

# Online Appendix: Measuring Geopolitical Risk

Dario Caldara

Matteo Iacoviello\*

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\*Caldara: Board of Governors of the Federal Reserve (email: [dario.caldara@frb.gov](mailto:dario.caldara@frb.gov)); Iacoviello: Board of Governors of the Federal Reserve (email: [matteo.iacoviello@frb.gov](mailto:matteo.iacoviello@frb.gov)).

# Online Appendix: Measuring Geopolitical Risk

## A Appendix on: Construction of the Geopolitical Risk Indexes

### A.1 Selection of the Words Entering the Index

As discussed in the main text, we use standard textual analysis techniques to inform the construction and organization of the dictionary of geopolitical terms used in the search query. Here we provide some additional details.

- We analyze the most frequent unigrams and bigrams found in two recent geopolitics books in order to get an idea for the range of topics covered by geopolitics. The book *Introduction to Geopolitics* (Flint, 2016) contains 48,759 bigrams, of which among the most common ones are ‘geopolit code’, ‘war [on] terror’, ‘geopolit agent’, ‘cold war’, ‘soviet union’, ‘world war’, and ‘foreign polic[y].’ The volume *The Geopolitics Reader*—edited by Simon Dalby, Paul Routledge, and Gearóid Tuathail—which is a compendium of 39 geopolitics essays written by different authors, contains 91,210 bigrams, of which the most common ones are ‘unit[ed] states’, ‘cold war’, ‘foreign polic[y]’, ‘nation secur[ity]’, ‘world war’, ‘world order’, ‘nation[al] state’, ‘gulf war’, ‘war II’, and ‘nuclear weapon.’
- We search in the corpus of Historical American English the most common collocates of the words war, military, conflict, terrorism, nuclear, peace and battle in order to set up and refine our dictionary. The first ten collocates of the word ‘war’ are world, civil, II, during, department, secretary, cold, declare, peace, Vietnam. Except for the word ‘declare’, we do not use the first ten words because they refer to a particular historical period or situation, rather than to obvious war risks or beginning of wars. Scrolling down the list of the first 100 collocates, we encounter words such as ‘outbreak’, ‘inevitable’, and ‘imminent’, that we include in the final dictionary of either risk or action words. When we repeat the same process for the word ‘military’, we add words such as ‘threat’, ‘coup’, ‘buildup.’ The ten most frequent collocates of the word ‘terrorism’ are war, against, act, international, fight, threat, political, expert, support, campaign. We single act and threat from this list. We repeat this procedure for other key words mostly to ensure there are no glaring omissions in our query.
- To organize the search query, we use high frequency words and their corresponding synonyms, as well as words that are more likely to appear on the front page of newspapers on days of high geopolitical tensions. To this end, we compare the text of the front pages of newspapers on days of high geopolitical tensions with the text of the front pages of newspapers on random days. The days of high geopolitical tensions are the days in which adverse geopolitical events are featured in a banner headline on the front page of *The New York Times*. The more likely (lemmatized) words on days of high geopolitical tensions are reported in Table A.1. For instance, ‘crisis’ has a term frequency of 0.254 percent on days of high geopolitical tensions, whereas its term frequency on average is 0.042 percent. Accordingly, an article containing the word ‘crisis’ is about 6.1 times more likely to belong to the high-GPR category.

Note that some potentially likely words are not included in the search in spite of their relatively high odds. Words such as ‘communique’ or ‘neutral’ or ‘civilian’ or ‘command’ are left out because of their ambiguous meaning. Words such as ‘combat’ or ‘tank’ or ‘submarine’ have a low average term frequency.

## A.2 Newspapers Coverage and Contribution of Search Categories

The recent geopolitical risk index is constructed by running a search query in the ProQuest Newsstand Database. We search the archives of the following newspapers (start date availability in parentheses): *Chicago Tribune* (1/1/1985); *The Daily Telegraph* (4/1/1991); *Financial Times* (5/31/1996); *The Globe and Mail* (1/1/1985); *The Guardian* (8/18/1992); *Los Angeles Times* (1/1/1985); *The New York Times* (1/1/1985); *USA Today* (4/1/1987); *The Wall Street Journal* (1/1/1985); and the *Washington Post* (1/1/1985).

For the historical index, we search the historical archives of the *Chicago Tribune*; *The New York Times*; and the *Washington Post*, starting on January 1, 1900.

To construct the numerator of the GPR index, we run one joint query across all categories. Note that a single article could belong to more than one category. The sum of the hits across categories is 15 percent higher than the number of articles belonging to the GPR index, thus suggesting some overlap across categories.

To construct the denominator of the GPR index, we search news articles that simultaneously contain the words ‘the’, ‘be’, ‘to’, ‘of’, ‘and’, ‘at’, and ‘in.’ These words are among the 20 most common words found in the historical archives since 1900. By searching for articles that simultaneously include several of the most frequent words in English, we exclude from the count one-line news, articles that are too short, or titles of articles that are sometimes erroneously classified as full articles.

For the recent period, newspaper-specific indexes are shown in Figure A.12, expressed as a share of news articles for each of the newspapers.<sup>2</sup> As the top left panel shows, coverage of geopolitical risks aligns with the benchmark GPR index for the three general interest newspapers that we use in the construction of the historical index. As the top right panel shows, coverage of geopolitical risks is slightly higher than the average for the two business newspapers in the sample, *The Wall Street Journal* and the *Financial Times*. Coverage also lines up with the average for the two U.S. newspapers not included in the historical index (middle left panel). Coverage of geopolitical events by non-U.S. general interest newspapers lines up with the average, but is slightly more volatile (middle right and bottom left panels).

Figure A.13 elaborates on the contribution of each search category of the index, this time focusing on the historical period. Nuclear threats are disproportionately important during the Cold War. Terror threats and acts trend higher over the sample period, spiking after 9/11, and remaining at elevated levels ever since. The categories relating to beginning and escalation of war exhibit two large spikes in corresponding of the world war.

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<sup>2</sup> The actual indexes are a normalization of the articles’ share.

### A.3 The Actual Search Query

For the interested researchers, here are the actual search queries as they are entered in the ProQuest database.

The articles mentioning geopolitical risks are found with the following query:

```
DTYPE(article OR commentary OR editorial OR feature OR front page article OR front page/cover
story OR news OR report OR review) AND (((war OR conflict OR hostilities OR revolution*
OR insurrection OR uprising OR revolt OR coup OR geopolitical) NEAR/2 (risk* OR warn*
OR fear* OR danger* OR threat* OR doubt* OR crisis OR troubl* OR disput* OR concern* OR
tension* OR imminen* OR inevitable OR footing OR menace* OR brink OR scare OR peril*))
OR ((peace OR truce OR armistice OR treaty OR parley) NEAR/2 (menace* OR reject* OR threat*
OR peril* OR boycott* OR disrupt*)) OR ((military OR troops OR missile* OR "arms" OR weapon*
OR bomb* OR warhead*) AND (buildup* OR build-up* OR blockad* OR sanction* OR embargo OR
quarantine OR ultimatum OR mobiliz* OR offensive)) OR (((("nuclear war" OR "nuclear warfare"
OR "nuclear warhead" OR "nuclear warheads" OR "nuclear wars") OR ("atomic war" OR "atomic
warfare" OR "atomic warheads" OR "atomic wars") OR ("nuclear missile" OR "nuclear missiles")
OR ("nuclear bomb" OR "nuclear bombardment" OR "nuclear bomber" OR "nuclear bombers" OR
"nuclear bombing" OR "nuclear bombs") OR ("atomic bomb" OR "atomic bombing" OR "atomic
bombings" OR "atomic bombs") OR "h-bomb*" OR ("hydrogen bomb" OR "hydrogen bombs") OR
"nuclear test") AND (risk* OR warn* OR fear* OR danger* OR threat* OR doubt* OR crisis
OR troubl* OR disput* OR concern* OR tension* OR imminen* OR inevitable OR footing OR
menace* OR brink OR scare OR peril*)) OR ((terroris* OR guerrilla* OR hostage*) NEAR/2
(risk* OR warn* OR fear* OR danger* OR threat* OR doubt* OR crisis OR troubl* OR disput*
OR concern* OR tension* OR imminen* OR inevitable OR footing OR menace* OR brink OR scare
OR peril*)) OR ((war OR conflict OR hostilities OR revolution* OR insurrection OR uprising
OR revolt OR coup OR geopolitical) NEAR/2 (begin* OR begun OR began OR outbreak OR "broke
out" OR breakout OR start* OR declar* OR proclamation OR launch* OR wage*)) OR ((allie*
OR enem* OR foe* OR army OR navy OR aerial OR troops OR rebels OR insurgen*) NEAR/2 (drive*
OR shell* OR advance* OR invasion OR invad* OR clash* OR attack* OR raid* OR launch* OR
strike*)) OR ((terroris* OR guerrilla* OR hostage*) NEAR/2 (act OR attack OR bomb* OR
kill* OR strike* OR hijack*)) NOT (movie* OR film* OR museum* OR anniversar* OR obituar*
OR memorial* OR arts OR book OR books OR memoir* OR "price war" OR game OR story OR history
OR veteran* OR tribute* OR sport OR music OR racing OR cancer))
```

The articles mentioning geopolitical risks are normalized by total number of articles. The total number of articles are found with the following query:

```
DTYPE(article OR commentary OR editorial OR feature OR front page article OR front page/cover
story OR news OR report OR review) AND ("THE" AND "BE" AND "TO" AND "OF" AND "AND" AND
"AT" AND "IN")
```

## B Appendix on: Validation of the Index

### B.1 Appendix on: Comparison with a Narrative GPR Index

We construct a ‘narrative’ GPR index by reading and scoring 44,000 daily front pages of *The New York Times* from 1900 through 2019. Figure A.2 shows examples of headlines coded as 5, 2, and 1 in the construction of the narrative GPR index.

In practice, together with a team of research assistants, we read all headlines above the fold of the daily front pages of *The New York Times* and score each day with a 0, 1, 2, or 5 depending on whether: no headline features rising or existing geopolitical tensions (score: 0); one headline—but not the lead headline—features geopolitical tensions (score: 1); the lead headline—but not a banner headline—features geopolitical tensions (score: 2); the banner headline features geopolitical tensions (score: 5).

The guide we used to implement uniform coding of the articles is available at [https://www.matteociacoviello.com/gpr\\_replication.htm](https://www.matteociacoviello.com/gpr_replication.htm).

In 1978, *The New York Times* was on strike from August 10 through November 4. We replace it with the Washington Post throughout that period.

To verify uniform coding, we select about 1,000 front pages that are coded simultaneously by more than one research assistant. We find that the Cronbach alpha for the articles coded by more than one research assistant is 0.9329, a number that indicates a very strong overlap among coding practices across research assistants. In particular, 85 percent of articles are given the same narrative rating by two different research assistants.

### B.2 Appendix on: Country-Specific GPR Measures

Country-specific GPR indexes are constructed for each country by counting the number of articles satisfying two criteria: (1) the article must satisfy conditions for inclusion in the GPR index; (2) the article must contain the name of the country (including any names and/or spelling variants from the past) or its capital or its main city. For instance, any article satisfying the conditions for inclusion in the GPR index and containing ‘Japan’ OR ‘Japanese’ OR ‘Tokyo’ OR ‘Tokio’ counts for inclusion in Japan’s country-specific GPR index.

### B.3 Appendix on: Comparison with News about Military Spending

The bottom four panels of Figure A.3 compare military spending news (Ramey, 2011) with surprises in the GPR index during selected historical episodes. During both world wars, some of the spikes in geopolitical risk align with jumps in the military spending news measure. Yet, the military spending news variable only spikes in the middle of the wars when U.S. intervention appears increasingly likely. At the onset of the Korean War, the largest jump in the GPR index coincides with a large shock to military spending news. Lastly, following 9/11, the largest spikes in GPR take place in 2001:Q3 and 2001:Q4, whereas Ramey’s variable increases in 2002:Q1 and 2007:Q4. In particular, the 2007 spike occurs on news of higher-than-projected costs of the Afghan and Iraq wars, while the GPR index barely moves.

## B.4 Appendix on: Comparison with War Deaths

Data on global war deaths measure death rate from conflicts (military and civilian, deaths per 100,000 people). Data on conflict deaths from 1900 through 1969 are from Peter Brecke’s Conflict Catalog (<https://brecke.inta.gatech.edu/research/conflict/>). Data from 1970 through 2015 combine deaths from conflict and terrorism and are constructed using data from the National Consortium for the Study of Terrorism (<https://start.umd.edu/>), the UCDP One-sided Violence Dataset (<https://ucdp.uu.se/downloads/>), the PRIO Battle Deaths Dataset <https://www.prio.org/Data/Armed-Conflict/Battle-Deaths/The-Battle-Deaths-Dataset-version-30/>, and the Defense Casualty Analysis System (<https://dcas.dmdc.osd.mil/dcas/pages/casualties.xhtml>). Data on population are from Our World in Data (<https://ourworldindata.org/world-population-growth>).

## B.5 Appendix on: Tests of Granger Causality

We run Granger-causality tests based on the following regression:

$$LGPR_t = \alpha + \sum_{i=1}^p \beta_i LGPR_{t-i} + \sum_{i=1}^p \Gamma'_{M,i} \mathbf{M}_{t-i} + \sum_{i=1}^p \Gamma'_{F,i} \mathbf{F}_{t-i} + \sum_{i=1}^p \Gamma'_{U,i} \mathbf{U}_{t-i} + \varepsilon_{LGPR,t},$$

where  $LGPR$  is the log benchmark GPR index;  $\mathbf{M}$  denotes a vector of macroeconomic variables;  $\mathbf{F}$  denotes a vector of financial variables; and  $\mathbf{U}$  denotes a vector of proxies for uncertainty. In our application,  $\mathbf{M}$  consists of the log-difference of U.S. industrial production, the log-difference of private employment, and the log of the WTI price of oil deflated by U.S. CPI;  $\mathbf{F}$  consists of the real return on the S&P500 index and the 2-year Treasury yield; and  $\mathbf{U}$  includes the VIX and the log the EPU index. We include in the regression a constant term and set  $p = 3$ . The sample runs from 1986:M1 through 2019:M12.

Column (1) of Table A.8 tabulates the results of the exogeneity test that we run for the log GPR index. Columns (2) and (3) show the results of the Granger causality tests when we replace the log GPR index with the log of GPA and GPT indexes, respectively. Both regressions include lags of both log GPA and log GPT as independent variables. As for the baseline GPR index, we do not find any significant impact of macroeconomic, financial, and uncertainty variables on the GPA and GPT indexes.

## B.6 Appendix on: Audit of the GPR Index

The full-scale audit consists of the construction of a human-generated GPR index and the evaluation of the computer-generated GPR index.

The set of newspaper articles used to construct the historical index—denoted by  $\mathcal{U}$ —contains about 10,000 articles, on average, each month. The audit underlying the construction of the historical human index was conducted from a subset of  $\mathcal{U}$ —denoted by  $\mathcal{E}$ —consisting of articles that contain any of the following words: *geopolitics*, *war*, *military*, *terrorism*/t. The subset  $\mathcal{E}$  contains about 1,600 articles per month, about 15 percent of the articles in  $\mathcal{U}$ . We focus on a subset of

articles containing the words above to make our audit more efficient and less prone to sampling error. Indeed, as shown by Table A.1, words such as *war* and *military* are very popular words both in days of high geopolitical risks and on days of low geopolitical risks. Among the articles belonging to set  $\mathcal{E}$ , 33 percent only refer to rising geopolitical tensions. This fraction would be much lower in the universe  $\mathcal{U}$ , thus requiring a much bigger audit sample. Of course, there remains the possibility that articles that do not mention these words also mention geopolitical risks. However, in a random sample of 585 articles not containing any of these words, the fraction of articles mentioning high geopolitical risks was only 2.6 percent, thus allaying our concerns.

To construct a human-generated GPR index, we randomly sampled 7,365 articles from  $\mathcal{E}$ —on average about 60 articles per year. For each year, we calculated the fraction of articles assigned to  $\mathcal{E}^1$ , multiplied this fraction by the quarterly rate  $\mathcal{E}/\mathcal{U}$ , and normalized the resulting index to 100 over the entire sample. In Figure A.14, we show the human-generated GPR index. The historical, computer-generated, index lines up well with an index that could be constructed by humans. The correlation between the two series is 0.93.

To evaluate the computer-generated GPR index, we randomly sampled 2,400 articles from the set of articles selected by the automated text-search algorithm, and classified them as either discussing high or rising geopolitical tensions or not. The fraction of articles that constitute the computer-generated GPR and mention high or rising geopolitical risks is 79 percent. Of the remaining articles, less than 1 percent mention low or decreasing geopolitical tensions. The remaining 20 percent false positives fall under various categories, for instance discussions of past geopolitical events and related personal experiences (e.g. trauma) without an immediate connection to current developments. The low incidence of articles discussing favorable geopolitical developments supports our claim that our choice of words captures negative risks to the geopolitical outlook.

Table A.3 presents additional results and lists the three alternative search queries that: do not remove the ‘excluded words’ from the query (GPRNOEW); use smaller sets of basic words highlighted in red in Table 1 (GPRBASIC); use the Boolean operator ‘AND’ for all search categories—as opposed to a search of two terms within two words from each other (GPRAND). For each alternative index, we randomly sample 500 articles. We code manually each article as either discussing high or rising geopolitical tensions or not. As shown in the table, the alternative indexes have a higher error rate.

## B.7 Appendix on: Does War Language Change over Time?

Any text search covering a long period of time must be flexible enough to accommodate neologisms and obsolete words, as well as semantic, syntactic, and spelling changes. The construction of our index reflects an extensive analysis of the most common words and sentences used in newspaper articles over time to describe risks to war and to peace, and acts of war and terror. In particular, our dictionary includes enough words to rule out the possibility that the inclusion or exclusion of a few words may bias the index in particular periods. Additionally, we verify that changes in language over time do not affect our automated index as follows:

1. We verify that there are no divergent trends between the narrative indexes, which is constructed



by human reading of actual newspaper front pages, and our automated index.

2. When we compare the period 1900-1959 with the 1960-2019 period—see Table A.2—we verify that commonly appearing words of the period are in our search and the search is focused on words that have a high signal to noise ratio. Words such as *communique*, *league*, *fleet*, and *men* were relatively more frequent in the past and words such as *television*, *vow*, *jet*, *target* and *oil* are relatively more frequent in recent decades, but in both instances their inclusion would have worsened the accuracy of the index.
3. We analyze term frequency for the words and word combinations used to construct the index. Tables A.4 and A.5 tabulate the results for the entire sample and across subperiods. We find that our query includes words that are more frequent in early part of the 20th century (such as *menace* or *peril*) as well as words that are more common in recent decades. We also show how our search focuses on words with high signal to noise ratio and excluded words that would have worsened the accuracy of the index. For instance, many of the words to indicate risk that are included in our search, such as ‘*menace*’, ‘*peril*’, and ‘*scare*’, are rarely used in the second half of the 20th Century.
4. In initial checks, we noticed that over time newspapers appear to have devoted increasingly more space to arts, history, sports, and entertainment, often borrowing some of their language from warfare and military terminology. For this reason, our search does not count as articles measuring geopolitical risks any of the articles containing any of the ‘excluded words’ listed in Table 1. Without these words, the index would have a slight upward trend throughout the historical period.

## B.8 Appendix on: Does Media Attention Measure the Underlying Risk?

In this subsection, we elaborate on the evidence that the GPR index is not unduly affected by issues related to media reporting of news such as unpredictable or seasonal newsworthy events, political slant of the media, or changes in societal norms.<sup>3</sup>

First, we show that there is little evidence that unpredictable and predictable newsworthy events can explain fluctuations in the index. In the top panel of Figure A.4, we show that there is little correlation between the GPR index and a news index of natural disasters, even if news about natural disasters attracts significant media attention. In the bottom panel, we confirm that the irrelevance of other newsworthy events still applies when we look at an index capturing newspapers’ attention towards recurring and predictable sport events, such as the Olympics or the World Series. More in general, we find little correlation between the GPR index and a swath of newsworthy events, as shown in Table A.6 in the Appendix.

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<sup>3</sup> There are many reasons that the GPR may fluctuate for reasons unrelated to latent geopolitical risks. For instance, the high levels of the index in the years following 9/11 may reflect public fear towards geopolitical tensions more than actual risk. Additionally, geopolitical issues may receive more or less coverage in the news depending on the attention of the press to other newsworthy events. Finally, the use of war and terrorism-related words may reflect issues that a newspaper likes to report on and that readers are passionate about, rather than objective geopolitical risks.



The political bias or slant of newspapers may also induce measurement error in our index. In our second check, we verify that there is little slant in the newspapers’ coverage of geopolitical risks. For the recent sample, when we split our 10 newspapers into five left-leaning and five right-leaning. The left-leaning newspapers are *The Globe and Mail*, *The Guardian*, *Los Angeles Times*, *The New York Times*, and *The Washington Post*. The right-leaning newspapers are *The Daily Telegraph*, the *Chicago Tribune*, the *Financial Times*, *USA Today*, and *The Wall Street Journal*. As shown in Figure A.5, the ‘left’ and ‘right’ versions of our GPR index move together closely, with a correlation of 0.87, suggesting that while different media outlets may cover geopolitical events with different intensity, the broad time-series properties of the index are robust to the political slant of newspapers.

War reporting could have changed over time as norms of patriotism or censorship shifted. Similarly, competition in the media industry may have encouraged some newspapers to cover more unconventional topics—from family to sports to technology to climate change—at the expense of the traditional events of the day. In our final check, we ask whether long-run shifts in the newspapers’ coverage of particular events may induce spurious trends in our index. We do so by checking whether there is a substantial divergence between news coverage and actual occurrence of ‘fear-based’ phenomena that are somewhat easier to count and quantify, such as murders or hijackings or nuclear tests. Figure A.6 in the Appendix shows a remarkably good correlation between occurrence and extent of murders, hijackings and nuclear tests on the one hand, and the media coverage of these events on the other.

In sum, there are many historical trends that may have affected the information content of our index, and researchers should be aware of these issues. However, we believe that these trends are unlikely to significantly affect its usefulness for economic analysis.

## B.9 Appendix on: Checking the Saiz and Simonsohn (2013) Conditions

Saiz and Simonsohn (2013) state a number of conditions that must hold to obtain useful document-frequency based proxies for variables, such as geopolitical risk, that are otherwise difficult to measure. Our audit, among other things, makes sure that these conditions are indeed satisfied in our application. We provide a point-by-point discussion on how we perform these data checks below.

1. We verify that our search terms are more likely to be used when geopolitical risk is high than when it is low (*Data check 1: Do the different queries maintain the phenomenon and keyword constant?*, and *Data check 3: Is the keyword employed predominately to discuss the occurrence rather than non-occurrence of phenomenon?*). Across all the documents in our human audit, we found that 79 percent of articles measure high geopolitical risk, whereas only a smaller fraction of these articles measure declining tensions. We therefore conclude that increases in GPR are far more likely to lead to the use of our preferred search terms.
2. The GPR index is a frequency, thus satisfying data check 2 (*Data check 2. Is the variable being proxied a frequency?*).

3. We verify that the average number of documents found is large enough for variation to be driven by factors other than sampling error (*Data check 4: Is the average number of documents found large enough [...]?*). In particular, we verify that spikes in GPR are easily attributable to well-defined historical events at both a monthly and at a daily frequency. For instance, the first spike in monthly data since 1985 is in April 1986, reflecting the events that culminated with U.S. air strikes against Libya on April 15. However, the index also spikes, within the month, on April 8, when the United States accused Muammar el-Qaddafi of sponsoring terrorist acts aimed at Americans (such as the Berlin discotheque bombing which occurred on April 5). It also spikes on April 18, when British police found a bomb in a bag that was taken onto an El Al aircraft.
4. We verify that measurement error is low enough (*Data check 3, and Data check 5: Is the expected variance in the occurrence-frequency of interest high enough to overcome the noise associated with document-frequency proxying?*), by choosing combinations of search terms that—unlike with a single keyword or a bi-gram—are unlikely to be used outside of the realm of rising geopolitical risk. For instance, a naïve geopolitical risk index that merely counts the share of articles containing *geopolitics*, *war*, *military*, or *terrorism*/*t* is nearly as high in March 1991 as in January 1991, whereas the benchmark GPR index is much lower in March 1991. This occurs because the naïve index fails to account for the fact that many articles comment on the aftermath of the Gulf War, but do not explicitly mention rising threats or risks, something that our index takes into account.
5. We have constructed and examined broader (GPRAND) and narrower (GPRBASIC) versions of the index around the benchmark index (see Table A.3), thus satisfying data check number 5.
6. We construct a version of the GPR index that excludes articles containing economics and finance related words. The resulting index, plotted in Figure A.15, is nearly identical to the benchmark index, with a correlation of 0.99 (*Data check 6: [...] Does the chosen keyword have as its primary or only meaning the occurrence of the phenomenon of interest?*, and *Data check 7: [...] Does the chosen keyword also result in documents related to the covariates of the occurrence of interest?*).
7. In robustness checks, we use the naïve index as a placebo document-frequency variable in our vector autoregression (VAR) analysis. In particular, there is the possibility that it is not geopolitical risks per se that are bad, but that the overall tendency to discuss geopolitical events rises during recessions. We verify that adding the naïve index to the VAR does not change the predictive power of GPR in the VAR. (*Data check 8: Are there plausible omitted variables that may be correlated both with the document-frequency and its covariates?*)

## B.10 Appendix on: Comparison with Other Indicators of Geopolitical Risk

Several studies have constructed quantitative proxies of war intensity or terrorism-related events. One widely used source is the ICB (International Crisis Behavior) database, which provides detailed information on 476 major international crises that occurred during the period from 1918 to 2015. This database has been used in the political science literature as well as in studies on war and economics. The proxy, which counts the number of international crises per month, is plotted alongside the GPR index in the top panel of Figure A.16. The ICB crisis index and the GPR index display some comovement in various historical periods, such as the aftermath of World War I, the Cold War in the early 1960s and late 1970s, the Gulf War, and the Iraq War. But there are also some remarkable differences, such as during World War II, when the ICB crisis index is remarkably low, or during the mid-1990s, when the ICB crisis index is higher than the GPR index. Some differences are due to the different nature of the indexes—the ICB index counts international crises, including those that might receive little press coverage. Moreover, the GPR index displays substantially more high-frequency variation.

The second panel of Figure A.16 compares the GPR index with the national security component of the economic policy uncertainty index (EPU) constructed by Baker, Bloom, and Davis (2016). Like our measure, the national security EPU spikes during the Gulf War, after 9/11, and during the Iraq War. However, the GPR index seems to better capture other spikes in geopolitical risk that are missed by the national security EPU. The correlation between the two measures is 0.69, a plausible value because the national security component of the EPU captures uncertainty about policy responses to events associated with national security (of which geopolitical events are a subset), which is not the same concept as the uncertainty generated by geopolitical events.

Finally, the third panel of Figure A.16 compares the GPR index with an outside measure of political risk related to wars, the U.S. External Conflict Rating (ECR) constructed by the International Country Risk Guide (ICRG). The ratings constructed by the ICRG are largely subjective, as they are based on the insights of various analysts following developments in a particular country or region. The ECR measure moves only occasionally over the sample, changing on average once a year, with more pronounced movements and more frequent changes around 9/11, when both the GPR index and ICRG index spike. The correlation between the two series is 0.41.

## C Appendix on: VAR Evidence on the Effects of Geopolitical Risk

### C.1 Data Sources

We describe the macroeconomic series used in the VAR first. They are:

- the VIX (CBOE Market Volatility Index; Haver mnemonics: SPVXO@USECON);
- the log of real business fixed investment per capita (FH@USECON—Real Private Fixed Investment—divided by LN16N@USECON—Civilian Noninstitutional Population: 16 Years and Over)
- the log of private hours per capita (LHTPRIVA@USECON—Nonfarm Payrolls in Private Sector—divided by LN16N@USECON)
- the log of the Standard and Poor’s 500 index, divided by the Consumer Price Index for All Urban Consumers (SP500@USECON—Stock Price Index: Standard Poor’s 500 Composite—divided by PCUN@USECON—CPI-U: All Items)
- the log of the West Texas Intermediate price of oil, divided by the Consumer Price Index for All Urban Consumers (PZTEXP@USECON—Spot Oil Price: West Texas Intermediate—, divided by PCUN@USECON)
- the yield on two-year U.S. Treasuries (FCM2@USECON, 2-Year Treasury Note Yield at Constant Maturity)
- the Chicago Fed National Financial Conditions Index (NFCI: source Chicago Fed National Financial Conditions Index, source: FRED database)
- EPU index, used for the robustness analysis of Figure A.7 (SEPUI@USECON—Economic Policy Uncertainty Index)
- real GDP per capita, used for the exercise described in Figure A.9 (GDPH@USECON, Real Gross Domestic Product—divided by LN16N@USECON)

### C.2 Estimation

All VAR models presented in the paper are estimated using Bayesian techniques by imposing an inverse-Wishart prior on the reduced-form VAR parameters. All the results reported in the paper are based on 20,000 draws from the posterior distribution of the structural parameters, where the first 4,000 draws were used as a burn-in period.

### C.3 Robustness.

The result from the VAR analysis that changes in geopolitical risk have substantial and significant effects on investment and hours is robust to a variety of alternative specifications. Figure A.7 illustrates our findings. We modify our baseline specification in five alternative ways: (1) we replace the GPR index with a variable that equals the GPR index in the case of the ten largest spikes in the index, and zero otherwise;<sup>4</sup> (2) we increase the number of lags in the VAR from two to four; (3) we estimate a small-scale VAR with only GPR, the two-year yield, the financial conditions index, and either investment or hours; (4) we order the GPR in the Cholesky factorization of the VAR residuals after the financial variables; (5) we add the EPU Index to the VAR. Across all specifications, the effects of a shock to the GPR index are within the 68 percent credible sets of the baseline specification.

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<sup>4</sup> The spikes are identified as the ten largest observations of the index divided by its lagged three-year moving average. The impulse response to the shock in the GPR-spikes variable are virtually identical to those that obtain using a dummy indicator variable in place of the spikes.

## D Appendix on: Tail Effects of Geopolitical Risk

### D.1 Appendix on: Effects on Disaster Probability

The list of countries included in the sample is Argentina, Australia, Belgium, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Italy, Japan, Korea, Mexico, Netherlands, Norway, Peru, Portugal, Russia, Spain, Sweden, Switzerland, Taiwan, United Kingdom, and the United States.

For 24 of the 26 countries in our panel, we follow the procedure in [Nakamura et al. \(2013\)](#) and data on consumption to construct the disaster episodes. For China and Russia, the two countries in our panel that are not part of the sample used by [Nakamura et al. \(2013\)](#), we defined disasters as windows of years for which GDP growth is consistently in the bottom fifth of all GDP for that country in our sample. Under our expanded definition of disaster, disaster occur 17.6% of the time, compared to 17.9% in the sample of 24 countries in [Nakamura et al. \(2013\)](#).

The real per capita GDP data are from [Barro and Ursúa \(2012\)](#), extended through 2019 using the World Bank World Development Indicators (WDI) for all countries except Taiwan, for which real per capita GDP is taken from Haver Analytics based on underlying data from national statistical offices (series mnemonics A528GCPC@EMERGE). Growth is calculated using [Barro and Ursúa's](#) data until 2005, and the WDI data from 2006 through 2019.

### D.2 Appendix on: Quantile Effects of Geopolitical Risk

The initial sample includes the 26 countries used in the disaster probability regressions and listed in subsection [D.1](#).

Data on TFP growth are taken from the Long-Term Productivity Database (version v2.4, updated on October 2020) described in [Bergeaud, Cetto, and Lecat \(2016\)](#). The data were retrieved from <http://www.longtermproductivity.com/>. The countries included in the regression are Australia, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Italy, Japan, Mexico, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States.

Data on military expenditures as a share of GDP are taken from [Roser and Nagdy \(2013\)](#) and extend through 2016 for the 26 countries in the panel. The data were retrieved from <https://ourworldindata.org/military-spending>. Coverage for six countries is available as early as 1900. The average number of observations per country is 103.

## E Appendix on: Geopolitical Risk and Firm-Level Investment

### E.1 Appendix on: Details on Industry Exposure Regressions

To compute industry exposure, we use daily stock market returns data for the 49 Industry Portfolios from the Kenneth French data library, which groups NYSE, AMEX, and NASDAQ stocks based on four-digit SIC codes. We also incorporate the daily excess return of the market over the risk-free rate, taken to be the one-month T-bill rate

Stock market-based exposure is measured using the estimated coefficient on GPR from regressions of daily industry portfolio excess returns—calculated as market returns minus daily returns on a T-bill—on daily GPR. Because printed newspapers report event with one day delay, the relevant GPR for stock returns for day  $t$  is the geopolitical risk index reported in newspapers for day  $t + 1$ .

### E.2 Appendix on: Firm-Level Variables from Compustat

Our firm-level data source is the Compustat North America database. Our firm-level variables are investment rate, cash flows, and Tobin’s Q.

1. We construct the investment rate as the ratio of quarterly capital expenditures (DCAPXY, defined as the first difference of CAPXY with a firm’s fiscal year) to the beginning-of-period stock of property, plants, and equipment (lag of PPENTQ). We consider only firms with headquarters located in the United States (Compustat variable LOC is “USA”). We drop the observations where DCAPXY is negative and all observations where PPENTQ is less than \$5 million in chained 2009 dollars. We drop observations where the capital stock (PPENTQ) decreases and then increases (or vice versa) more than fifty percent between two successive quarters. We only include a firm if it has at least ten quarters of nonempty observations. We winsorize the variable at the 1st and 99th percentile.
2. We measure Tobin’s Q as the market value of equity plus the book value of assets minus book value of equity plus deferred taxes, all divided by the book value of assets. We normalize cash flows by beginning of period assets.

We construct Tobin’s Q using the quarterly Compustat items PRCCQ (share price at close), CSHOQ (common shares), ATQ (total assets), and CEQQ (common equity). The measure is equal to  $\frac{(PRCCQ * CSHOQ) + ATQ - CEQQ}{ATQ}$ . We winsorize the variable at the 1st and 99th percentile.

We construct cash flows using the ratio of Compustat item CHEQ (cash and short-term investments) to beginning-of-period PPE, which is the first lag of PPENTQ in our sample. The variable is winsorized at the 1st and 99th percentile.

3. We match Compustat firms to the 49 Fama-French industries using each firm’s unique SIC Code and following the industry definitions in [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data\\_Library/changes\\_ind.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/changes_ind.html).



### E.3 Appendix on: Search Terms for Firm-Level Geopolitical Risk

We perform text analysis on 157,000 transcripts of quarterly earnings calls of firms listed in U.S. stock markets for the sample 2005-2019 that we are able to match with the corresponding quarterly firm-level Compustat data. We obtain the conference call transcripts from the Fair Disclosure Wire and from Standard & Poor. We construct a firm-quarter variable that counts the occurrence of mentions of geopolitical risks in the earnings call. Specifically, we count the joint occurrences of risk and adverse event words within ten words of ‘geopolitical’ words, and normalize the number of joint occurrences by the total number of words in the transcript. For instance, if a firm’s earnings call reads like “We have been *worried* because of the *war*. Additionally, we have scaled back our investment plans because of *concerns* about *war-related* sanctions,” its firm-specific geopolitical risk index will equal  $\frac{2}{22}$ , where 2 are the instances of mentions, and 22 are the total words in the transcript.

The number of joint occurrences is zero for 81.5 percent of the firm-quarter observations, one for 12.1 percent of observations, two for 3.6 percent of observations, and greater than two for 2.5 percent of observations.

The list of ‘geopolitical’ terms in the earnings calls is: *war*, *military*, *terror\**, *geopolitical*, *conflict*, *"Middle East"*, *Iraq*, *Afghanistan*, *Iran*, *Syria*, *Libya*, *Ukrain\**, *Russia\**, *"North Korea"*, *Venezuela*, *coup*, *expropriation*, *confiscation*, *nationalism*, *security*, *protest\**, *country*, *countries*, *political*, *retaliation*, *unrest*, *geograph\**, *troop\**, *sanction*, *sanctions*, *embargo*, *wars*, *warfare*, *army*, *navy*, *weapon\**, *combat*, *missile\**, *immigration*, *diplomacy*.

We require the ‘risk-related’ terms to be within ten words of one following risk/adverse event terms. The list of risk/act terms is: *risk\**, *uncertain\**, *variab\**, *chance\**, *possib\**, *pending*, *doubt\**, *prospect\**, *bet*, *bets*, *betting*, *exposed*, *likel\**, *threat\**, *probab\**, *unknown\**, *potential*, *concern\**, *tension\**, *issue\**, *instability*, *cautio\**, *fear\**, *volatil\**, *varying*, *unclear*, *speculative*, *hesitant*, *headwind\**, *backlog\**, *dispute*, *disrupt\**, *worry\**, *worries*, *hurdle\**, *obstacle\**, *disturbance\**, *hostil\**, *unrest*, *conflict*, *pressure\**, *crisis*, *trigger\**, *impact*, *peril\**, *effect\**, *acts*, *attack\**, *incident\**.

In an earlier version of this paper (see [https://www.matteoiacoviello.com/gpr\\_files/GPR\\_PAPER\\_DEC\\_2019.pdf](https://www.matteoiacoviello.com/gpr_files/GPR_PAPER_DEC_2019.pdf)), the list of geopolitical terms included *China*. We removed references to China in later versions since many firm-level ‘GPR hits’ in 2019 appeared to refer to the ‘trade war’ between United States and China.

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Table A.1: Most and Least Likely Words in Newspapers on Days of High Geopolitical Tensions, Relative to any Day in the Sample.

Word	Word Type	Term Frequency High-GPR Days	Term Frequency Average	Odds
blockad	Event	0.069	0.006	11.6
terror	Event	0.186	0.019	9.7
invas	Act	0.117	0.015	8.0
communiqu		0.064	0.008	7.9
war	Event	1.710	0.237	7.2
terrorist	Event	0.116	0.016	7.2
militari	Event	0.599	0.090	6.6
coup	Event	0.053	0.008	6.3
crisi	Threat	0.254	0.042	6.1
troop	Actor	0.605	0.104	5.8
threat	Threat	0.183	0.034	5.4
armi	Actor	0.744	0.146	5.1
attack	Act	0.720	0.143	5.0
alli	Actor	0.403	0.081	5.0
peac	Event	0.540	0.111	4.8
neutral		0.068	0.015	4.6
combat		0.057	0.012	4.6
invad	Act	0.063	0.014	4.4
bomber	Event	0.057	0.013	4.3
enemi	Actor	0.121	0.028	4.3
missil	Event	0.089	0.021	4.2
fear	Threat	0.259	0.063	4.1
command		0.183	0.046	4.0
conflict	Event	0.077	0.020	3.9
tank		0.069	0.018	3.8
submarin		0.064	0.017	3.8
strike	Act	0.416	0.119	3.5
forc		0.662	0.189	3.5
civilian		0.062	0.018	3.5
soldier		0.145	0.042	3.4
...	...	...	...	...
season		0.006	0.064	0.1
percent		0.007	0.084	0.1
photo		0.004	0.074	0.1
sport		0.008	0.181	0.0
ms		0.001	0.058	0.0

Note: Top 30 words (and bottom 5 words) on days of extremely high geopolitical tensions, relative to any day in the sample (The days of high geopolitical tensions are the days in which adverse geopolitical events are featured in a banner headline on the front page of *The New York Times*). The term frequency on high-GPR days (*TFH*) is the relative occurrence of the word (expressed in percent) on days in which adverse geopolitical events are featured in a banner headline on the front page of *The New York Times*. The average term frequency (*TFA*) is the relative occurrence of the word on any day. The ‘Odds’ column reports *TFH/TFA*. The sample runs from 1900 and 2019. Proper nouns, stop-words and uncommon (not in the top-400 either on days of high tensions or on any other day) words are excluded from the list. Words that are featured in the headline GPR index are labeled in the ‘Word Type’ column.

Table A.2: Most Likely Words in Newspapers on Days of High Geopolitical Tensions: Comparing the 1900-59 sample with the 1960-2019 sample.

Relatively more frequent words in Early Sample					Relatively more frequent words in Late Sample			
Rank	Word	Term Frequency Early	Term Frequency Late	Odds Early	Word	Term Frequency Late	Term Frequency Early	Odds Late
1	communiqu	0.093	0.004	24.8	terrorist	0.352	0.004	87.8
2	submarin	0.091	0.007	12.9	televis	0.103	0.001	77.3
3	leagu	0.146	0.012	12.4	nuclear	0.138	0.003	41.5
4	marshal	0.096	0.008	12.0	missil	0.261	0.007	39.1
5	neutral	0.095	0.010	9.7	terror	0.532	0.023	23.4
6	labor	0.180	0.020	9.1	vow	0.089	0.004	21.1
7	fleet	0.093	0.013	7.3	senior	0.077	0.004	20.5
8	committe	0.215	0.032	6.7	ceasefir	0.088	0.006	15.2
9	red	0.113	0.018	6.3	jet	0.080	0.006	12.9
10	treati	0.175	0.031	5.7	target	0.145	0.020	7.4
11	repli	0.089	0.016	5.4	weapon	0.137	0.022	6.3
12	men	0.344	0.065	5.3	alert	0.084	0.014	6.0
13	deleg	0.094	0.021	4.5	role	0.114	0.021	5.4
14	receiv	0.120	0.028	4.3	sanction	0.077	0.015	5.1
15	confer	0.225	0.059	3.8	coup	0.112	0.024	4.6
16	situat	0.139	0.037	3.8	ground	0.182	0.040	4.5
17	board	0.129	0.034	3.8	respons	0.190	0.042	4.5
18	navi	0.216	0.058	3.7	led	0.086	0.022	4.0
19	present	0.118	0.034	3.5	famili	0.087	0.023	3.8
20	session	0.092	0.027	3.4	region	0.101	0.028	3.7
21	result	0.100	0.030	3.4	combat	0.109	0.032	3.4
22	food	0.085	0.026	3.3	launch	0.106	0.033	3.3
23	servic	0.186	0.059	3.1	just	0.145	0.046	3.1
24	coast	0.084	0.027	3.1	support	0.295	0.097	3.0
25	ship	0.257	0.089	2.9	militari	1.098	0.363	3.0
26	hear	0.086	0.030	2.9	past	0.077	0.026	3.0
27	statement	0.149	0.053	2.8	oil	0.125	0.043	2.9
28	naval	0.117	0.042	2.8	emerg	0.111	0.043	2.6
29	appeal	0.114	0.042	2.7	school	0.100	0.039	2.6
30	repres	0.090	0.034	2.7	began	0.125	0.049	2.5
31	plant	0.087	0.033	2.6	conflict	0.131	0.051	2.5
32	assert	0.093	0.036	2.6	mission	0.080	0.032	2.5
33	discuss	0.101	0.040	2.5	fear	0.436	0.174	2.5
34	gun	0.102	0.041	2.5	try	0.085	0.035	2.4
35	foe	0.105	0.043	2.5	week	0.096	0.040	2.4
36	drive	0.145	0.060	2.4	threat	0.302	0.126	2.4
37	declar	0.295	0.122	2.4	polit	0.197	0.083	2.4
38	vote	0.223	0.093	2.4	attack	1.173	0.506	2.3
39	pass	0.095	0.040	2.4	tank	0.111	0.049	2.3
40	taken	0.109	0.046	2.4	blockad	0.112	0.049	2.3
41	depart	0.192	0.083	2.3	turn	0.140	0.064	2.2
42	headquart	0.099	0.043	2.3	crisi	0.397	0.186	2.1
43	train	0.125	0.054	2.3	assault	0.089	0.042	2.1
44	port	0.090	0.039	2.3	administr	0.220	0.106	2.1
45	sea	0.120	0.053	2.3	withdraw	0.104	0.051	2.0
46	worker	0.130	0.058	2.3	begin	0.152	0.076	2.0
47	enemi	0.147	0.066	2.2	southern	0.077	0.039	2.0
48	line	0.207	0.095	2.2	look	0.080	0.040	2.0
49	point	0.136	0.063	2.2	thousand	0.122	0.062	2.0
50	sent	0.112	0.053	2.1	leader	0.369	0.190	1.9

Note: Top 50 words ranked by relative odds on days of extremely high geopolitical tensions in two subsamples. The early (late) sample runs from 1900 (1960) through 1959 (2019). Proper nouns, stop-words, and uncommon words (not in the top 200) are excluded from the list. The ‘Odds Early’ (‘Odds Late’) column is calculated as  $TFE/TFL$  ( $TFL/TFE$ ), where  $TFE$  is ‘Term Frequency Early’, and  $TFL$  is ‘Term Frequency Late’.

Table A.3: Validation of GPR Index: Subsample Averages and Correlations with Narrative Index

Index	Share of Articles	Index: 1900-1959	Index: 1960-2019	Corr.with Narrative	Corr.with Narrative, 1900-1959	Corr.with Narrative, 1960-2019	Type I error (%)
NARRATIVE	17.9	109.0	91.0				—
GPR	3.6	112.7	87.3	0.76	0.86	0.58	21
GPRNOEW	6.9	102.4	97.6	0.73	0.86	0.51	27
GPRBASIC	3.1	98.9	101.1	0.72	0.84	0.50	31
GPRAND	12.7	123.5	76.5	0.53	0.81	0.35	40

Note: All indexes are normalized to have mean equal to 100 in the sample 1900-2019.

The NARRATIVE GPR is hand-coded scoring articles above the fold in *The New York Times*. The article share for the narrative index is constructed so that a 100 percent share would indicate that every day there is a banner article on geopolitical risks in the print edition of the *New York Times*.

The GPRNOEW index does not exclude from the search the excluded words listed in Table 1.

The GPRBASIC index only searches for the most frequent words highlighted in red in Table 1 and does not exclude from the search the words listed in Table 1.

The GPRAND index replaces the ‘N/2’ proximity operator in Table 1 with the Boolean operator ‘AND’.

Table A.4: Validation of Geopolitical Risk: Historical Frequency of Individual Words

Rank	Variable	Word Type	Correlation with GPR	Share of Articles	Share 1900-1939	Share 1940-1979	Share 1980-2019
1	War	WAR	0.86	25.0	25.4	31.8	17.9
2	Revolution	WAR	-0.14	3.9	4.0	3.8	3.9
3	Conflict	WAR	0.13	3.5	2.4	3.3	4.9
4	Hostilities	WAR	0.46	1.0	1.2	1.0	0.8
5	Revolt	WAR	0.13	0.9	1.1	1.0	0.5
6	Coup	WAR	-0.08	0.9	0.5	1.0	1.1
7	Uprising	WAR	-0.03	0.6	0.5	0.5	0.7
8	Insurrection	WAR	-0.10	0.2	0.3	0.1	0.1
9	Geopolitical	WAR	-0.09	0.1	0.0	0.0	0.2
1	Concern	RISK	-0.20	16.2	14.2	15.0	19.5
2	Threat	RISK	-0.03	10.5	8.0	10.0	13.7
3	Trouble	RISK	-0.37	10.5	10.8	9.2	11.6
4	Fear	RISK	-0.22	9.9	9.6	8.2	11.9
5	Warning	RISK	0.17	9.8	7.5	10.2	11.6
6	Doubt	RISK	-0.07	9.0	11.7	7.7	7.7
7	Danger	RISK	0.02	7.8	8.6	6.8	8.0
8	Risk	RISK	-0.15	5.6	2.4	3.5	10.8
9	Dispute	RISK	-0.17	4.7	3.2	5.0	5.9
10	Crisis	RISK	0.00	4.4	2.3	4.2	6.6
11	Tension	RISK	-0.12	2.0	0.6	2.1	3.3
12	Inevitable	RISK	0.06	1.5	1.2	1.4	1.6
13	Peril	RISK	0.37	1.4	1.7	1.3	1.1
14	Menace	RISK	0.33	1.1	1.8	1.0	0.4
15	Scare	RISK	-0.19	0.8	0.6	0.6	1.1
16	Imminent	RISK	0.29	0.7	0.6	0.6	0.9
17	Footing	RISK	0.08	0.4	0.5	0.3	0.5
18	Brink	RISK	-0.13	0.4	0.3	0.4	0.7
1	Begin	WARBEGIN	-0.16	34.5	28.2	32.1	43.1
2	Start	WARBEGIN	-0.16	34.3	26.7	32.8	43.3
3	Declare	WARBEGIN	0.14	14.6	23.1	13.4	7.3
4	Launch	WARBEGIN	0.13	4.0	2.5	3.8	5.8
5	Outbreak	WARBEGIN	0.58	1.0	1.3	0.9	0.7
6	Breakout	WARBEGIN	0.17	0.8	0.6	0.9	1.0
7	Proclamation	WARBEGIN	0.39	0.5	0.8	0.5	0.3
1	Army	ACTOR	0.79	12.6	13.2	17.1	7.5
2	Navy	ACTOR	0.65	6.9	7.9	9.2	3.5
3	Allied	ACTOR	0.83	4.7	4.4	5.9	3.8
4	Enemy	ACTOR	0.87	4.4	4.8	5.5	2.8
5	Foe	ACTOR	0.59	2.0	2.6	2.2	1.2
6	Rebels	ACTOR	-0.18	1.1	0.8	0.8	1.6
7	Aerial	ACTOR	0.61	0.9	1.0	1.2	0.5
8	Insurgents	ACTOR	-0.26	0.7	0.8	0.4	1.1
1	Sanction	BUILDUP	-0.13	1.4	1.2	0.9	2.2
2	Buildup	BUILDUP	0.13	1.0	0.6	1.3	1.2
3	Mobilize	BUILDUP	0.72	0.8	0.8	1.1	0.7
4	Blockade	BUILDUP	0.44	0.5	0.6	0.6	0.3
5	Embargo	BUILDUP	0.26	0.5	0.5	0.4	0.5
6	Ultimatum	BUILDUP	0.28	0.3	0.5	0.3	0.2
7	Quarantine	BUILDUP	-0.03	0.2	0.4	0.1	0.1
1	Drive	FIGHT	0.14	17.0	13.5	17.4	20.2
2	Attack	FIGHT	0.73	13.2	11.8	13.7	14.2
3	Advance	FIGHT	0.46	11.8	13.7	11.7	9.8
4	Strike	FIGHT	0.07	7.5	6.9	8.3	7.2
5	Launch	FIGHT	0.13	4.0	2.5	3.8	5.8
6	Raid	FIGHT	0.72	3.1	3.0	3.6	2.7
7	Shell	FIGHT	0.78	3.1	2.7	3.2	3.1
8	Invasion	FIGHT	0.73	3.0	2.8	3.3	2.8
9	Offensive	FIGHT	0.41	2.8	1.5	2.6	4.4
10	Clash	FIGHT	0.01	2.1	2.1	2.1	2.2
1	Military	MILITARY	0.81	11.3	8.2	13.9	11.9
2	Troops	MILITARY	0.87	6.0	6.0	7.2	4.6
3	Bomb	MILITARY	0.70	5.5	2.5	7.9	6.1
4	Arms	MILITARY	0.35	5.2	5.1	5.0	5.3
5	Weapon	MILITARY	0.03	4.1	1.8	4.2	6.3
6	Missile	MILITARY	-0.02	1.3	0.2	1.7	2.1
7	Warhead	MILITARY	-0.06	0.2	0.0	0.2	0.3
1	Peace	PEACE	0.58	7.6	8.2	8.7	5.8
2	Treaty	PEACE	-0.01	2.7	3.5	2.9	1.7
3	Parley	PEACE	0.16	0.7	0.9	1.1	0.0
4	Truce	PEACE	0.06	0.5	0.4	0.8	0.5
5	Armistice	PEACE	0.25	0.5	0.8	0.6	0.1
1	Threat	PEACEDISRUPT	-0.03	10.5	8.0	10.0	13.7
2	Reject	PEACEDISRUPT	-0.12	5.1	2.7	5.6	6.9
3	Peril	PEACEDISRUPT	0.37	1.4	1.7	1.3	1.1
4	Disrupt	PEACEDISRUPT	-0.06	1.3	0.4	1.2	2.4
5	Menace	PEACEDISRUPT	0.33	1.1	1.8	1.0	0.4
6	Boycott	PEACEDISRUPT	-0.19	0.8	0.5	0.9	0.9
1	Terrorism/t	TERROR	0.00	2.0	0.3	0.9	4.8
2	Guerrilla	TERROR	0.00	1.0	0.1	1.3	1.7
3	Hostage	TERROR	-0.02	0.6	0.1	0.4	1.3
1	Kill	TERRORACT	-0.05	14.8	13.1	13.0	18.2
2	Act	TERRORACT	-0.03	14.5	16.0	13.8	13.7
3	Attack	TERRORACT	0.70	10.8	9.4	11.2	11.8
4	Strike	TERRORACT	0.07	7.5	6.9	8.3	7.2
5	Bomb	TERRORACT	0.70	5.5	2.5	7.9	6.1
6	Hijack	TERRORACT	0.02	0.3	0.0	0.3	0.6

Note: The table shows key summary statistics for the risk-related, act-related, and war-related words used in the construction of the GPR index.

Table A.5: Validation of Geopolitical Risk: Historical Frequency of Selected Word Combinations

Rank	Search Terms	Bigram Type	Correlation with GPR	Share of Articles	Share 1900-1939	Share 1940-1979	Share 1980-2019
1	War Escalation Terms	—	0.87	0.97	0.93	1.45	0.52
2	Military Buildup Terms	—	0.62	0.93	0.73	1.07	0.98
3	War Begin Terms	—	0.84	0.82	1.14	0.93	0.40
4	War Risk Terms	—	0.73	0.52	0.63	0.63	0.30
5	Nuclear Risk Terms	—	0.00	0.39	0.00	0.61	0.58
6	Terror Act Terms	—	0.06	0.32	0.02	0.25	0.71
7	Peace Risk Terms	—	0.23	0.13	0.12	0.19	0.07
8	Terror Risk Terms	—	0.02	0.11	0.01	0.05	0.26
1	Risk Words N/2 War	War Threat	0.75	0.79	0.89	0.97	0.52
2	Risk Words N/2 Conflict	War Threat	0.03	0.11	0.08	0.11	0.16
3	Risk Words N/2 Revolution	War Threat	0.05	0.07	0.11	0.05	0.04
4	Risk Words N/2 Revolt	War Threat	0.11	0.03	0.05	0.03	0.01
5	Risk Words N/2 Hostilities	War Threat	0.09	0.03	0.03	0.03	0.03
6	Risk Words N/2 Coup	War Threat	-0.03	0.02	0.01	0.02	0.03
7	Risk Words N/2 Uprising	War Threat	0.02	0.02	0.03	0.01	0.01
8	Risk Words N/2 Geopolitical	War Threat	-0.06	0.01	0.00	0.00	0.02
9	Risk Words N/2 Insurrection	War Threat	-0.00	0.00	0.01	0.00	0.00
1	Military Words AND Sanction	Military Buildups	-0.03	0.52	0.28	0.25	1.05
2	Military Words AND Mobilize	Military Buildups	0.71	0.42	0.46	0.52	0.29
3	Military Words AND Buildup	Military Buildups	0.22	0.38	0.12	0.57	0.45
4	Military Words AND Blockade	Military Buildups	0.46	0.26	0.24	0.33	0.21
5	Military Words AND Embargo	Military Buildups	0.20	0.23	0.17	0.19	0.33
6	Military Words AND Ultimatum	Military Buildups	0.39	0.13	0.17	0.13	0.09
7	Military Words AND Quarantine	Military Buildups	0.10	0.05	0.08	0.04	0.03
1	Nuclear Weapons AND Risk Words	Nuclear Threat	-0.09	0.43	0.00	0.40	0.90
2	Nuclear War AND Risk Words	Nuclear Threat	-0.03	0.16	0.00	0.19	0.29
3	Atom Bomb AND Risk Words	Nuclear Threat	0.08	0.15	0.00	0.32	0.12
4	Nuclear Test AND Risk Words	Nuclear Threat	-0.00	0.06	0.00	0.11	0.07
5	Nuclear Bomb AND Risk Words	Nuclear Threat	-0.07	0.06	0.00	0.06	0.12
6	Nuclear Missile AND Risk Words	Nuclear Threat	-0.05	0.06	0.00	0.03	0.14
7	Hydrogen Bomb AND Risk Words	Nuclear Threat	0.00	0.05	0.00	0.12	0.03
8	Atomic War AND Risk Words	Nuclear Threat	0.04	0.03	0.00	0.08	0.01
9	H Bomb AND Risk Words	Nuclear Threat	0.01	0.03	0.00	0.07	0.01
1	War-Begin Words N/2 War	War Begin	0.86	1.53	1.92	1.68	0.98
2	War-Begin Words N/2 Revolution	War Begin	-0.03	0.13	0.17	0.10	0.11
3	War-Begin Words N/2 Hostilities	War Begin	0.49	0.08	0.14	0.07	0.02
4	War-Begin Words N/2 Conflict	War Begin	0.28	0.06	0.04	0.04	0.08
5	War-Begin Words N/2 Revolt	War Begin	0.07	0.04	0.05	0.04	0.02
6	War-Begin Words N/2 Uprising	War Begin	-0.06	0.03	0.02	0.02	0.07
7	War-Begin Words N/2 Coup	War Begin	-0.04	0.01	0.01	0.01	0.02
8	War-Begin Words N/2 Insurrection	War Begin	-0.04	0.01	0.01	0.01	0.00
9	War-Begin Words N/2 Geopolitical	War Begin	-0.01	0.00	0.00	0.00	0.00
1	Actor Words N/2 Attack	War Escalation	0.85	0.72	0.68	1.00	0.47
2	Actor Words N/2 Advance	War Escalation	0.77	0.20	0.27	0.25	0.07
3	Actor Words N/2 Drive	War Escalation	0.79	0.18	0.21	0.25	0.07
4	Actor Words N/2 Invasion	War Escalation	0.68	0.17	0.14	0.26	0.12
5	Actor Words N/2 Raid	War Escalation	0.75	0.13	0.11	0.21	0.07
6	Actor Words N/2 Offensive	War Escalation	0.74	0.12	0.09	0.19	0.08
7	Actor Words N/2 Launch	War Escalation	0.71	0.09	0.06	0.13	0.08
8	Actor Words N/2 Shell	War Escalation	0.76	0.09	0.09	0.12	0.04
9	Actor Words N/2 Strike	War Escalation	0.62	0.08	0.07	0.11	0.06
10	Actor Words N/2 Clash	War Escalation	0.21	0.08	0.05	0.09	0.08
1	Terror Words N/2 Attack	Terror Act	0.07	0.44	0.01	0.11	1.22
2	Terror Words N/2 Kill	Terror Act	-0.05	0.13	0.01	0.15	0.24
3	Terror Words N/2 Act	Terror Act	-0.01	0.11	0.01	0.06	0.25
4	Terror Words N/2 Bomb	Terror Act	-0.07	0.08	0.01	0.06	0.16
5	Terror Words N/2 Strike	Terror Act	0.06	0.03	0.00	0.01	0.06
6	Terror Words N/2 Hijack	Terror Act	0.03	0.02	0.00	0.02	0.04

Note: The table shows key summary statistics for selected two-word combinations used in the construction of the GPR index. The first 8 entries in the table correspond to the eight meta-categories behind the construction of the index. The next entries are selected slices of the meta-categories, calculated without removing from the search the excluded words listed in Table 1: for this reason, the entries in a category may be larger than the meta-categories themselves.



Table A.6: Correlations of Geopolitical Risk with Selected News-based Indexes of Other Phenomena

Keyword	Correlation	Share:1900-2019	Share:1900-59	Share:1960-2019
GPR		3.61	4.07	3.15
INFLATION	0.30	7.48	6.49	8.47
SPORT	0.07	2.30	0.87	3.74
OLYMPIC	-0.03	1.17	0.42	1.91
DISASTER	-0.16	1.74	1.08	2.40
FLU	0.01	0.73	0.76	0.70
PRESIDENT	-0.03	1.47	0.57	2.37
CAMPUS	0.05	0.13	0.07	0.19
MURDER	-0.38	5.94	4.90	6.99
COALSTRIKE	-0.06	0.53	0.87	0.19
WEDDING	0.16	3.95	4.56	3.33

Note: Pairwise correlations of GPR Index with selected indexes capturing selected news. Specifically, we construct news-based indexes of the phenomena above calculating the share of articles containing any of the following words or word combinations:

INFLATION: inflation\* OR ((price\* OR wage\* OR cost\*) N/2 (rise OR rising OR high\* OR increas\*))

SPORT: (olympics OR olympiad OR "olympic games" OR "world cup" OR "world series").

OLYMPIC: (olympics OR olympiad OR "olympic games").

DISASTER: (hurricane\* OR earthquake\* OR tsunami\* OR wildfire\* OR tornado\*).

FLU: (flu OR influenza).

PRESIDENTELECTION: (president\* N/2 election\*).

CAMPUSPROTEST: (campus OR college\* OR university\* OR school\*) N/2 (riot\* OR protest\*).

MURDER: (murder\* OR homicide\*).

COALSTRIKE: (coal AND strike).

WEDDING: (wedding).

Table A.7: Geopolitical Risk and Firm-Level Investment: Robustness Analysis

$IK(t+2)$	(1)	(2)
$\Delta GPR \times \text{Industry Exposure}$	-0.19 (0.08)	-0.18 (0.17)
$\Delta GPR$	-1.72 (1.32)	
Cash Flow	2.72 (0.46)	2.78 (0.46)
Tobin's Q	8.91 (1.68)	7.93 (1.56)
$IK(t-1)$	0.31 (0.01)	0.30 (0.01)
Observations	374,727	374,727
Firm Fixed Effects	Yes	Yes
Time Effects	No	Yes
R-squared	0.45	0.47
Sample	85Q1-19Q4	85Q1-19Q4
Standard errors in parentheses		

Note: The table shows robustness results from regressions of firm-level investment on geopolitical risk at the industry level. In the main text, the industry exposure measure is a dummy variable equal to one for industries with above-median exposure, and zero otherwise. Here we replace the dummy variable used in columns 1 and 2 of Table 5 with the beta coefficients estimated from regression 6 in the main text, with the sign switched so that positive values indicate high exposure.

The dependent variable is  $IK$  (100 times the log of the investment rate) two quarters ahead. All variables (except the dummy exposure variable) are standardized. The standard errors are clustered by industry and quarter.

Table A.8: Granger Causality Tests

<i>Variable Groups</i>	(1)	(2)	(3)
	LGPR	LGPR	LGPR
Macro	1.02 (0.42)	0.87 (0.55)	0.91 (0.52)
Financial	1.33 (0.24)	1.34 (0.24)	1.71 (0.12)
Uncertainty	1.09 (0.36)	0.37 (0.90)	1.50 (0.18)
LGPR	106.88 (0.00)		
LGPR		136.90 (0.00)	0.91 (0.44)
LGPR		0.30 (0.83)	49.40 (0.00)
Adj. $R^2$	0.60	0.63	0.52

Note: The entries in the table are the test statistics and p-values (in parentheses) for the joint hypothesis that all lags of the variables included in each group are equal to zero. See Appendix B.5 for additional details.

Figure A.1: Selected Articles Mentioning Geopolitical Risk by Subcategory



(a) War Threats: September 1938



(b) Peace Threats: April 1946



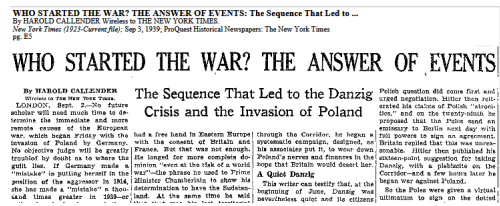
(c) Military Buildup: October 1962



(d) Nuclear Threats: August 1963



(e) Terrorist Threats: October 2001



(f) Beginning of War: September 1939



(g) Escalation of War: June 1944



(h) Terrorist Acts: September 2001

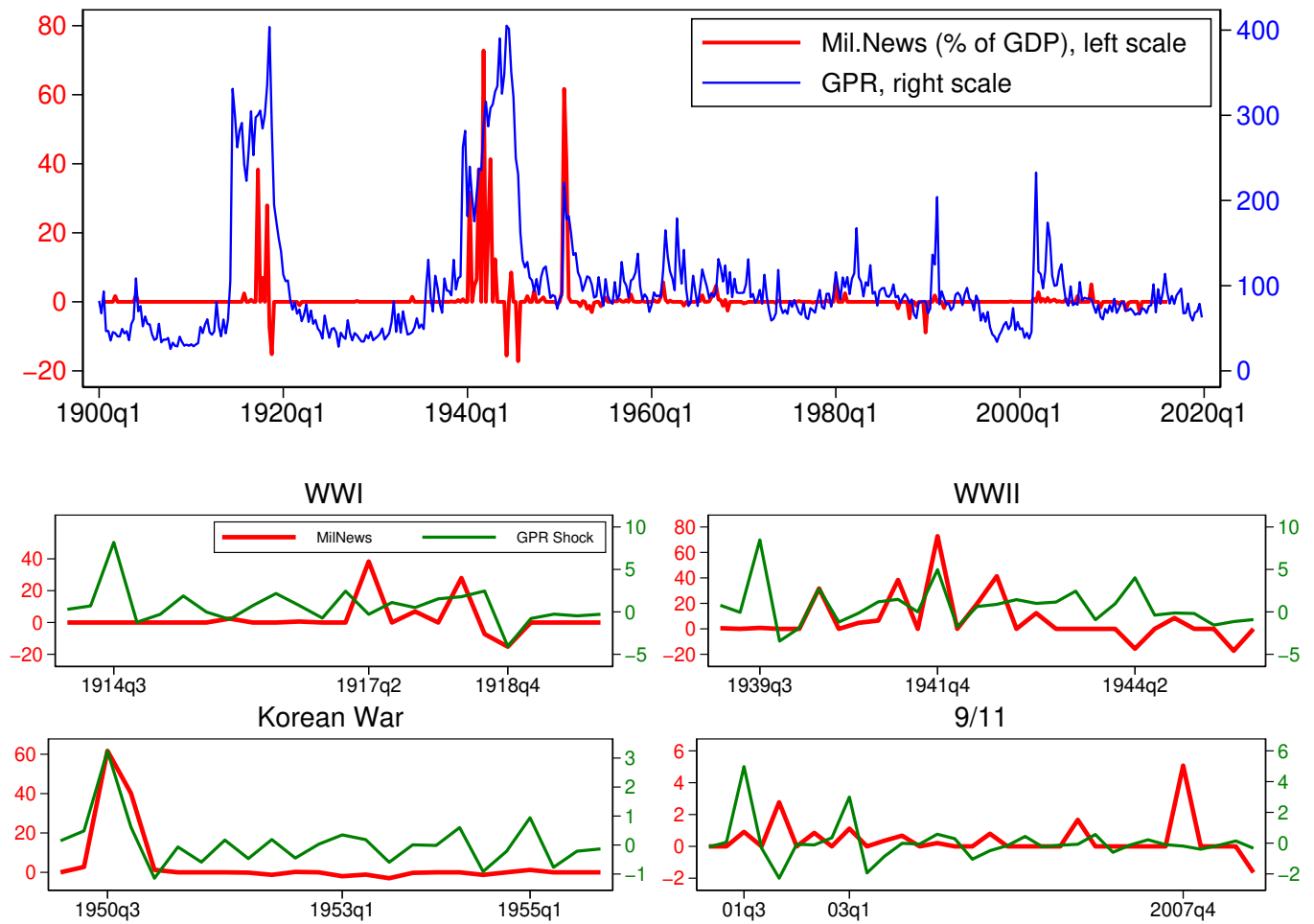
Note: Examples of newspaper articles capturing each of the 8 subcategories of geopolitical risk described in Table 1.

Figure A.2: Banner Headlines and Narrative GPR Index



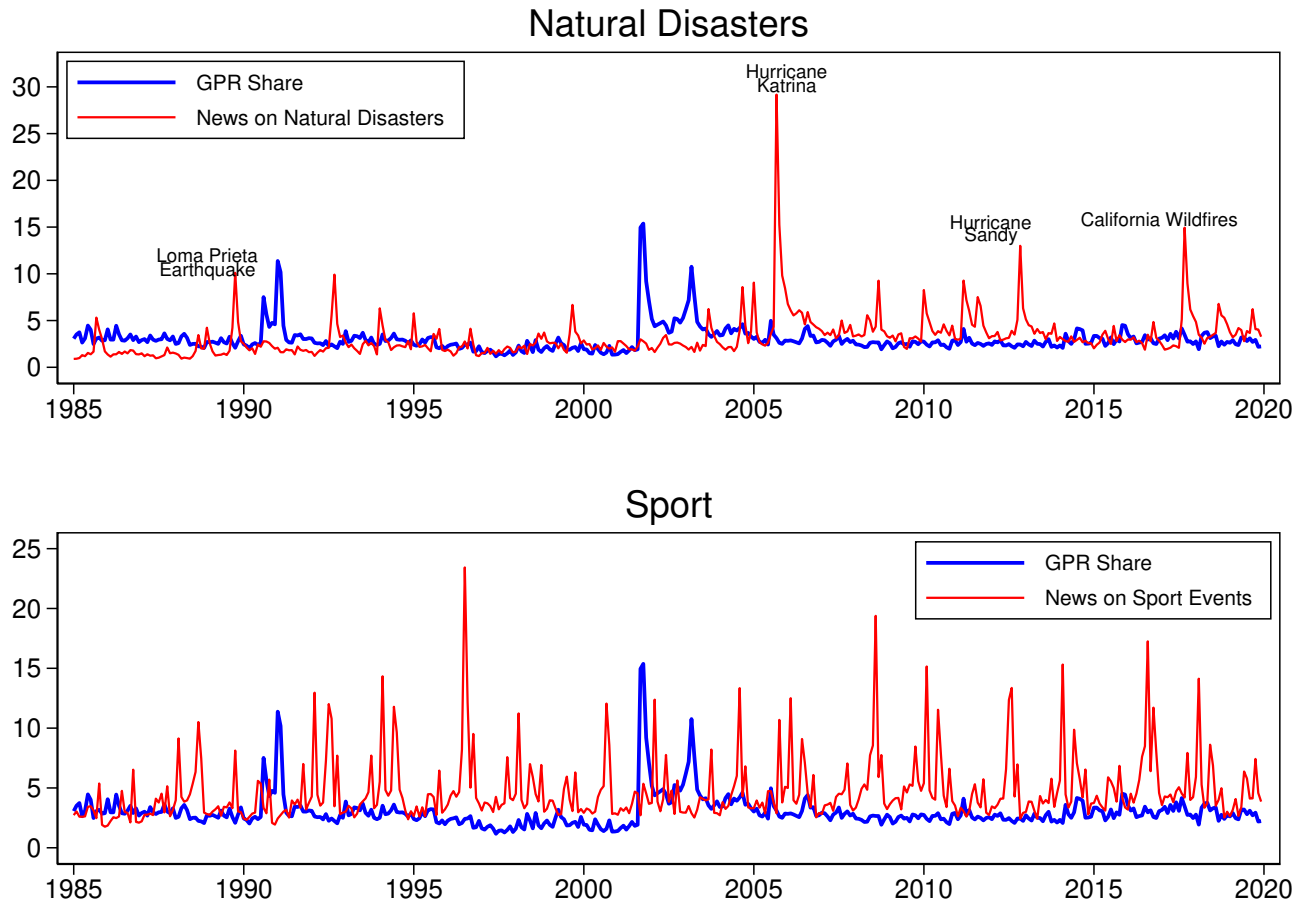
Note: Examples of front-page headlines coded respectively as 5 (top), 2 (middle) and 1 (bottom) in the construction of the narrative GPR index.

Figure A.3: Comparison with Military Spending News Variable: Detail on Specific Events



Note: Detailed Time-Series Comparison of the quarterly GPR Index (top panel) and selected quarterly GPR shocks (bottom four panels) with Military Spending News variable from [Ramey \(2011\)](#). The GPR shocks are calculated as the residual of a monthly autoregression of geopolitical risk on three lags, averaged over the quarter, and standardized.

Figure A.4: GPR and News on Natural Disasters and Sport Events

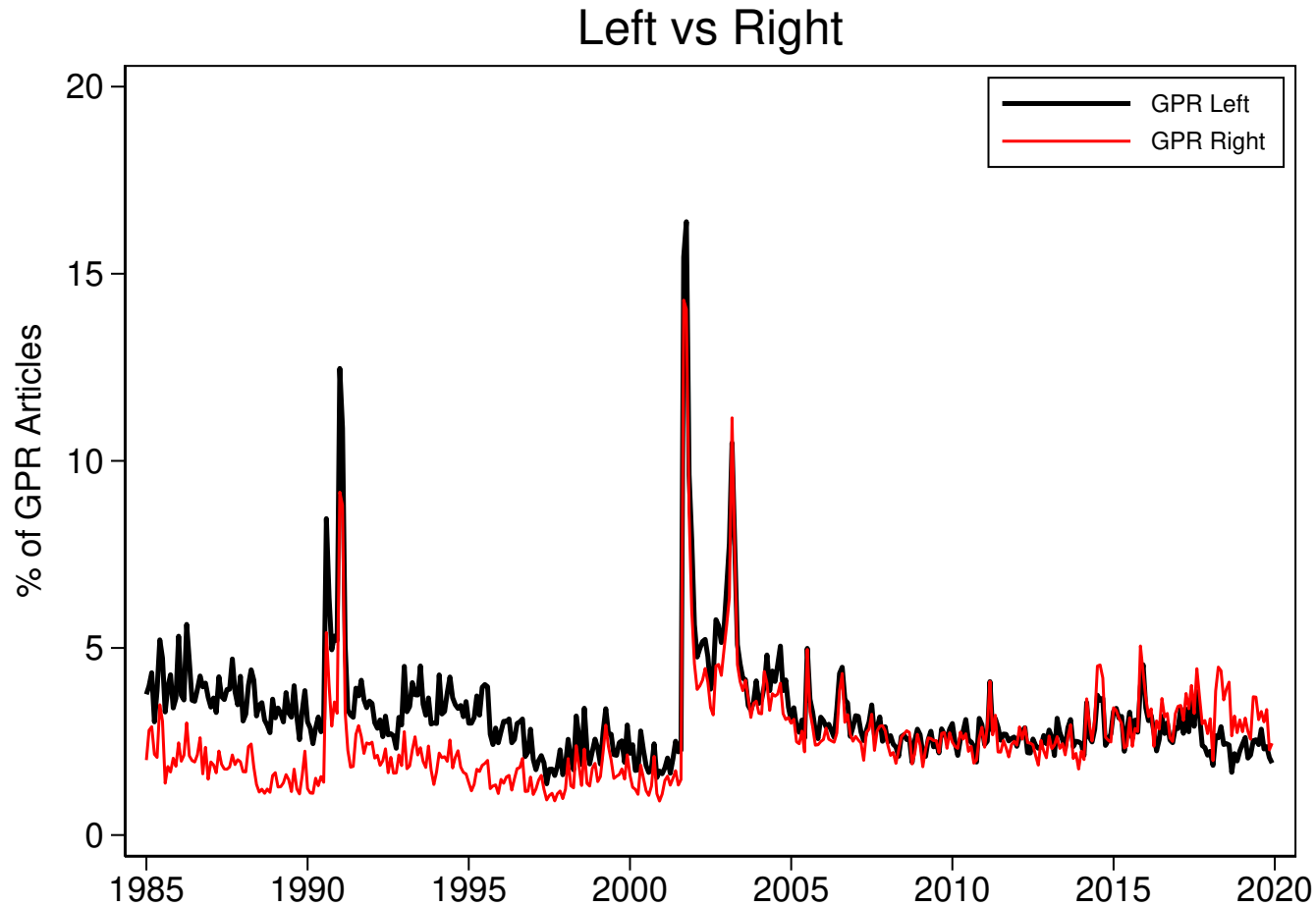


Note: The top panel of the figure compares the recent GPR index with a news-based index of natural disasters, constructed by counting the share of newspapers articles mentioning any of the following words: earthquake(s), hurricane(s), tornado(es), tsunami(s), or wildfire(s).

The bottom panel compares the GPR index with a news-based index of sport popularity, constructed by counting the share of articles mentioning: ‘Olympics’ OR ‘olympiad’ OR ‘Olympic Games’ OR ‘World Cup’ OR ‘World Series.’

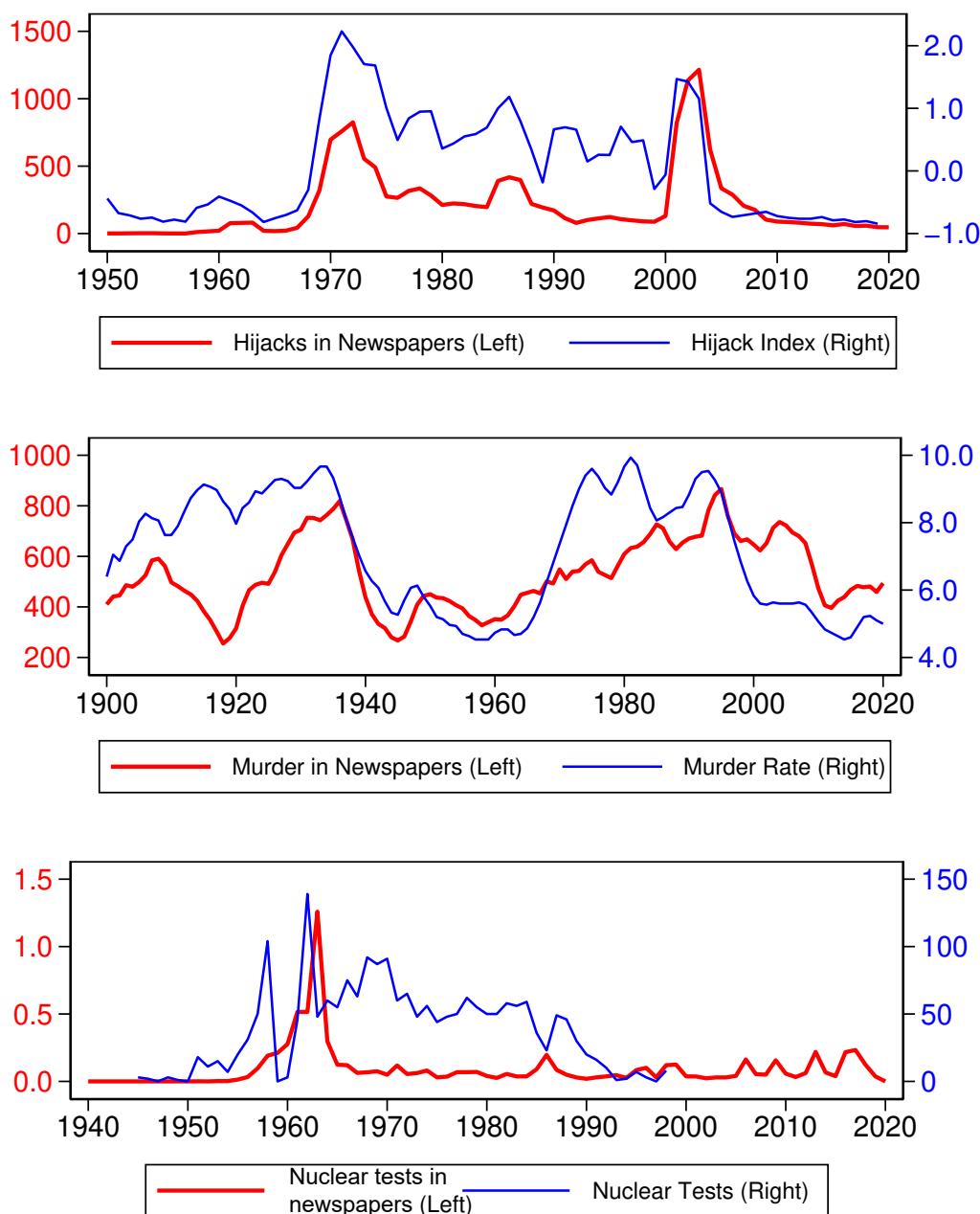


Figure A.5: GPR and Political Slant



Note: Geopolitical Risk Index for left-leaning and right-leaning newspapers. See text for list of newspapers.

Figure A.6: Hijackings, Murders, Nuclear Tests and Media Mentions

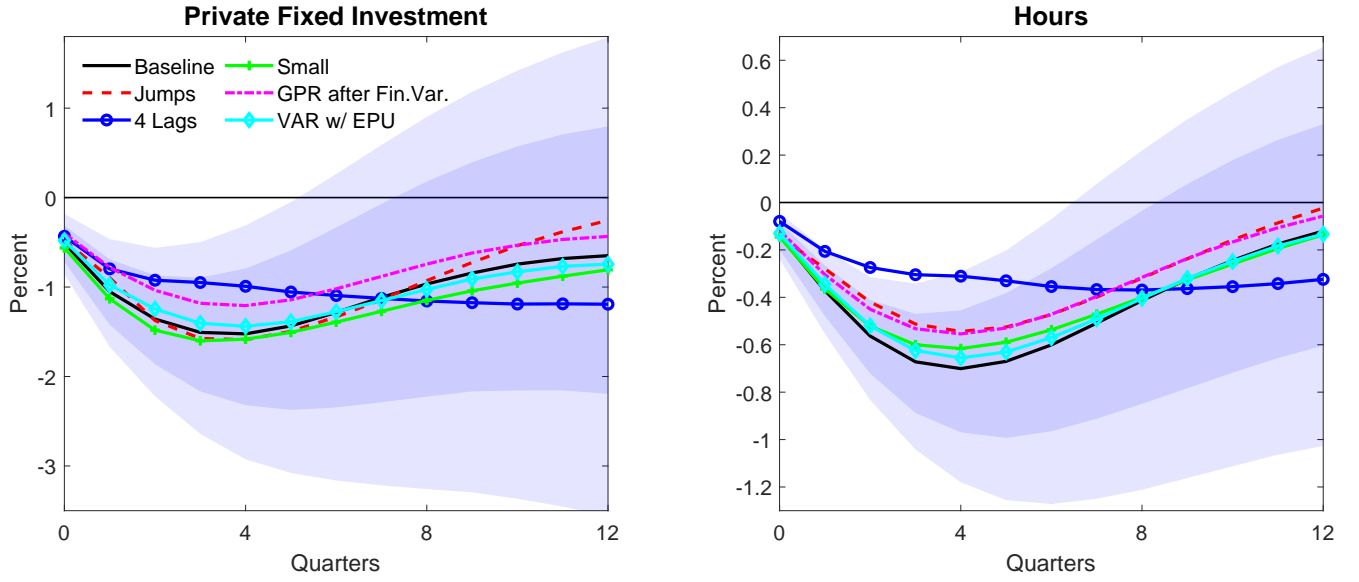


Note: Top panel: Comparison between monthly number of newspaper articles containing the expression  $\text{hijack} * N/2$  (plane OR airplane OR air OR aircraft OR airline\*) and the first principal component of (1) global number of hijacking incidents and (2) fatalities from hijacking incidents (source: Aviation Safety Network).

Middle panel: Comparison between number of newspaper articles containing the expressions ‘was murdered’ OR ‘was slain’ OR ‘was shot and killed’ and the U.S. murder rate (sources: [Eckberg \(1995\)](#) and <http://www.disastercenter.com/>).

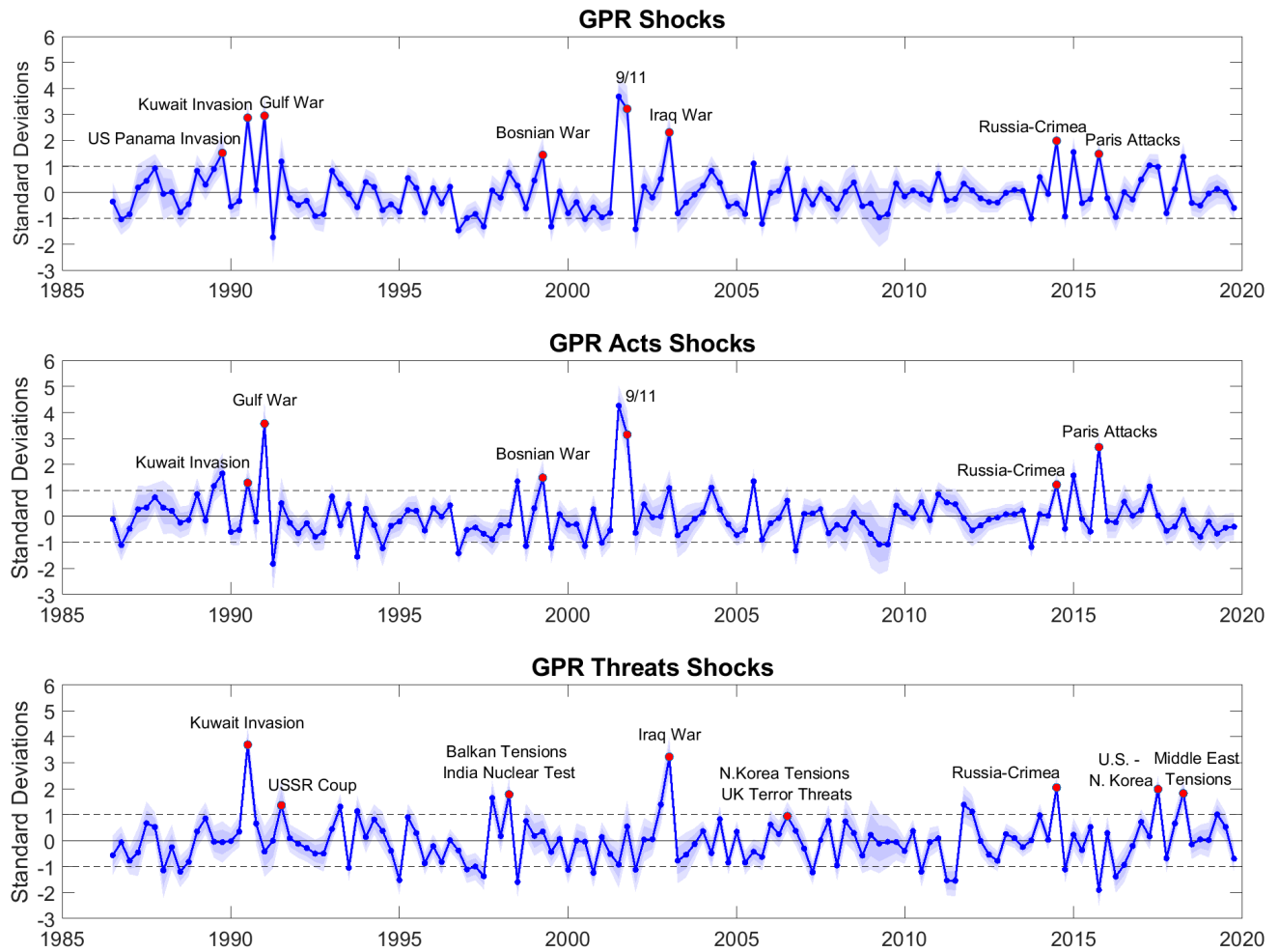
Bottom panel: Comparison between share of number of newspaper articles containing the expression ‘nuclear test’ and one risk-related word, and total nuclear tests in the world (source: <https://ourworldindata.org/nuclear-weapons>).

Figure A.7: The Impact of Increased Geopolitical Risk: Robustness



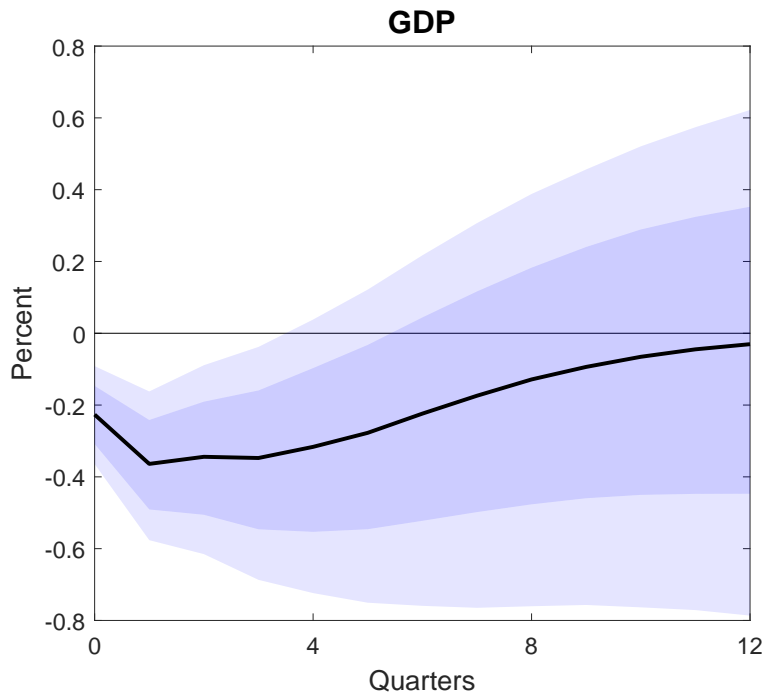
Note: The black solid line depicts the median impulse response of private fixed investment and hours to a two-standard-deviations increase in the GPR index under the benchmark model, with their respective 68 and 90 percent pointwise credible sets. The other lines depict median responses from alternative specifications of the VAR discussed in the main text.

Figure A.8: Time Series of the VAR-identified Geopolitical Shocks



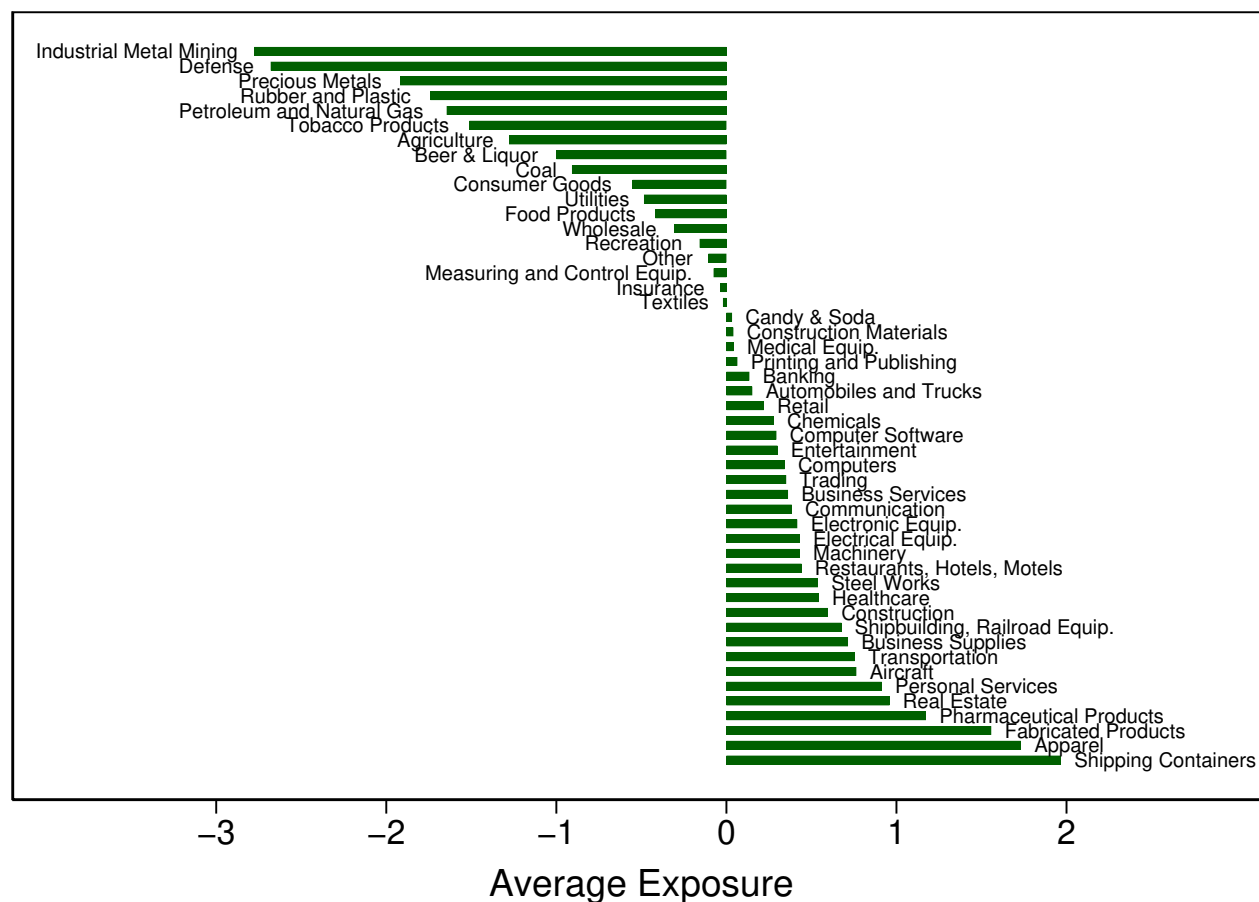
Note: The solid-dotted lines plot the median time series of GPR shocks (top panel, VAR described in subsection III.A) and of GPR Acts and GPR Threats shocks (middle and low panel, VAR described in subsection III.B). Shaded areas are 68 percent and 90 percent credible sets.

Figure A.9: The Impact of Increased Geopolitical Risk on GDP



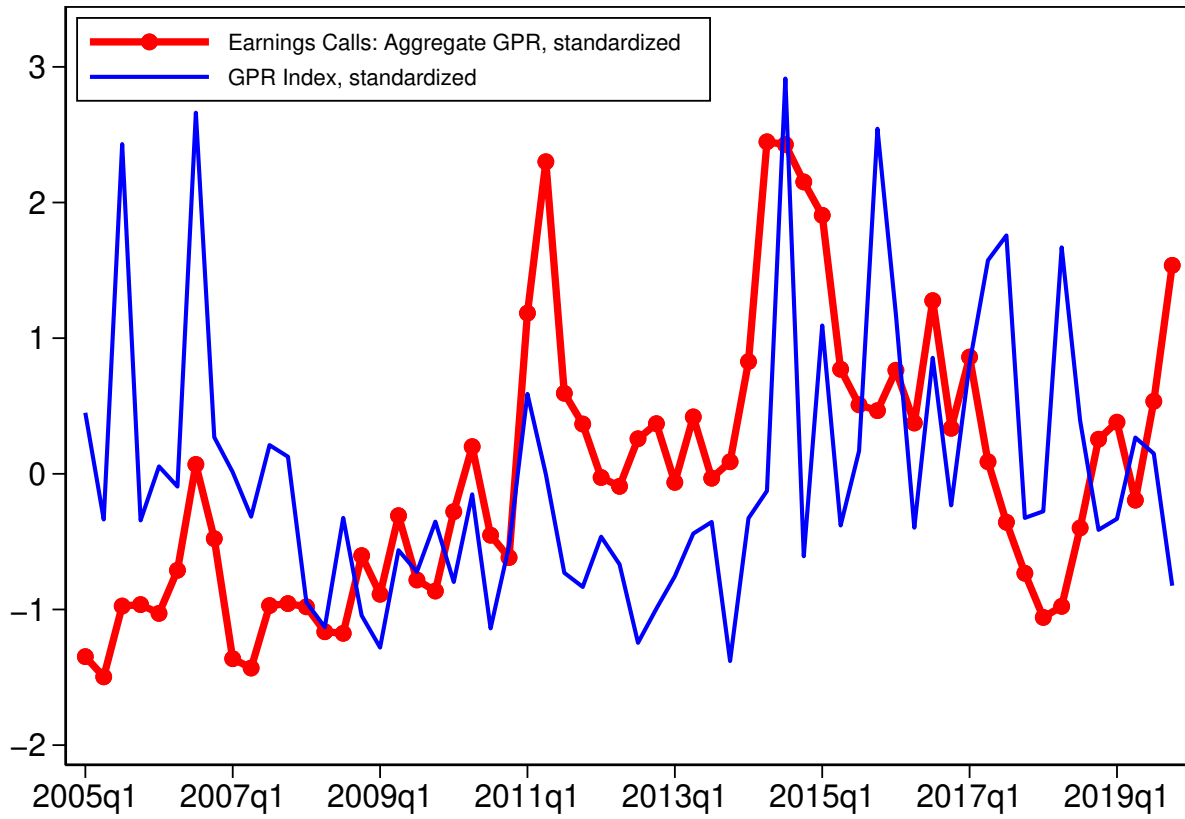
Note: The black solid line depicts the median impulse response of GDP to a two-standard-deviations increase in the GPR index. The VAR model is the same as the baseline specification of Section III with the addition of GDP (ordered after GPR). The dark and light shaded bands represent the 68 percent and 90 percent pointwise credible sets, respectively.

Figure A.10: Exposure to GPR by Industry Using Stock Returns



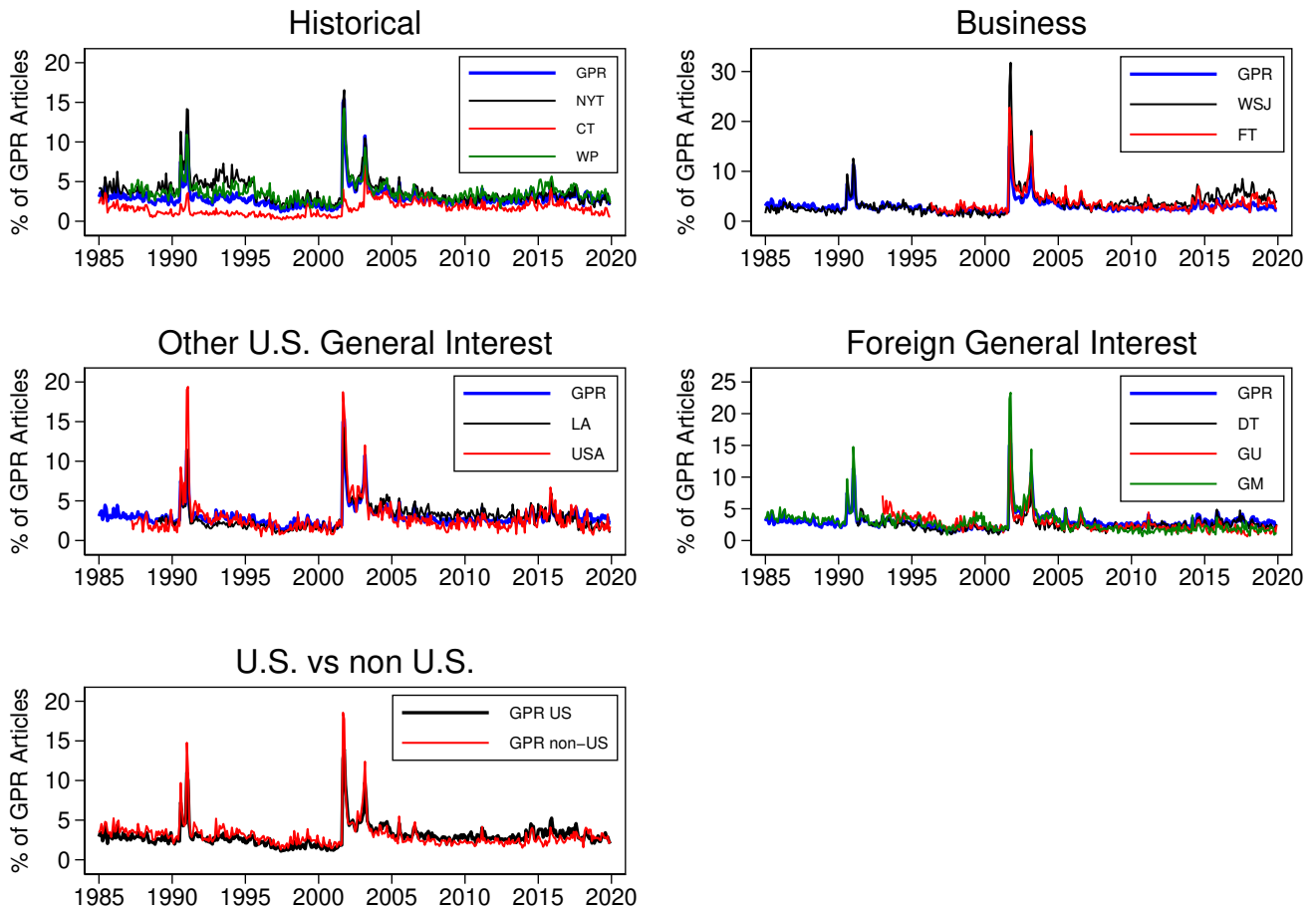
Note: Industry exposure to adverse geopolitical risk: values estimated on sample from 1985 through 2019, standardized to have zero mean and unit standard deviation. Higher values indicate a larger decline in industry daily stock returns after an increase in daily geopolitical risk.

Figure A.11: GPR Index and Firms' Perception of Geopolitical Risk



Note: The GPR Index from the listed firms' earnings calls transcripts is the average share of phrases mentioning geopolitical risks. Both measures have been transformed to have zero mean and unit standard deviation in the 2005-2019 period.

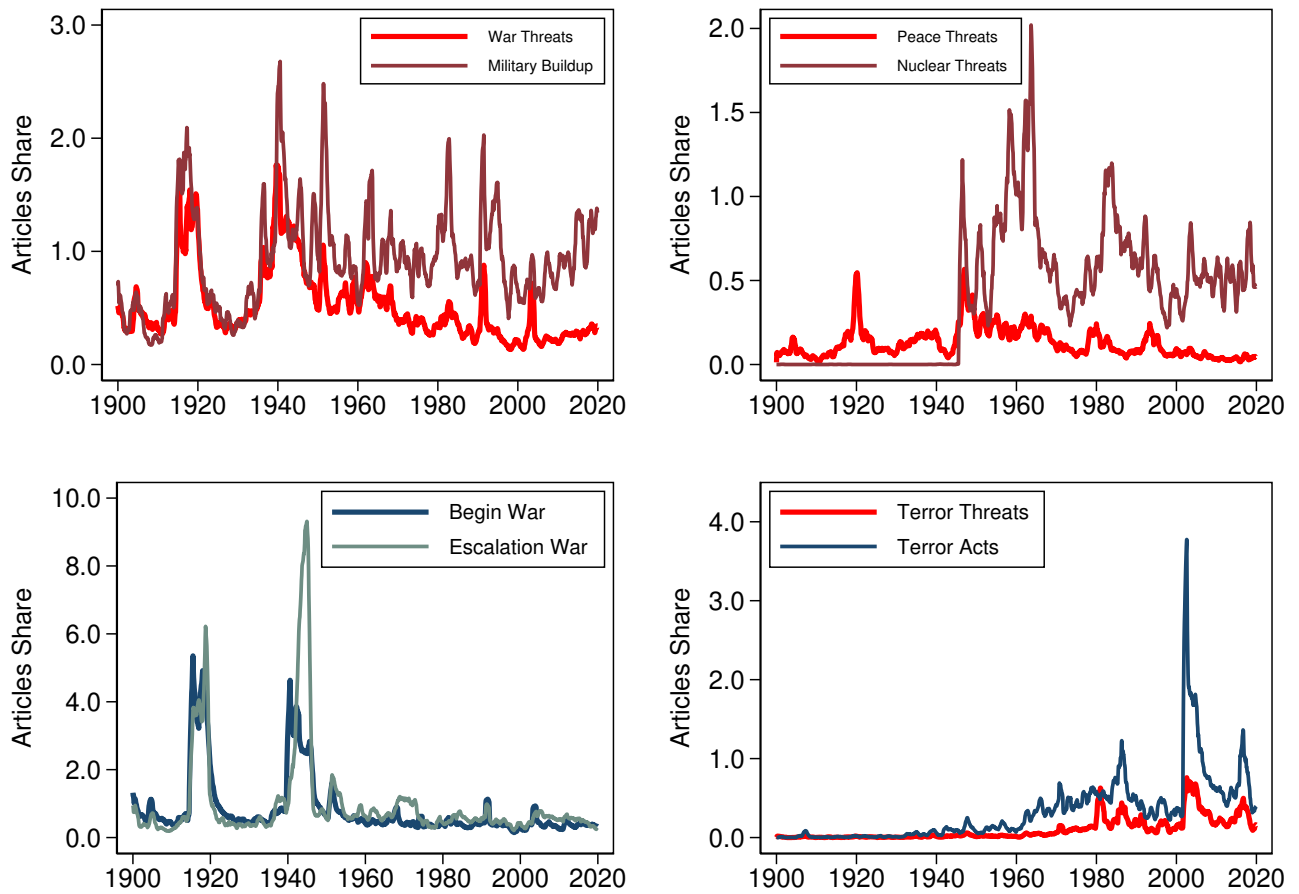
Figure A.12: Share of GPR Articles by Individual Newspapers



Note: Each panel plots the share of articles containing words related to geopolitical risk for each of the 10 newspapers used to construct the baseline GPR index.

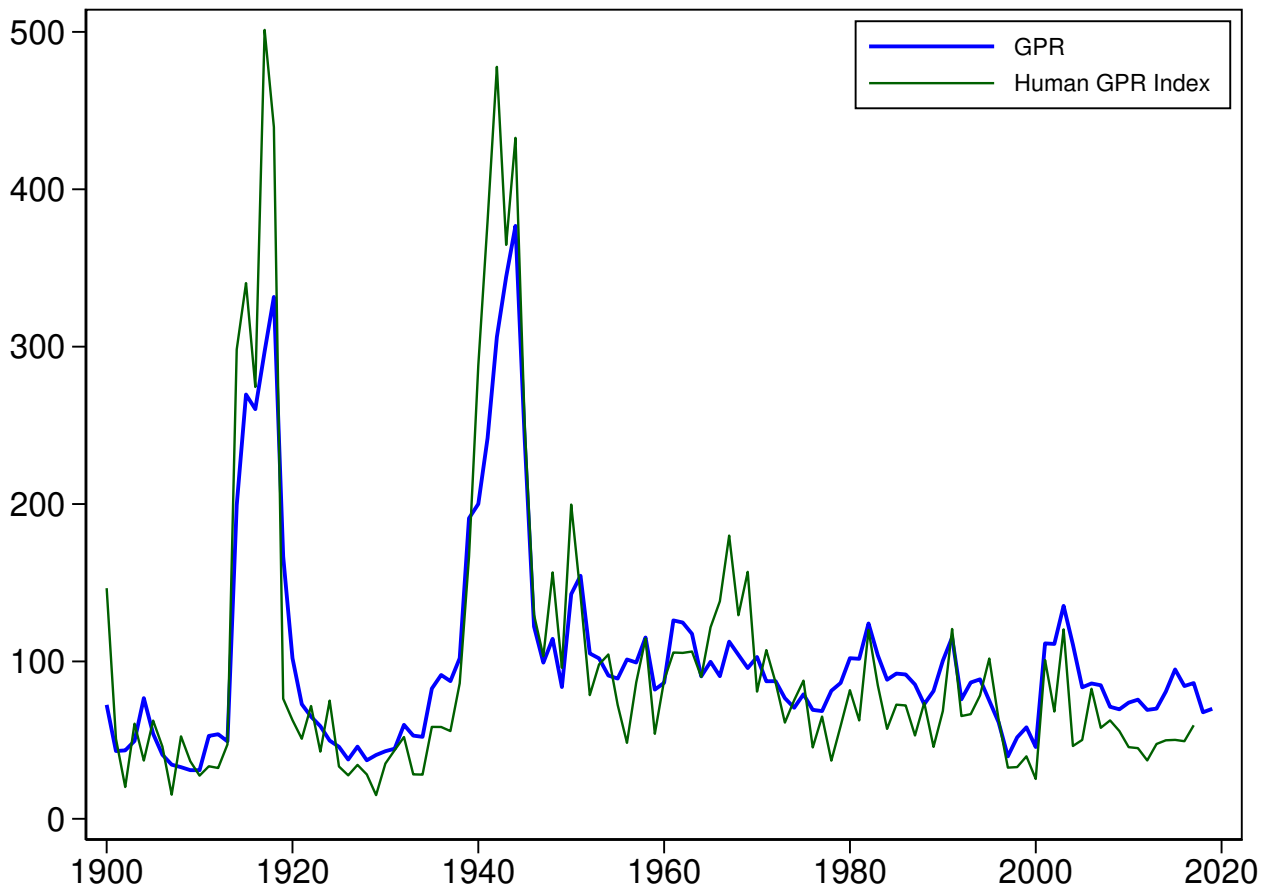


Figure A.13: The Geopolitical Risk Index:  
Contribution of the Search Categories



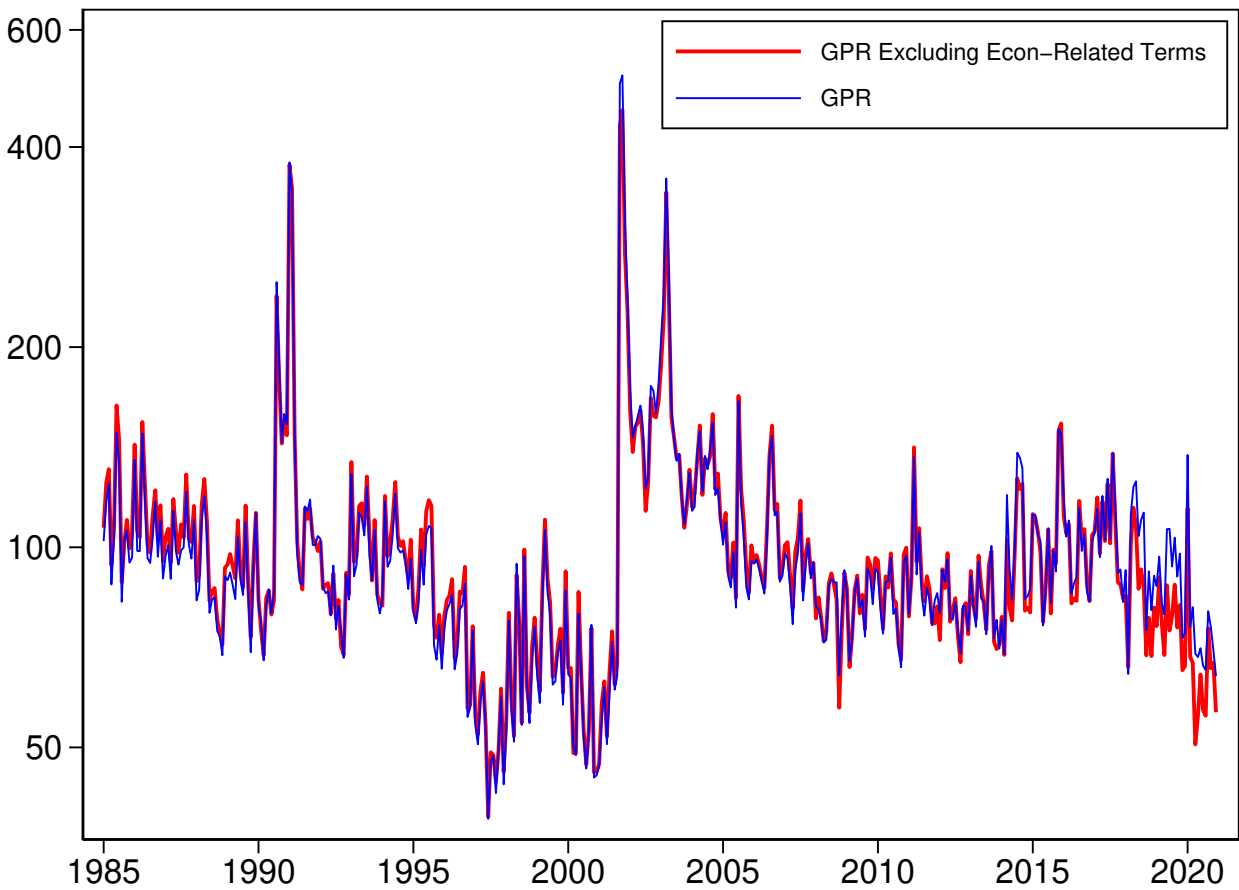
Note: The chart plots the relative contributions to the GPR index of the articles associated with the search categories described in Table 1. Each monthly series is plotted as a 12-month moving average. Each series plots the share of articles belonging to each of the categories listed in Table 1.

Figure A.14: Human Index



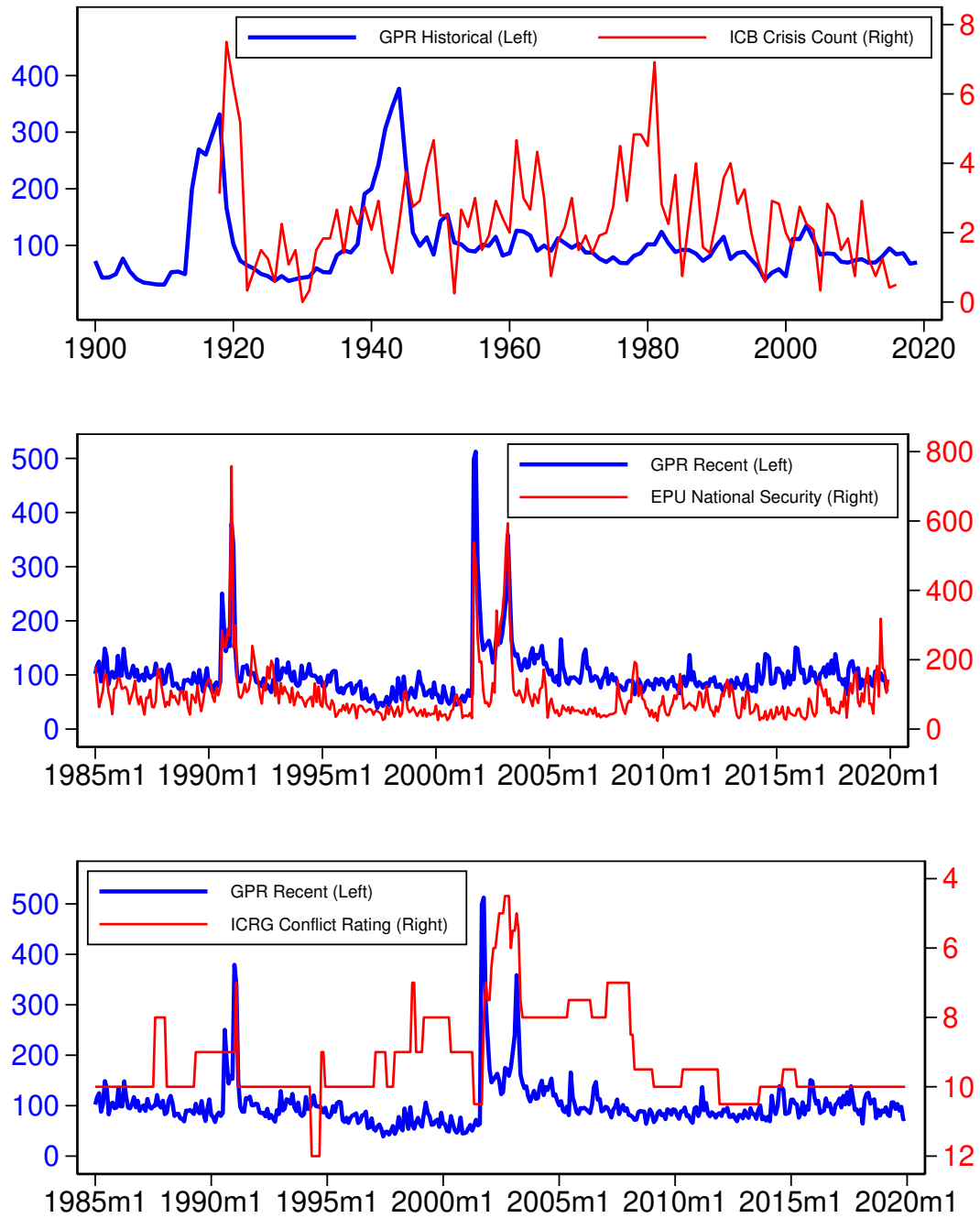
Note: Comparison of the historical GPR index (blue thick line) with the human index constructed by reading 7,416 articles (green thin line). Both series are plotted at yearly frequency and indexed to equal 100, on average, throughout the sample.

Figure A.15: The GPR Index Excluding Economics-Related Terms



Note: The figure compares the recent GPR index with a version of the index constructed excluding the search terms ‘economy’ OR ‘stock market\*’ OR ‘financial market\*’ OR ‘stock price\*.’ The correlation between the resulting index and the GPR index is 0.989. Both indexes are normalized to equal 100 in the 1985-2019 period and are plotted on a log scale.

Figure A.16: The Geopolitical Risk Index and Other Proxies for Geopolitical Risk



Note: In the top panel, the historical GPR and the ICB Crisis Count are annualized.