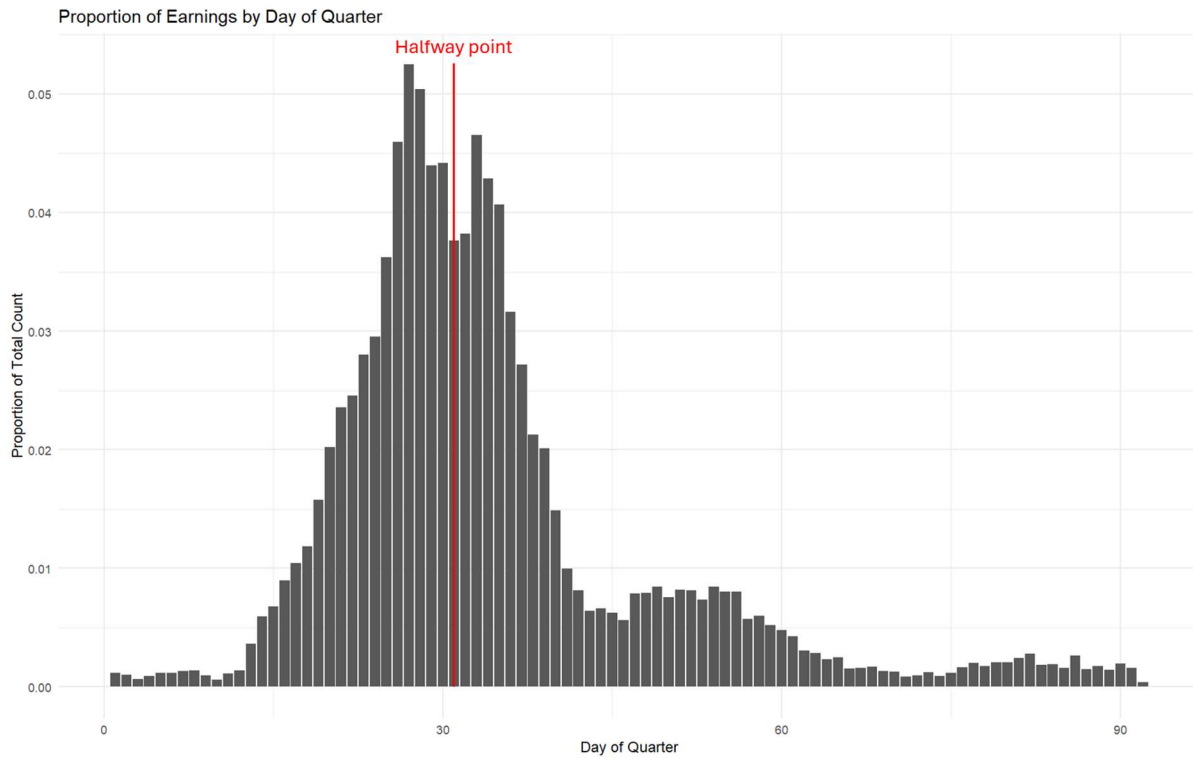
$$GPRisk_{i,t} = \frac{1}{B_{i,t}} \sum_b^{B_{i,t}} \left(\left(I[b \in \mathbb{G} \setminus \mathbb{N}] \times (I[|b - r| < 10] + I[|b - r| \in [10, 20]] \times \frac{20 - |b - r|}{10}) \right) \times \frac{f_{b,G}}{B_G} \right) \quad (3)$$

In this specification, bigrams in the transcript found in the window of the 10 words on either side of the synonyms of *risk* or *uncertainty* are treated the same way as in (1). The difference between (1) and (3) is that the bigrams further away than 10 words from the risk synonym in (3) are included but with decreasing weight. This behavior captured by extending the conditioning with: $I[|b - r| \in [10, 20]] \times \frac{20 - |b - r|}{10}$.

It seems natural that the closer a bigram is to a synonym of *risk* or *uncertainty*, the more strongly associated with risk it likely is. This speaks for choosing (2) or (3) as our specification. Overall, specifications (2) and (3) varied over time in a manner similar to our preferred specification (1); however, all three specifications produced distinctly different transcript rankings for geopolitical risk. Although (2) and (3) both favor bigrams closer to a risk word, we found that neither (2) nor (3) were substantially better at identifying discussions centering around geopolitical risk. Accordingly, we proceeded with (1) as our specification for its relative elegance and lower complexity as well as its extensive validation and popularity in the previous literature.

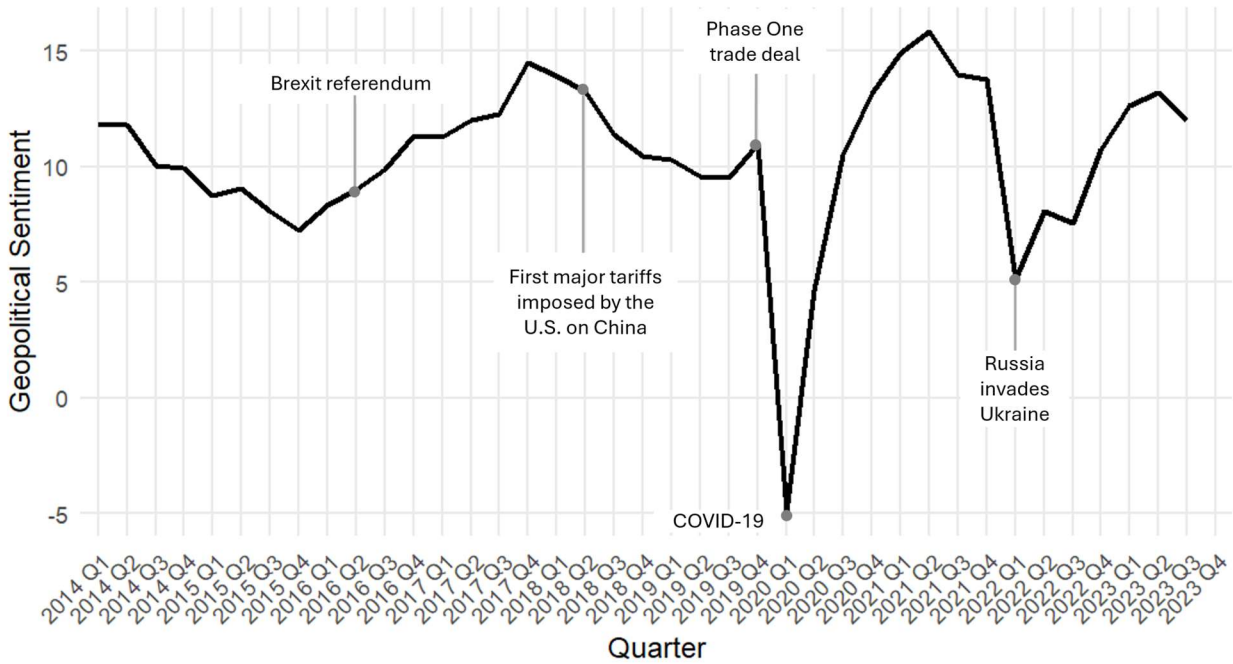
Appendix Figure 1: Distribution of earnings calls

This figure plots a histogram of the proportion of the total earnings calls held on a given day in a given quarter in our sample. The “halfway point,” marked with a red line, is where half of the earnings calls on average have been held.



Appendix Figure 2: Variation in mean $GPSentiment_{i,t}$ over time

This figure plots the quarterly mean of $GPSentiment_{i,t}$ scaled by a factor of 10^8 . Key geopolitical events are indicated. We lead $GPSentiment_{i,t}$ such that the value plotted in quarter t was generated from transcripts from quarter $t+1$. For more details, see Footnote 6.



Appendix Table 1: Variable descriptions

Variable	Description	Source
$\text{GPRisk}_{i,t}$	Measure of geopolitical risk based on share of transcript devoted to discussing geopolitical risks	Earnings conference calls (Eikon Advanced Events)
$\text{GPSentiment}_{i,t}$	Measure of geopolitical sentiment based on textual analysis discussions in earnings calls	Earnings conference calls (Eikon Advanced Events)
$\text{Sentiment}_{i,t}$	Measure of overall sentiment based on textual analysis of discussions in earnings calls	Earnings conference calls (Eikon Advanced Events)
Total Assets	Total Assets (in millions)	Compustat
Capex	Quarterly capital expenditures in millions derived from year-to-date capital expenditures [capxy]	Compustat
Sales	Quarterly sales in millions [saleq]	Compustat
Emp	Number of employees in thousands [emp]	Compustat
Monthly stock price return	Stock price return [ret] from CRSP	CRSP
90 day realized volatility	Standard deviation of stock price returns (returns [ret] from CRSP) based on a 90 day window	CRSP
GPR Index	Newspaper-based measure of aggregate geopolitical risk with focus on war and terrorism	Caldara, D., and M. Iacoviello (2022).

Appendix Table 2: Synonyms of risk and uncertainty

This table lists all the synonyms of risk and uncertainty used to construct $GPRisk_{i,t}$. The synonyms were obtained from the Oxford Dictionary following Hassan et al. (2019).

ambivalence	dubious	inconstancy	quandary	unconfident
ambivalent	endanger	indecision	queries	undecided
apprehension	equivocating	indecisive	query	undependable
bet	equivocation	insecure	reservation	undetermined
chance	erratic	insecurity	risk	unforeseeable
chanciness	exposed	instability	risked	unknown
chancy	faltering	irregular	riskier	unpredictability
changeability	fear	irresolute	riskiest	unpredictable
changeable	fickleness	irresolution	riskiness	unreliability
changeableness	fitful	jeopardize	risking	unreliable
changeful	fitfulness	jeopardy	risks	unresolved
chariness	fluctuant	likelihood	risky	unsafe
danger	fluctuating	menace	scruple	unsettled
dangerous	gamble	misgiving	skepticism	unstable
debatable	gnarly	niggle	speculative	unsure
defenseless	hairy	oscillating	sticky	unsureness
dicey	halting	parlous	suspicion	untrustworthy
diffidence	hazard	pending	tentative	vacillating
diffident	hazardous	peril	tentativeness	vacillation
dilemma	hazy	perilous	threat	vague
disquiet	hesitancy	perilousness	torn	vagueness
disquietude	hesitant	possibility	treacherous	variability
dodgy	hesitating	precarious	tricky	variable
doubt	iffy	precariousness	uncertain	varying
doubtful	imperil	probability	uncertainties	wager
doubtfulness	incalculable	prospect	uncertainty	wariness
dubiety	incertitude	qualm	unclear	wavering

Appendix Table 3: Portfolio sorts

The table shows results from regressions of portfolio monthly excess return on different risk factors. P1 contains stocks with low $GPRisk_{i,t}$ while P3 contains stocks with high $GPRisk_{i,t}$. The portfolios are constructed at the end of each quarter based on $GPRisk_{i,t}$ as the sorting variable. The firms in each portfolio are kept until the end of the next quarter when portfolios are rebalanced again. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:								
	Portfolio Excess Return								
	[P1 - Low]	[P2]	[P3 - High]	[P1 - Low]	[P2]	[P3 - High]	[P1 - Low]	[P2]	[P3 - High]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market excess return	1.09632*** (0.05961)	1.07111*** (0.05213)	1.07831*** (0.04543)	1.06221*** (0.03553)	1.00626*** (0.03114)	1.03838*** (0.01988)	1.05370*** (0.03659)	1.00166*** (0.02372)	1.02443*** (0.02085)
HML				0.21325*** (0.03872)	0.20780*** (0.02979)	0.25353*** (0.03235)	0.20661*** (0.04151)	0.20421*** (0.03176)	0.24264*** (0.03290)
SMB				0.13681*** (0.02808)	0.28346*** (0.06712)	0.15966*** (0.02874)	0.12907*** (0.02820)	0.27929*** (0.07485)	0.14699*** (0.02952)
UMD							-0.02817 (0.02719)	-0.01520 (0.03964)	-0.04617 (0.02988)
Constant	0.00031 (0.00169)	0.00145 (0.00171)	0.00250 (0.00160)	0.00115 (0.00097)	0.00277** (0.00117)	0.00349*** (0.00098)	0.00123 (0.00099)	0.00281** (0.00114)	0.00362*** (0.00097)
Model:	CAPM	CAPM	CAPM	FF3	FF3	FF3	FFC	FFC	FFC
Observations	117	117	117	117	117	117	117	117	117
R ²	0.91937	0.89019	0.91323	0.95461	0.94922	0.96391	0.95493	0.94932	0.96481

Note:

*p<0.1; **p<0.05; ***p<0.01