The Pricing of Geopolitical Tensions over a Century

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Abstract

We study the asset pricing implications of geopolitical tensions using nearly 100 years of data. Leveraging widely adopted news-based geopolitical risk indices, we find that geopolitical threats (GPT) and acts (GPA) have markedly different effects. GPT aligns closely with geopolitical *risk perceptions* and *decisions* of investors and firms. Thus, GPT is priced across individual US stocks, equity anomalies, international equity and bond indices, and it forecasts country-level equity premia. In contrast, GPA exhibits weaker and less stable links to the beliefs and decisions of investors and firms as well as to variation in risk premia across assets and over time. Importantly, our results are incremental to existing news-based indices of macro-financial uncertainty, including those capturing war-related discourse and economic or trade policy risk. Overall, our findings underscore the importance of forward-looking measures like GPT for understanding how news-based uncertainty affects investment decisions and asset prices.

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Introduction

The Russia-Ukraine conflict and the Middle East crisis have brought geopolitical tensions to the forefront of economic and policy debates. The IMF and the World Bank warn that such tensions can significantly affect global trade, financial stability, and real economic outcomes (IMF (2023, 2024) and World Bank (2025)). Geopolitical tensions also adversely impact consumers' expectations about future economic conditions (Gorodnichenko et al. (2025)). In fact, geopolitical tensions are now considered the primary risk to global growth according to a recent survey of central banks and sovereign wealth funds (Invesco (2024)). In addition, a growing literature documents the impact of geopolitical tensions on many economic outcomes, including production, investment, employment, consumption, inflation, innovation, trade, and oil prices (see our literature review).

As geopolitical tensions shape macroeconomic dynamics, it is crucial to understand their effect on risk premia. Addressing this issue entails two key challenges. First, geopolitical tensions reflect both the *realization* of adverse events and the *expectation* or *threat* of future developments, which may have distinct risk premia effects in forward-looking markets.[1] Second, geopolitical tensions are infrequent and cluster over time. During calm periods, investors may worry less about such risks, reducing their risk premia. Hence, evaluating geopolitical risk premia requires a long sample with enough episodes of elevated geopolitical tensions.

In this paper, we address these challenges by leveraging a century-long dataset of news-based geopolitical risk indices developed by Caldara and Iacoviello (2022). A distinctive feature of their work is the decomposition of their geopolitical risk (GPR) index into a geopolitical threats (GPT) index, which captures expectations of future adverse geopolitical events, and a geopolitical acts (GPA) index, which captures realizations of such events.[2]

[1] In this spirit, Clayton, Maggiori, and Schreger (2025a) and Clayton et al. (2025) demonstrate (theoretically and empirically) that current and threat-based geoeconomic pressures affect firm behavior differently.

[2] Following Caldara and Iacoviello (2022), we define geopolitical risk as "the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relation." While we retain the "acts" and "threats" labels, we interpret GPA as realizations of adverse geopolitical events and GPT as geopolitical uncertainty.

These indices are available monthly and are widely adopted in the literature. They are constructed based on the fraction of newspaper articles discussing geopolitical conflicts in the New York Times, Chicago Tribune, and Washington Post. The GPT index considers articles on geopolitical threats (e.g., military buildups and terrorist threats) while the GPA index considers articles on geopolitical acts (e.g., beginning of wars and terrorist attacks).

We provide novel evidence that GPT is strongly linked to the geopolitical *risk perceptions* and *decisions* of both investors and firms, and in turn to *risk premia* in the US and global financial markets. Specifically, we document three main findings. First, we show that GPT aligns closely with subjective geopolitical risk measures from professional risk ratings and fund manager surveys, and that investors allocate less capital to stocks with higher GPT exposure. Second, we find that higher GPT levels are associated with higher investment-risk ratings and lower future investment both in the aggregate and in the cross-section of firms, where GPT exposures negatively forecast future investment. Third, we document that GPT is priced in the cross-section of U.S. equities, anomaly portfolios, and global equity and bond indices, and that it forecasts time variation in country-level equity risk premia. In contrast, GPA exhibits weaker and less stable links to risk perceptions, investment decisions, and risk premia, underscoring the importance of distinguishing between anticipated geopolitical threats and realized geopolitical acts when studying the asset pricing implications of geopolitical risks.

Importantly, the impact of GPT on risk premia is incremental relative to the e ects of many other risk indices. We consider news-based indices of war discourse (WAR from Hirshleifer, Mai, and Pukthuanthong (2025b)), economic policy uncertainty (EPU from Baker, Bloom, and Davis (2016)), expected market volatility (EMV from Manela and Moreira (2017) and Baker et al. (2025)), and trade policy uncertainty (TPU from Caldara et al. (2020)). We also consider broad real, macroeconomic, and financial uncertainty indices (RUI, MUI, and FUI from Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021)). By jointly studying these important risk indices, we provide the first consistent and comprehensive analysis of their risk premia over a long period.

Unpacking our Analysis

We begin by showing that GPT appears more "forward-looking" than GPA as GPT rises in anticipation of major geopolitical conflicts while GPA increases once those events materialize. Consistent with this, GPT also aligns much more strongly with how investors and firms perceive and act upon geopolitical risks. For instance, we show that time variation in GPT (unlike GPA) is linked to subjective assessments of geopolitical risk from the International Country Risk Guide (ICRG) ratings of the PRS Group and from surveys of global fund managers conducted by the Bank of America (BofA). Moreover, in 13F portfolio holdings, investors allocate less capital to stocks with higher GPT exposure (β_{GPT}) but not higher β_{GPA}, with this effect strengthening during periods of high GPR (which captures overall attention to geopolitical risks). GPT also relates to firm investment as increases in GPT (but not GPA) raise perceived investment risk and forecast lower future aggregate and industry-level investment. At the firm level, firms with higher β_{GPT} (but not higher β_{GPA}) systematically cut back capital expenditures, an effect that also strengthens when GPR is high.

Having established that GPT (but not GPA) is strongly connected to the beliefs and decisions of investors and firms, we move to the link between geopolitical risks and risk premia. We show that GPT captures risk premia variation across assets and over time. In contrast, other risk indices (including GPA) are linked to some forms of variation in risk premia, but not in a consistent manner across different forms of risk premia variation.

In terms of variation across assets, we start by studying individual US stocks through standard portfolio sorts from 1930 to 2024. We construct portfolios sorted on rolling window univariate betas of stock returns onto the growth rate in each of the aforementioned risk indices (these betas are analogous to β_{GPT}). We find that only β_{GPT} sorts produce an economically and statistically significant risk premium. Moreover, the GPT risk premium remains present (in the form of alpha) after controlling for the risk indices we study, the CAPM and ICAPM (from Chabi-Yo, Gonçalves, and Loudis (2025)), and many other widely used characteristics-based factor models. We also find that the GPT risk premium is present both across and within industries, is positive throughout our sample period, and is elevated in periods of high levels of GPR (or GPT). This last result is consistent with our findings on portfolio holdings and firm investment, and it suggests that investors price GPT more strongly when attention to geopolitical risks (whether warranted or not) is high. This result further highlights the importance of a long sample. Without it, we could mistake the conditional risk premium on geopolitical tensions for its unconditional risk premium.

We then study the cross-section of equity anomaly portfolios using the Supervised Principal Component Analysis (SPCA) proposed by Giglio, Xiu, and Zhang (2025). While we also provide results over our full 1930-2024 sample, we focus on an analysis that starts in 1963 as there are many more anomalies over that period. We find that the GPT mimicking factor provides an economically and statistically significant risk premium that remains present after controlling for the CAPM and ICAPM or the mimicking factors of the other risk indices we study. In this case, many of these other risk indices also lead to mimicking factors with strong risk premia. However, the GPA and GPR mimicking factors have negative and statistically insignificant alphas after controlling for the GPT mimicking factor.

As our last cross-section, we consider country-level equity and government bond indices from the Jordà et al. (2019) dataset, covering annual returns on 16 developed countries. Since the SPCA method is not applicable for such a small cross-section, in this case we build mimicking factors using standard Fama and MacBeth (1973) regressions of returns on univariate betas relative the growth rate in GPT (and in other risk indices). As with the other two cross-sections, we find that the GPT mimicking factor provides an economically and statistically significant risk premium, which remains present after controlling for the World CAPM (note that the standard CAPM and ICAPM are not appropriate for an analysis of international asset prices). In this case, whether other risk indices (including GPA) produce economically and statistically significant risk premia varies by index, time period, and cross-section (equities vs bonds) analyzed.

We then explore time variation in risk premia using the same Jordà et al. (2019) dataset of country-level indices. We find that GPT (but not GPA) significantly predicts equity premia variation over time. This finding is particularly strong (and robust) at long horizons (e.g., 3 or 5 years), being more sensitive to empirical specification for 1-year returns. In contrast, GPT and GPA have no clear link to bond risk premia variation over time, which could be due to a flight to safety e ect in which bonds become more attractive than equities when GPT increases. These results also hold when using only US returns (from Goyal and Welch (2008)) and when controlling for other risk indices, including the WAR variable we focus on (from Hirshleifer, Mai, and Pukthuanthong (2025b)) as well as the alternative WAR variable used for time-series return predictability in Hirshleifer, Mai, and Pukthuanthong (2025a).

Finally, we evaluate several channels that could explain why GPT carries a higher risk premium than GPA. Each builds on GPT's forward-looking nature and on the fact that geopolitical tensions are infrequent but economically significant, which can generate non-linearities in asset prices. We first consider non-linear market risk, where returns may respond non-linearly to increases in geopolitical threats but not to the realization of adverse geopolitical events since prices anticipate these events. However, this mechanism cannot explain our findings because stocks more exposed to GPA (not GPT) also load more on non-linear market risk. We then examine disaster risk. In models with Epstein-Zin preferences, investors price news about long-run disaster prospects, and we find that GPA predicts only short-term consumption disasters, whereas GPT predicts long-term cumulative disasters, suggesting variation in GPT better reflects variation in objective risk from the perspective of Epstein-Zin investors. Our final mechanism is investor overreaction to geopolitical threats, which predicts that rational investors perceive undervaluation when GPT rises. Yet, BofA surveys of fund managers show the opposite: GPT increases are associated with perceived overvaluation in equity markets (with GPA linked to undervaluation). Thus, among the channels we analyze, only disaster risk plausibly contributes to the geopolitical risk premia we document. However, our analysis focuses on a few channels and evaluates them in reduced form rather than specifying a full structural model for each. This choice reflects our view that multiple mechanisms likely contribute to the empirical patterns we document.

Contribution to the Literature

We contribute to the broad literature on the economic effects of geopolitical tensions.[3] We build on Caldara and Iacoviello (2022), who construct a geopolitical risk (GPR) index by combining geopolitical threats (GPT) and acts (GPA). While they also study the properties of GPT and GPA, their main focus is on the aggregate GPR measure and its effects on macro-financial outcomes such as consumption and investment. Our contribution relative to Caldara and Iacoviello (2022) (and this literature more broadly) is not on the measurement front but on the pricing of geopolitical risks, which they do not study. We distinguish explicitly between the effects of GPT and GPA and show that GPT is much more closely linked to how investors and firms perceive and respond to geopolitical risks. As a result, GPT (but not GPA) consistently captures variation in risk premia across assets and over time.

A few other papers also study geopolitical risk premia. Most notably, Hirshleifer, Mai, and Pukthuanthong (2025b) find that GPR is not priced in the cross-section of stocks.[4] Their findings do not contradict ours as GPR mainly reflects GPA and we show that GPT (but not GPA) is consistently linked to risk premia in the cross-section and time-series. In addition, a paper contemporaneous to ours (Sheng, Sun, and Wang (2025)) constructs a new geopolitical risk index that incorporates trade tensions and shows that it is a successful predictor of aggregate US stock market returns in the period from 1984 to 2025. While they focus on the time-series return predictability of a new index of overall geopolitical risk, we use a long sample and well-established geopolitical risk indices to uncover the fundamental differences between geopolitical threats and acts in terms of their links to risk premia as well as to the risk perceptions and decisions of investors and firms.

[3] See, for example, Bańkowska et al. (2021), Caldara and Iacoviello (2022), Góes and Bekkers (2023), Caldara et al. (2024), Mignon and Saadaoui (2024), Wang, Wu, and Xu (2024), Franconi (2025), Gopinath et al. (2025), Crosignani, Han, and Macchiavelli (2025), Pinchetti (2025), Federle et al. (2025a,b), and Gorodnichenko et al. (2025). See also Aiyar, Presbitero, and Ruta (2023) and Clayton, Maggiori, and Schreger (2025b) for the adverse effects of geoeconomic fragmentation and Clayton, Maggiori, and Schreger (2025a) and Clayton et al. (2025) for analyses of threat-based geoeconomic pressures.

[4] In contrast to the Hirshleifer, Mai, and Pukthuanthong (2025b) finding of no GPR pricing in the cross-section of stocks, Zaremba et al. (2022) show that changes in country-level GPR predict emerging market returns and Ma, Lu, and Tao (2022) find that GPR and GPT predict S&P 500 returns over one month.

We also contribute to the literature on the pricing of risks related to uncertainty in economic variables. Building on classical intertemporal asset pricing models, a large part of this literature focuses on the pricing of shocks to volatility and uncertainty in market returns (e.g., Campbell et al. (2018)) or macroeconomic variables (e.g., Bali and Zhou (2016)). Some other papers study the pricing of specific forms of uncertainty that have a stronger connection to geopolitical risks, such as economic policy uncertainty, general political uncertainty, and war uncertainty.[5] We broadly contribute to this literature by providing a consistent and comprehensive analysis of the pricing of geopolitical risks together with multiple other risk indices studied in this literature (for almost 100 years). These other risk indices cover war discourse (Hirshleifer, Mai, and Pukthuanthong (2025a,b)), expected market volatility (Manela and Moreira (2017) and Baker et al. (2025)), economic policy uncertainty (Baker, Bloom, and Davis (2016)), trade policy uncertainty (Caldara et al. (2020)), as well as general real, macroeconomic, and financial uncertainty (Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021)).

Among the papers discussed above, the closest to ours are Hirshleifer, Mai, and Pukthuanthong (2025a,b) as their WAR variables can be viewed as a component of geopolitical tensions. We add to these papers by showing that geopolitical threats (but not acts) are connected to risk premia across assets and over time, with these results also holding after controlling for WAR. In fact, GPT is the only uncertainty index we study that is economically and statistically linked to variation in risk premia across individual stocks. Moreover, GPT closely aligns with geopolitical risk perceptions and actions by investors and firms,

[5] Pástor and Veronesi (2012) provide a model where government policy uncertainty is priced, with Baker, Bloom, and Davis (2016) constructing an economic policy uncertainty (EPU) index and Caldara et al. (2020) building a trade policy uncertainty (TPU) index. Several papers use EPU, TPU, and other measures to empirically study the asset pricing e ects of policy uncertainty (e.g., Belo, Gala, and Li (2013), Brogaart and Detzel (2015), Bianconi, Esposito, and Sammon (2021), Liu and Shaliastovich (2022), and Gala, Pagliardi, and Zenios (2023)). Similarly, Pástor and Veronesi (2013) build a model in which general political uncertainty is priced, with multiple papers studying the economic e ects of political uncertainty, including its risk premium (e.g., Berkman, Jacobsen, and Lee (2011), Kelly, Pástor, and Veronesi (2016), Liu, Shu, and Wei (2017), Hassan et al. (2019), Brogaard et al. (2020), Gala, Pagliardi, and Zenios (2023), Gala et al. (2023), and Liu and Shaliastovich (2023)). Uncertainty can also arise from wars, with Hirshleifer, Mai, and Pukthuanthong (2025a,b) studying the pricing of war discourse.

which sheds light on the mechanism through which geopolitical threats are priced.

Finally, our work broadly contributes to the literature on disaster risk (see Tsai and Wachter (2015) for a review). In particular, we show that GPA and GPT are associated with the probability of consumption disasters over the short- and long-term, respectively, with the latter reflecting a risk factor for Epstein-Zin investors. These overall results highlight the importance of changes in the likelihood of long-term disasters for asset pricing.

The rest of this paper is organized as follows. Section 1 covers the geopolitical risk indices we study, highlighting that GPT and GPA have di erent links to historical geopolitical episodes as well as to the beliefs and decisions of investors and firms. In turn, Sections 2 and 3 present results on how geopolitical risks relate to cross-sectional and time-series risk premia. Then, Section 4 discusses some potential channels for our geopolitical risk premia findings. Finally, Section 5 concludes. Internet Appendix A provides the sources for the data used throughout the paper, Internet Appendix B reports additional empirical findings, and Internet Appendix C contains technical derivations.

1 Geopolitical Risk Indices: Threats vs Acts

This section covers the geopolitical risk indices we focus on. Section 1.1 describes their construction, sample period, and correlations. Section 1.2 illustrates the differences between geopolitical threats and acts using two historical episodes as examples. Sections 1.3 and 1.4 also highlight the di erences between geopolitical threats and acts, but focusing on their links to the risk perceptions and decisions of investors and firms.

1.1 The Geopolitical Risk Indices

Our analysis centers on two complementary indices of geopolitical risk. They are the geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022), updated to 12-2024. These indices are available monthly since 1900 and are constructed based on the fraction of newspaper articles discussing (i.e., containing key expressions related to) geopolitical conflicts in the New York Times, Chicago Tribune, and Washington Post. The GPT index is based on articles that discuss geopolitical threats (e.g., military buildups and terrorist threats) while the GPA index is based on articles that discuss geopolitical acts (e.g., beginning of wars and terrorist attacks). We also consider their overall geopolitical risk (GPR) index, which is based on both threats and acts.

While Caldara and Iacoviello (2022) provide a detailed discussion of the construction of these geopolitical risk indices, our Figure 1 highlights the essence of what they capture. It plots the expressions used in the construction of GPT (in blue) and GPA (in orange), with their relative sizes based on the relative frequency in which these expressions are used in the construction of their respective indices. The expressions used in the construction of GPT are connected to threats or expectations of future adverse geopolitical events (e.g., "conflict fear," "war risk," and "terrorist menace"). In contrast, the expressions used in the construction of GPA are connected to the realization of adverse geopolitical events (e.g., "conflict start," "war begin," and "terrorist attack").

Given the forward looking nature of asset prices, we argue that geopolitical threats (reflected in GPT) are more likely to command a risk premium than geopolitical acts (reflected in GPA). After all, what matters for the risk premium of a risk factor is the extent to which asset prices tend to systematically decline upon an adverse shock to that factor. While asset prices should systematic decline when GPT increases, their reaction to an increase in GPA is more ambiguous since at least part of each adverse geopolitical event is likely anticipated by the market through the buildup of geopolitical threats (reflected in GPT).

Table 1 reports the sample period and correlations for the GPT, GPA, and GPR indices (as well as the other risk indices described in Section 2.1). GPT and GPA have a moderately high correlation of 0.45, indicating that they reflect di erent aspects of geopolitical risks. Interestingly, GPR is much more correlated with GPA (0.96) than with GPT (0.68), indicating that geopolitical acts are more reflected in GPR than geopolitical threats are. This fact provides an explanation for why Hirshleifer, Mai, and Pukthuanthong (2025b) find that GPR commands no risk premium: GPR mainly reflects geopolitical acts, not threats.

Figures 2(a) and 2(b) provide a graphical representation of the correlation of GPT with GPA and GPR. It is visually evident that there are many periods of high GPT with low GPA and GPR (and vice versa). The next three sections show that these differences are economically meaningful, broadly indicating that GPT is a more appropriate index for asset pricing than GPA (and, consequently, than GPR as well).

1.2 Geopolitical Threats vs Acts: Link to Historical Episodes

Figure 4 in Caldara and Iacoviello (2022) provides an analysis of some important historical episodes to highlight key di erences between GPT and GPA. Our Figure 3 plots the z-scores of GPT and GPA during two of these episodes.

The first historical episode is World War II, shown in Figure 3(a). We observe large di erences in the behavior of GPT (in blue) and GPA (in orange) over this period. The years leading up to the war show little movement in GPA but two prominent GPT spikes linked to rising geopolitical tensions. The first spike corresponds to September 1938, when Germany issued an ultimatum and exerted strong diplomatic pressure on Britain and France to permit the annexation of the Sudetenland from Czechoslovakia. This crisis culminated in the Munich Agreement (signed on September 30), which ceded the Sudetenland to Germany in an e ort to avert war. The second spike occurs in March 1939, when Germany violated that agreement by invading and occupying the remainder of Czechoslovakia. The contrasting behavior of GPT and GPA during this time underscores GPT's forward-looking nature: it spikes in response to events that signal an increase in the likelihood of future major geopolitical conflicts.

Subsequently, the official outbreak of World War II in September 1939, with Germany's invasion of Poland, generates a sharp increase in both GPT and GPA. This indicates that a major adverse geopolitical event had occurred (explaining the GPA spike) and that expectations of further escalation had risen sharply (explaining the GPT spike). Thereafter, GPA gradually increases as newspapers report on the unfolding war. In contrast GPT, though remaining above average, does not trend upward steadily. Instead, it exhibits isolated spikes associated with key turning points in the conflict. For example, GPT spikes again in June 1940, when France signed an armistice with Germany that ended the Battle of France and resulted in the occupation of northern and western France. Another surge appears in December 1941, following Japan's attack on Pearl Harbor (December 7) and the U.S. declaration of war (December 8), which marked a major global escalation of the conflict.

Toward the end of the war, GPA peaks in June 1944 (the month of D-Day) and then gradually declines toward pre-war levels. In contrast, GPT shows no spike at D-Day since the beginning of the liberation of western Europe from Nazi occupation did not increase the threat of future adverse geopolitical events. Nevertheless, GPT rises sharply in August 1945, when the U.S. detonated atomic bombs in Japan. Although these bombings led to Japan's surrender (announced August 15, 1945), they introduced an entirely new dimension of geopolitical threat through the advent of nuclear weapons.

The second historical episode, shown in Figure 3(b), focuses on the early 1960s, a period characterized by recurring Cold War confrontations but limited direct military conflict. Throughout this period, GPA (in orange) remains largely flat, consistent with the absence of major acts of geopolitical aggression or warfare. In contrast, GPT (in blue) displays pronounced short-lived spikes that capture surges in perceived geopolitical threats linked to key diplomatic crises.

The first major GPT spike occurs in mid-1961, during the Berlin Crisis. Following Khrushchev's ultimatum demanding that Western forces withdraw from West Berlin, tensions escalated sharply as the United States and its allies refused. This confrontation culminated in the construction of the Berlin Wall in August 1961, which solidified the East-West divide but did not involve open conflict, explaining the muted GPA response despite the GPT surge. The second and most prominent GPT spike appears in October 1962, corresponding to the Cuban Missile Crisis, when the discovery of Soviet nuclear missiles in Cuba brought the world to the brink of nuclear war. GPT jumps sharply as expectations of a potential global confrontation rise, while GPA remains comparatively subdued because the crisis was resolved diplomatically before any military action occurred. A third GPT increase emerges around

July and August 1963, reflecting heightened uncertainty surrounding the negotiation and signing of the Partial Nuclear Test Ban Treaty between the United States, the Soviet Union, and the United Kingdom. Newspapers at the time devoted intense coverage to the treaty and the surrounding debates, which included doubts about enforcement credibility and the first visible signs of ideological fragmentation within the communist bloc. This temporary rise in GPT illustrates how news-based perceptions of geopolitical tension can intensify even in the absence of overt conflict.

Overall, the behavior of GPT and GPA around major historical episodes showcases that they convey di erent information. That is, while GPT reflects changes in the expectation about future adverse geopolitical events, GPA better captures the realization of such events.

1.3 Geopolitical Threats vs Acts: Link to Investors' Beliefs and Allocations

We now show that, beyond appearing more "forward looking" than GPA, GPT is also more connected to investors' perceptions of geopolitical risk and portfolio allocations.

We consider three measures of geopolitical risk perceptions from institutional investors. The first is the geopolitical risk score from the International Country Risk Guide (ICRG) ratings of the PRS Group.[6] It reflects an unbalanced panel of annual data for 138 countries between 1984 and 2021. Since the ICRG geopolitical risk ratings are designed such that high values reflect low risk, we use the negative of their values. Table 2 provides panel regressions (with country-fixed e ects) of the ICRG rating onto GPT and GPA (all in z-score units). A 1.0 standard deviation increase in GPT is associated with a significant 0.30 standard deviation increase in the ICRG rating ($t_{stat} = 3.61$). In contrast, a 1.0 standard deviation increase in GPA is associated with an insignificant 0.10 standard deviation decline in the

[6]Note that while the ICRG geopolitical risk rating reflects the risk views of the PRS group (a single entity), it likely influences the subjective views of a large range of other economic agents, including institutional investors. For instance, according to the International Political Science Association (https://www.ipsa.org/profile/prs-group-inc), "The PRS Group - and the geopolitical risk data and forecasts included in the International Country Risk Guide (ICRG) - has been the world's leading quant-driven geopolitical risk forecasting and rating firm. The firm's clientele includes the world's largest institutional investors, transnational companies, multilateral agencies (IMF), central banks, and leading research scientists at such institutions as Harvard, Princeton, Yale, and LSE."

ICRG rating. Moreover, in a joint analysis, the positive (negative) association of GPT (GPA) with the ICRG risk rating gets stronger.

One caveat with our use of this ICRG rating as a measure of subjective geopolitical risk is that the PRS group refers to it as "geopolitical risk" in some instances and as "political risk" in other instances. In fact, the academic literature largely treats this ICRG rating as reflecting political risk in general rather than geopolitical risk specifically (e.g., Bekaert et al. (2014), Gourio, Siemer, and Verdelhan (2015), and Gala et al. (2023)). The reason is that the ICRG rating incorporates a diverse set of twelve categories, many of which are more reflective of dimensions of the political environment outside of geopolitics (e.g., "law and order" and "democratic accountability"). So, our second measure of subjective geopolitical risk is the component of the ICRG rating attributed only to the two categories that are more connected to geopolitical tensions, "internal conflicts" and "external conflicts". Consistent with the results using the general ICRG rating, Table 2 shows that GPT (but not GPA) has a significant positive association with this alternative ICRG geopolitical risk rating.

Our third measure of subjective geopolitical risk is based on the global fund manager surveys conducted monthly by the Bank of America (BofA). While this series is available for a shorter sample (from 07-2007 to 12-2024), it represents an ideal measure of the subjective geopolitical risk perception of institutional investors as it reflects the average rating that global fund managers assign to geopolitical risk in surveys.[7] As Table 2 shows, GPT is strongly related to this BofA subjective geopolitical risk measure, with a correlation of 0.63 and with a 1.0 standard deviation increase in GPT being associated with a 1.07 standard deviation increase in subjective geopolitical risk. While GPA is also positively related to subjective geopolitical risk, its e ect weakens (and becomes statistically insignificant) when GPT and GPA are jointly included in the analysis.

A natural question is whether investors also trade accordingly to their geopolitical believes. So, we also study investors' decisions by exploring their allocations to single stocks. For that,

[7]Internet Appendix Section B.1 further explores the other six subjective risk measures present in the BofA surveys. See Couts et al. (2024) for details about the data we use from the BofA surveys and Bastianello and Peng (2025) for a comprehensive analysis of BofA surveys.

we consider the exact same setup and data used in Koijen and Yogo (2019). Specifically, we estimate a logistic demand system each quarter (from 1980Q1 to 2024Q4) for each investor in the 13F dataset (and one outside investor). We deviate from Koijen and Yogo (2019) by adding stock-level exposures to GPT and GPA (β_{GPT} and β_{GPA}) as characteristics to the system, with the details on how we estimate β_{GPT} and β_{GPA} provided later in Subsection 2.2.[8] This procedure yields demand parameters θ_{GPT} and θ_{GPA} for each investor-quarter.

The first bar of Figure 4(a) shows the point estimate and 95% confidence interval for the average θ_{GPT}, with Figure 4(b) being analogous but for θ_{GPA}. While the average θ_{GPA} is positive, the average θ_{GPT} is negative, indicating that, ceteris paribus, investors tend to hold a lower fraction of their portfolios in stocks with higher GPT exposure, consistent with the idea that investors view GPT (but not GPA) as capturing a relevant risk. In terms of magnitudes, on average, investors' allocations tend to be (approximately) 2% lower for a stock with a one standard deviation higher β_{GPT}.[9]

We also explore whether investors allocate capital di erently when geopolitical risks are low vs high. For that, the last five bars of each panel in Figure 4 consider the average θ_{GPT} and θ_{GPA} values conditioned on di erent levels (time-series quintiles) of the overall geopolitical risk index, GPR. The average θ_{GPT} almost doubles when attention to geopolitical risks is in its highest quintile. In contrast, if anything, the average θ_{GPA} is slightly higher when GPR is highest (but it is not statistically significant). These results are consistent with the view that investors view GPT as a relevant risk factor, particularly when attention to geopolitical risks is high.

Overall, the results indicate that GPT closely aligns with the geopolitical risk perceptions and portfolio allocations of investors. In contrast, GPA has weaker, more unstable links to

[8] Note that we cannot add GPT and GPA directly to the demand system since these indices do not vary across stocks, and thus are absorbed by the investor-quarter intercept of the logistic demand equation.

[9] Since the Koijen and Yogo (2019) estimation provides no instrument for the characteristics in the demand system (only for prices), we cannot interpret θ_{GPT} and θ_{GPA} as elasticities (see also Binsbergen, David, and Opp (2025) for limitations with interpreting price elasticities in the Koijen and Yogo (2019) setting). So, Figure 4 should simply be interpreted as evidence for a negative correlation between portfolio allocations and $_{\text{GPT}}$ holding fixed firm size, market-to-book, profitability, investment, dividends over book equity, market beta, and $_{\text{GPA}}$.

geopolitical risk perceptions and portfolio allocations. This finding is likely a consequence of the fact that GPT behaves in a more "forward looking" manner than GPA, making it more consistent with how investors form expectations and make portfolio allocation decisions.

1.4 Geopolitical Threats vs Acts: Link to Firms' Beliefs and Investment

We now show that the results from investors' risk perceptions and portfolio allocations extend to firms. That is, GPT is more connected to perceived investment risk and firm investment than GPA is.

To start, Table 3 reports panel regressions (with country fixed e ects) of ICRG perceived investment risk (i.e., the "Investment Profile" variable of the ICRG risk ratings explored in the previous subsection) onto the geopolitical risk indices we study. A one standard deviation increase in GPT is associated with a 0.34 standard deviation increase in perceived investment risk ($t_{stat} = 1.65$). Moreover, this e ect increases to 0.50 ($t_{stat} = 3.15$) after controlling for GPA. In contrast, if anything, an increase in GPA is associated with a decline in investment risk.

Moving to firm decisions, Table 3 also reports regressions of log aggregate investment onto a time trend and our lagged geopolitical risk indices using quarterly U.S. data from 1947Q1 to 2024Q4.[10] Following Gennaioli, Ma, and Shleifer (2015), aggregate investment is the U.S. real private nonresidential fixed investment from the FRED (using real private fixed investment as in Caldara and Iacoviello (2022) yields similar results). A one standard deviation increase in GPT is associated with a 3% decline in investment next quarter ($t_{stat} = -1.61$), and this e ect increases to a 4% decline ($t_{stat} = -3.04$) when controlling for GPA. In contrast, analogous to the investment risk analysis, the e ect of GPA goes in the wrong direction.

Table 3 further considers regressions of log investment onto lagged log capital and lagged geopolitical risk indices using U.S. industry-level data from 1947 to 2024 (with industry fixed

[10]Untabulated statistical tests strongly reject the hypothesis that investment is not trend stationary (i.e., they suggest a deterministic linear trend is enough to capture the investment trend). Moreover, we find similar (untabulated) results in a stochastic trend specification that includes log GPD in the regression (also when adding the log S&P 500 price as in Caldara and Iacoviello (2022)).

e ects included). Following Bai et al. (2022), industry-level investment is measured as real current-cost investments in private nonresidential equipment and structure and industry-level capital is current-cost capital stocks in private nonresidential equipment and structure (both obtained from the BEA). Similar to the aggregate investment analysis, a one standard deviation increase in GPT is associated with a 3% decline in investment, with t_{stat} values around -1.80 whether we controls for GPA or not. In this case, the e ect of GPA on investment is also negative, but statistically insignificant.

While Table 3 shows a consistent time-series link between firm investment and GPT at the country and industry levels, we also consider firm-level regressions to show a more general link between firm investment and geopolitical risk exposures. Specifically, we estimate panel regressions of firm-level quarterly investment (capital expenditures over lagged assets) onto lagged firm-level variables (including β_{GPT} and β_{GPA}) with fixed e ects for firm, time, fiscal quarter, and calendar quarter (using COMPUSTAT data from 1990Q1 to 2024Q4).[11]

The estimate and 95% confidence interval for the slope coefficient on β_{GPT} is reported on the first bar of Figure 5(a), with Figure 5(b) being analogous but for β_{GPA}. A one standard deviation increase in β_{GPT} is associated with a (close to) 0.1% decline in annualized investment. While this e ect may seem small, firm-level betas are known to contain substantial estimation error, which induces an attenuation bias in regressions (this is why we rely on portfolio sorts when studying geopolitical risk premia from single stocks). So, to get a better sense of the economic relevance of β_{GPT}, we perform the same exercise using market beta. We find that a one standard deviation increase in market beta also induces (approximately) a 0.1% decline in annualized investment. So, the β_{GPT} e ect on investment is as strong as the analogous market beta e ect. In contrast, the β_{GPA} e ect on investment is substantially smaller and statistically insignificant.

[11] This firm-level investment analysis follows Wang, Wu, and Xu (2024), who also study the link between firm investment and geopolitical risk. That is, we use the same data source, initial quarter, and fixed e ects used in the first column of their table 2. We also rely on the same firm-level investment and control variables (cash flow over lagged assets, sales growth, Tobin's q, total assets, and leverage). We only deviate from them by replacing GPR as an independent variable with $_{\text{GPT}}$ and $_{\text{GPA}}$ (as in the prior subsection) and by adding time fixed e ects to control for macro variables (since $_{\text{GPT}}$ and $_{\text{GPA}}$ vary by firm and time).

Analogous to the portfolio allocation analysis, the next five bars of Figure 5 show the effects of β_{GPT} and β_{GPR} conditioned on different levels (time-series quintiles) of the overall geopolitical risk index, GPR. The β_{GPT} effect roughly doubles when GPR is in its highest quintile. In contrast, the GPA effect turns positive (but remains statistically insignificant).

So, overall, an increase in GPT (but not in GPA) predicts an increase in perceived investment risk and a decline in future firm investment. Moreover, these findings are consistent whether we look at time variation in aggregate and industry-level investment or overall variation in firm-level investment.

2 Geopolitical Risks and the Cross-Section of Risk Premia

We now turn to the link between geopolitical risks and the cross-section of risk premia. Section 2.1 introduces other risk indices we use in our analysis of risk premia, Section 2.2 studies US individual stocks through portfolio sorts, Section 2.3 explores equity anomalies, and Section 2.4 covers an international panel of country-level equity and bond portfolios. Measurement details for risk indices and asset returns are provided in Internet Appendix A.

2.1 Other Risk Indices

When studying risk premia, we also use risk indices beyond the geopolitical risk indices described in the prior section for two reasons. First, they allow us to show that our geopolitical risk results hold when controlling for other important risk indices (most of which are also based on news). Second, incorporating them into our study leads to a consistent and comprehensive analysis of the pricing of multiple risk indices over a long sample, which is an important contribution of our paper relative to the prior literature.

Our initial set of risk indices is selected to capture important aspects of risk and uncertainty over a long sample. It contains three indices, all available monthly and based on news articles (similar to the geopolitical risk indices we use). The first is the war discourse (WAR) index from Hirshleifer, Mai, and Pukthuanthong (2025b) (available since 01-1927), which is constructed by applying a seeded Latent Dirichlet Allocation estimation to news articles targeting the theme "war".[12] The second is the US historical economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016) (available since 01-1900), which is constructed based on the fraction of newspaper articles simultaneously discussing (i.e., containing key words related to) economics, policy, and uncertainty. The third is an expected market volatility (EMV) index that we construct by splicing the news-implied volatility index of Manela and Moreira (2017) (from 01-1900 to 12-1984) and the news-based expected market volatility index of Baker et al. (2025) (from 01-1985 to 12-2024), both in z-score units. The splicing is necessary since nether index covers our full sample. An alternative approach would be to use an econometric model to estimate expected market volatility using realized market returns. However, this would deviate from our general objective, which is to relate asset returns to external variables (like news coverage) rather than to second moments of asset returns.

We also consider four extra risk indices that have data starting in the early 1960s. The first is the trade policy uncertainty (TPU) index of Caldara et al. (2020) (available since 01-1960), which is constructed based on the fraction of newspaper articles that discuss trade policy uncertainty. This index encapsulates key dimensions of today's global environment amid an unfolding trade war. The other three indices (available since 07-1960) are the real uncertainty index (RUI), macro uncertainty index (MUI), and financial uncertainty index (FUI), all from Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021). These three indices are based on an econometric model that summarizes the forecasting uncertainty associated with a large number of macroeconomic and financial variables. The MUI and FUI indices partially rely on asset prices, and thus deviate from the objective of linking asset returns to external variables. We still include them to capture overall macro-financial uncertainty.[13]

[12] Note that we use the WAR index from Hirshleifer, Mai, and Pukthuanthong (2025b) because most of our risk premia analyses are in the cross-section (the risk premia dimension studied in Hirshleifer, Mai, and Pukthuanthong (2025b)). We also consider the WAR index from Hirshleifer, Mai, and Pukthuanthong (2025a) in robustness checks of our results related to the time-series of risk premia (the risk premia dimension studied in Hirshleifer, Mai, and Pukthuanthong (2025a)). Internet Appendix Section B.8 provides more details.

[13] Engle and Campos-Martins (2023) introduce a measure of global common volatility (COVOL), which proxies for global financial risk and is estimated using data from 47 country equity ETFs. Since global COVOL is only available starting in June 2000, we instead use FUI as our proxy for overall financial uncertainty.

Table 1 provides the sample period for each risk index as well as the full correlation matrix across all risk indices. While some pairs of indices display high correlation, the correlations across indices tend to be low. These low correlations indicate that these indices allow us to study geopolitical risks while controlling for multiple dimensions of risk and uncertainty.

Figure 2 plots the time-series of each risk index (in orange) against GPT (in blue). WAR is the only index highly correlated with GPT (other than GPA and GPR). This is not surprising since war is one of the categories of words included in the construction of the geopolitical risk indices. However, there is still substantial independent variation in GPT as the correlation between WAR and GPT is 0.51 (similar to the 0.45 correlation between GPA and GPT). As a consequence, our analyses of the link between geopolitical risks and risk premia are based on the period starting in 01-1927 (the first month WAR is available) whenever possible, which allows us to provide risk premia results for GPT with and without controlling for WAR.

2.2 The Cross-Section of Individual Stock Risk Premia

We begin from the cross-section of individual stocks in the US using standard portfolio sorts as these are tradable in real time (next subsections explore other cross-sections and methods). Each month, we compute the univariate beta coefficient for each stock's excess return relative to the (negative of the) growth rate in each index using a 3-year rolling window.[14,15] We then sort the stocks into value-weighted quintile portfolios (with NYSE breakpoints) based on these beta estimates (removing utilities and financials). While our empirical choices are common, Internet Appendix B.3 provides a comprehensive sensitivity analysis that considers alternative definitions of index shocks, alternative number of portfolios, alternative portfolio

However, Engle and Campos-Martins (2023) report that the correlation between COVOL^2 and GPR changes is 0.08, indicating the geopolitical risk e ects we study are not strongly reflected in COVOL.

[14]Note that, following Herskovic, Moreira, and Muir (2019) and Chabi-Yo, Gonçalves, and Loudis (2025), our sorts use univariate betas (instead of multivariate betas controlling for a given factor model). The reason is that risk prices (i.e., the b vector in $SDF_t = a - b'f_t$) are proportional to the projection of future returns onto univariate betas (not multivariate betas). See Chapter 13.4 of Cochrane (2005) for details.

[15]Increases in risk reflect adverse events. As such, we use betas on the negative of the growth rate on each risk index, ensuring that a high-low portfolio has positive risk premium if its underlying risk index is priced.

weights, and alternative sorting betas. The overall results are consistent across specifications.

Given that the WAR index is available since 01-1927 and the RUI, MUI, and FUI indices are available since 07-1960, our beta sorting procedure yields two samples that allow us to compare the high-low (HML) portfolios of the given indices: 01-1930 to 12-2024 (our long sample) and 08-1963 to 12-2024 (our modern sample). The results in this section focus on the long sample, which yields a more comprehensive analysis of the geopolitical risk premium. The exception is that results for TPU, RUI, MUI, and FUI are based on the modern sample due to data available. For completeness, Internet Appendix B.2 replicates the main results from this section using only the modern sample for all indices.

2.2.1 Unconditional Risk Premia

Table 4 provides results for the HML portfolio of each risk index. Following Ang et al. (2006), the first row of Table 4 analyses the HML betas on the mimicking portfolios for their respective indices (hereafter, simply "mimicking betas").[16] With the exception of the WAR, all HML portfolios display a positive mimicking beta (most of which are also statistically significant), and thus should deliver positive risk premia if their respective indices are priced.

The second row of Table 4 reports results for HML risk premia. The GPT-based HML portfolio delivers a sizable and statistically significant annualized risk premium of 4.17% ($t_{stat} = 2.85$). In contrast, HML portfolios constructed from all other indices (including GPA) yield smaller and statistically insignificant premia. This finding underscores the fundamental di erence between GPT and GPA from an asset-pricing perspective. The forward-looking nature of geopolitical threats makes GPT more closely linked to investor and firm decisions (as shown in the previous section), which in turn translates into a stronger connection between GPT and cross-sectional risk premia. This distinction suggests that separating threats

[16]The analogue of the Ang et al. (2006) mimicking factor would be to project our index growth rates onto their respective quintile portfolios. We instead use the mimicking factors from the Supervised Principal Component Analysis (SPCA) of Section 2.3. This method ensures the positive mimicking betas are not mechanical as each mimicking factor reflects a combination of anomaly portfolios instead of a combination of the beta quintile portfolios under analysis. However, we find (in untabulated results) even stronger mimicking betas when using the method in Ang et al. (2006) to create mimicking factors.

from actions in other measures of uncertainty (such as EPU) may be crucial for isolating their true asset-pricing e ects, an avenue that o ers a promising direction for future research.

Since market prices can decline when geopolitical tensions increase, it is possible that the GPT risk premium is entirely a consequence of a positive market beta for the GPT HML. The third row of Table 4 shows that this is not the case as the CAPM alpha of the GPT HML is even stronger than its risk premium (4.84% with $t_{stat} = 3.23$). In contrast, the CAPM alphas for the other risk indices are weak. The only exception is the GPR HML, which has a CAPM alpha t_{stat} of 1.90 (close to statistically significant at the 5% level). However, GPR combines geopolitical threats and acts so that its risk premium and alphas partially capture the GPT e ect.

Similarly, the GPT risk premium can also be due to exposure to news about long-term expected returns and volatility, which are priced in the ICAPM (see Campbell et al. (2018)). So, the fourth row of Table 4 provides ICAPM alphas using the intertemporal factor model of Chabi-Yo, Gonçalves, and Loudis (2025), which contains tradable factors for long-term news to expected returns and volatility beyond the market factor. We find that the GPT HML continues to deliver a strong alpha (4.84% with $t_{stat} = 2.91$), whereas HML portfolios of other risk indices display weak and insignificant alphas (in this case, even GPR has a weak alpha). This result indicates that, from the perspective of intertemporal asset pricing theory, the GPT risk premium must be related to exposure to tail risk, which is not accounted for in the ICAPM of Campbell et al. (2018) and Chabi-Yo, Gonçalves, and Loudis (2025). We return to this issue in Section 4, which connects our findings to macro-finance models.

Beyond traditional risk-based factors, we also examine tradable characteristic-based factors. We find that the GPT risk premium cannot be attributed to the GPT HML portfolio's exposure to this alternative class of factors. Specifically, Internet Appendix B.4 reports the GPT HML alphas relative to the widely used factor models of Fama and French (1993), Carhart (1997), Fama and French (2015, 2018), Hou, Xue, and Zhang (2015), Hou et al. (2021), and Daniel, Hirshleifer, and Sun (2020). In all cases, the GPT alphas are higher than the GPT risk premia over the matched periods. The only exception is the Fama and French

(2015) factor model, which leads to an annualized GPT alpha that is 0.12% lower than the GPT risk premium over the same period (a small e ect).

The analyses above consider the risk premia and alphas of each index in isolation. The last two rows of Table 4 consider spanning tests. The first of them provides the alphas of the GPT HML relative to each index HML while the second provides each index HML alpha relative to the GPT HML. The results remain similar in that the GPT alpha is strong and statistically significant regardless of the control index whereas the alphas of the other indices relative to GPT tend to be weak and statistically insignificant. So, overall, the strong GPT risk premium we uncover is not explained by exposure to the HML of other risk indices.

Figure 6 provides results (mimicking betas, risk premia, and alphas) for all the GPT beta quintile portfolios (in excess of quintile 1). As the figure shows, the increases in betas, risk premia, and alphas are monotonic from quintile 1 to quintile 5 (albeit the increases from quintiles 3 to 4 tend to be small). This monotonicity highlights that our results capture a consistent risk pricing relation, with higher GPT exposure associated with higher risk premia and alphas across all quintile portfolios.

In the spirit of Cohen and Polk (1998) and Asness, Porter, and Stevens (2000), we further show that the GPT risk premium arises from di erentials in geopolitical risk exposures both across industries and within industries. Specifically, at each month t, we construct two beta measures for each stock n within each industry i: $\overline{\beta}_{n,t}^{GPT} = \beta_{i,t}^{GPT}$ and $\widetilde{\beta}_{n,t}^{GPT} = \beta_{n,t}^{GPT} - \beta_{i,t}^{GPT}$, where $\beta_{i,t}^{GPT}$ is the GPT beta of the industry stock n belongs to in month t. Given their construction, variation in $\overline{\beta}^{GPT}$ across stocks captures variation in geopolitical risk across industries whereas variation in $\widetilde{\beta}^{GPT}$ across stocks captures variation in geopolitical risk within industries. Figure 7 plots the risk premia and CAPM alphas of HML portfolios constructed from $\overline{\beta}^{GPT}$ and $\widetilde{\beta}^{GPT}$ using the industry definitions from Fama and French (1997), with the updated data obtained from Kenneth French's webpage. We consider multiple specifications that di er based on the number of industries (varying from 12 industries to 48 industries).[17]

[17] Note that, as standard, our baseline analysis removes utilities and financials (which are heavily regulated industries). This implies that the number of industries used in Figure 7 is always lower than the number of industries shown in the x-axis of the figure. For instance, our stocks get assigned to 10 industries when using

For all industry definitions, we have positive GPT risk premia and CAPM alphas across and within industries. The only caveat is that, when using 12 industries, the across-industry risk premium continues to be positive but is statistically insignificant. However, this statistical result is expected as in this case we have too few industries to assign to different portfolios.

2.2.2 Time-Varying Risk Premia

Figure 8(a) explores the realized risk premia on the GPT HML portfolio on rolling windows of 10, 20, and 30 years. As it is clear from the figure, the realized GPT risk premia tend to strongly vary over time, with many periods of 10 years providing negative realized risk premia. This result is natural since the realized GPT HML risk premia contain both the ex-ante GPT risk premia as well as the unexpected returns to the GPT HML portfolio, which are negatively a ected by the realization of adverse geopolitical events. As we look at longer windows, the e ect of unexpected returns declines (because unexpected returns are asymptotically zero on average), making the realized GPT HML risk premia more reflective of the (averaged) ex-ante GPT risk premia. In fact, the realized GPT risk premia are always positive in any period of 30 years within our sample. As such, our finding of a positive GPT risk premium on average is not driven by any particular major period that induced large realized returns on the GPT HML portfolio. Instead, the GPT HML has delivered a positive risk premium throughout our entire sample period.

For comparison, Figure 8(b) provides an analogous graph for the market factor. The level of variation in the realized GPT risk premia is comparable to that of the realized market risk premia. The market risk premia display a little more variation, but this is in line with the fact that the market risk premium is higher on average. This result further enforces the finding that the GPT risk premium is consistently positive throughout our sample period (at least as consistently positive as the market risk premium is). So, the positive average GPT risk premium we measure is not due by a particular historical period.

While the above results indicate that the (averaged) ex-ante GPT risk premia are positive

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the 12-industry definition from Fama and French (1997).

throughout our sample period, it is reasonable to expect some variation in the conditional GPT risk premium. In particular, given that portfolio allocations and firm investment are more connected to β_{GPT} during periods of higher attention to geopolitical risks, one would expect a higher GPT risk premium during these same periods. To explore this issue more directly, Figure 9(a) plots the average GPT HML return (with 95% confidence intervals) conditioned on di erent levels of attention to geopolitical risks based on lagged quintiles of the historical GPR distribution (as in our analyses of portfolio allocations and firm investment in the prior section). The results indicate that the GPT risk premium concentrates in periods of high attention to geopolitical risks. In particular, the GPT risk premium is roughly twice as large (than the unconditional 4.17% premium) following the highest quintile of the GPR distribution. Moreover, we cannot reject the hypothesis of a zero conditional GPT risk premium for the other quintiles (albeit the conditional GPT risk premia estimates are consistently positive). These results indicate that investors price GPT more strongly when attention to geopolitical risks is elevated (whether that attention is warranted or not). This finding is consistent with the results (detailed in the prior section) that both portfolio allocations and firm investment reflect geopolitical risks more strongly in periods of high attention to geopolitical risks.[18]

To better interpret the findings on the conditional GPT risk premia, Figure 9(b) plots an analogous graph for the market risk premium conditioned on levels of the market dividend yield. The result is similar in that the market risk premium concentrates in periods of high dividend yield (in line with previous findings in the literature). So, the role of the level of geopolitical risks for the GPT risk premium is similar to the role of the market dividend yield for the market risk premium.

[18]Note that our analysis of the conditional GPT risk premia uses GPR as the conditioning variable because this approach matches our analysis in Section 1 and GPR captures the total attention to geopolitical risks (whether priced or not). However, as demonstrated in Internet Appendix Figure IA.1, we find similar results when conditioning on GPT instead of GPR.

2.3 The Cross-Section of Equity Anomaly Risk Premia

We now turn to the cross-section of equity anomaly portfolios. In this case, we apply the Supervised Principal Component Analysis (SPCA) of Giglio, Xiu, and Zhang (2025), which allows us to efficiently create mimicking factors using large sets of test portfolios.[19] Given that most anomalies are based on signals that require at least some COMPUSTAT data (which are only free of survivorship bias starting in the early 1960s), we focus our analysis of the cross-section of equity anomaly risk premia on our modern sample starting in 08-1963. We provide results over our long sample (with a much smaller set of anomalies) in Internet Appendix B.5, with the overall results being similar to what we find over the modern sample.

The SPCA method is designed for large cross-sections. As such, we use a large set of anomaly portfolios for this analysis. Specifically, we use a total of 2,620 anomaly portfolios from two sources, requiring only that portfolios have returns over our entire modern sample. The first source of anomaly portfolios is the Open Source Asset Pricing (OSAP) dataset of Chen and Zimmermann (2022), which yields 2,344 decile portfolios from 115 anomaly signals (one set based on value-weights and one set based on equal-weights). The second source of anomaly portfolios is the factor dataset of Jensen, Kelly, and Pedersen (2023), which yields 276 long-short portfolios based on 138 anomaly signals (one set based on value-weights and another based on equal-weights). For the SPCA tuning parameters, we use five factors and 786 test portfolios (30% of the 2,620 test portfolios), with a sensitivity analysis provided in Internet Appendix B.6.

Table 5 provides the results from our analysis of the cross-section of equity anomalies. For comparability, we normalize the mimicking factors of each index to have an annualized volatility of 20%, which is similar to the market annual volatility. The first row shows that the SPCA method yields mimicking factors that display non-trivial correlations with the (negative of the) growth rate in their respective risk indices. The second row demonstrates

[19]The non-tradable factors we use in the SPCA are the negative of the growth rate on each risk and uncertainty index. This approach is consistent with our portfolio sorts (see Footnote 15) and ensures that a mimicking factor has positive risk premium if its underlying uncertainty index is priced.

that the GPT mimicking factor risk premium is strong (3.03% per year) and statistically significant ($t_{stat} = 4.11$). However, in this case, the other risk indices also provide significantly positive risk premia (except for MUI). The third and fourth rows provide CAPM and ICAPM alphas, highlighting that the GPT mimicking factor also provides positive and statistically significant alphas while the mimicking factors for some other indices do not. The fifth row shows the GPT alpha relative to each other index, which demonstrates that the GPT risk premium is not due to exposure to any of the other risk indices we study as the GPT alpha is always positive and statistically significant. The last row shows that the converse is also true: most indices provide an alpha relative to GPT. Two important exceptions are the GPA and GPR, which have mimicking factors that deliver negative (and statistically insignificant) alphas relative to GPT.

In summary, these results demonstrate that GPT is priced in the cross-section of anomaly portfolios. Moreover, this findings is not driven by exposure to other risk indices. However, in contrast to our portfolio sorting analysis, in this case many other risk indices are also priced in the cross-section of anomaly portfolios even after controlling for GPT. Importantly, GPA and GPR are two exceptions as their alphas are statistically zero after controlling for GPT.

2.4 The Cross-Section of Country-Level Equity and Bond Risk Premia

As our last cross-section, we consider country-level equity and government bond portfolios from the Jordà et al. (2019) dataset, covering annual returns form the beginning of our long sample until 2020 on 16 developed countries (with excess returns measured relative to the country-specific bill rate). Since the SPCA method is not applicable for such a small cross-section, in this case we build mimicking factors using standard Fama and MacBeth (1973) regressions of annual returns on univariate betas relative the (negative of the) growth rate in GPT and in other risk indices.[20] The annual slopes on these regressions represent consistent

[20] Since returns are annual, in this case we take the average of each index within the year before computing the growth rate needed for the univariate betas. This approach is in line with the fact that the monthly geopolitical risk indices are given by the average of their respective daily indices for the period over which daily indices are available (starting in 1985).

estimators for the annual returns on the mimicking factors of the respective indices (see Balduzzi and Robotti (2008) for a detailed analysis of this econometric result). As in our analysis of equity anomaly portfolios, we normalize the mimicking factor of each index to have an annual volatility of 20%, which is similar to the market annual volatility.

Table 6 provides the results from this analysis. It focuses on the sample from 1930 to 2020, covering most of our long sample. Internet Appendix B.7 provides results over the period from 1961 to 2020, covering most of our modern sample.

Table 6 (Panel A) focuses on equities, showing that the GPT risk premia are strong economically and statistically (8.84% with $t_{stat} = 4.33$). However, most of this risk premium is due to market exposure in the context of the World CAPM (WCAPM).[21] In particular, the WCAPM alpha for the GPT mimicking factor is much lower than its risk premium (2.73% with $t_{stat} = 1.92$). We see a similar pattern for the other risk indices. One exception is WAR, which has a negative risk premium and WCAPM alpha.

Table 6 (Panel B) focuses on government bonds. The GPT risk premium is strong economically and statistically (6.90% with $t_{stat} = 3.61$). In this case, the WCAPM alpha for the GPT mimicking factor is only a little lower than the risk premium (5.85% with $t_{stat} = 2.60$). Results are more mixed for some of the other risk indices. While in this case the WAR index provide strong risk premium and WCAPM alpha, some other indices (like EPU, EMV, and TPU) have negative risk premia and WCAPM alphas.

Table 6 (Panel C) combines equities and government bonds, resulting in a broader cross-section to construct the mimicking factors. The GPT risk premium is strong economically and statistically (9.49% with $t_{stat} = 4.49$). Moreover, while the WCAPM alpha of GPT is much lower than its risk premium, it remains strong economically and statistically (3.44% with $t_{stat} = 2.49$). The results for other risk indices are more mixed, mirroring the findings from Panels A and B. In particular, the WAR index has a negative risk premium and WCAPM

[21]For the world market portfolio, we use the returns on the 16 countries under analysis weighted by lagged GDP (also from the Jordà et al. (2019) dataset) since we do not have market capitalization weights over our sample period. Note that the standard CAPM and ICAPM models used in Sections 2.2 and 2.3 are not relevant here since they only account for exposure to the US market.

alpha. Moreover, some other risk indices (e.g., TPU) have a strong risk premium and a relatively weak WCAPM alpha.

Note that GPA has strong risk premia and WCAPM alphas in this analysis of country-level equity and bond portfolios. However, as shown in Internet Appendix B.7, the WCAPM alphas associated with GPA are much weaker and statistically insignificant in the modern sample whenever equity portfolios are included.

The overall results suggest that GPT is priced in the cross-section of country-level equity and bond returns. Moreover, while WCAPM betas explain a non-trivial portion of the GPT risk premia, WCAPM alphas remain generally strong. In contrast, other risk indices display more mixed results, being positively priced in the cross-section bonds but not in the cross-section of equities (or vice versa).

3 Geopolitical Risks and the Time-Series of Risk Premia

We now turn to the time-series link between geopolitical risks and risk premia. Section 3.1 focuses on equity risk premia while Section 3.2 explores bond risk premia. Throughout this section, we continue to rely on the international panel of annual equity and bond excess returns from 16 developed countries starting in 1927 used in Section 2.4 (from Jordà et al. (2019)).[22] However, we stop the sample in 2019 (instead of 2020) to keep the same sample period for forecasting regressions with and without the WAR index (results are similar either way). Internet Appendix B.8 provides an analysis focused on the US returns (the key findings are similar to the ones we report in the main text).

3.1 The Time-Series of Equity Risk Premia

Table 7 (Panel A) provides predictability results for 1-year returns through panel regressions with country fixed e ects and Driscoll and Kraay (1998) standard errors, which account

[22] We continue to use the WAR index from Hirshleifer, Mai, and Pukthuanthong (2025b) (a cross-sectional paper) to be consistent with our analysis of the cross-section of risk premia. However, Internet Appendix B.8 replicates our analysis of the time-series of risk premia using the WAR index from Hirshleifer, Mai, and Pukthuanthong (2025a) (a time-series paper). The results are similar to the ones we report in the main text.

for residual correlation across countries and over time. The estimated values suggest GPT is positively linked to future returns. However, the statistical link is relatively weak. In particular, the predictability coefficient on GPT is only statistically significant at the 5% level once we control for WAR or all variables combined. In economic term, however, the predictability is non-trivial: a one standard deviation increase in GPT is associated with an increase in the next year equity premium of 3.00% (for the specification with GPT and GPA) and 3.99% (controlling for all risk indices).

Table 7 (Panel B) shows that the predictability results get much stronger at a long horizon of 5 years (we find similar results with a 3-year horizon). In particular, GPT is economically and statistically significant in all specifications considered, whether we control for WAR or not. For instance, in a univariate sense, a one standard deviation increase in GPT is associated with a 25.77% ($t_{stat} = 2.79$) higher equity excess return over the next 5 years.

While the findings above indicate GPT a ects equity risk premia variation over time, it is important to put these results in perspective. The R^2_{within} values are generally small. For instance, GPT has $R^2_{within} = 1\%$ at a 1-year horizon and $R^2_{within} = 6\%$ at a 5-year horizon. As such, geopolitical threats induce some time-variation in equity risk premia, but are far from being the only or most important source of equity risk premia variation over time. This result is intuitive: investors care about geopolitical threats, but the equity premium is also a ected by time variation in many other sources of risk.

3.2 The Time-Series of Bond Risk Premia

Internet Appendix Table IA.8 shows that (whether we focus on 1-year of 5-year returns), GPT has a very weak (e ectively null) link to bond risk premia. This is true both economically and statistically. In fact, no risk or uncertainty index among the ones we study is a good predictor of future bond returns. One exception is that EMV statistically predicts future bond returns (more so at a 5-year horizon than at a 1-year horizon).

These results are consistent with the view that geopolitical threats have two opposing e ects on bond risk premia. One one hand, as geopolitical threats increase, investors become more averse to risky assets in general, inducing an increase in bond risk premia. On the other hand, within risky assets, the increase in geopolitical threats makes investors prefer bonds over equities, inducing a decline in risk premia. The two effects largely offset each other so that the total effect of geopolitical threats on bond risk premia is small and statistically insignificant (albeit the point estimates tend to be negative).

4 Potential Channels for Geopolitical Risk Premia

The previous sections reveal a striking asymmetry: asset prices embed a risk premium for geopolitical threats (GPT) but not for geopolitical acts (GPA). We argue systematically that this difference arises because GPT reflects expectations of future adverse geopolitical events, whereas GPA captures their realizations. As Section 1 shows, the decisions of investors and firms are forward-looking, so they are linked to GPT rather than GPA. Consequently, equilibrium asset prices inherit this forward-looking nature, embedding a risk premium for GPT even in the absence of one for GPA.

These results are consistent with the broad economic insight that uncertainty about an event rather than the event itself should be priced. This section explores several channels in asset pricing models that can formalize this logic and examines whether, empirically, these channels help explain our findings on the pricing of geopolitical tensions. We focus on a few channels and evaluate them in reduced form rather than specifying a full structural model for each. This choice reflects our view that multiple mechanisms likely contribute to the empirical patterns we document. The unifying theme across these channels is the fundamental distinction between expectations of adverse geopolitical events (captured by GPT) and their realizations (captured by GPA).

4.1 Non-Linear Market Risk Exposures

Our empirical analysis shows that the GPT risk premium is not due to market risk exposure in the standard CAPM. However, the standard CAPM is based on a linear SDF, which is theoretically justifiable only if we approximate the utility function as quadratic or returns as normally distributed. Neither of these approximations is appealing when considering geopolitical risks, which likely affect high order moments of investors' utility functions and can induce tail events in returns.

So, one potential channel for the pricing of GPT is non-linear market risk exposures. Specifically, without approximations, the non-linear CAPM implies the covariance with $-\partial U(R_{m,t})$ is priced rather than the covariance with $R_{m,t}$ as in the standard CAPM. So, market returns, $R_m = 1 + r_m$, may respond non-linearly to increases in geopolitical threats but not to the realization of adverse geopolitical events (since prices anticipate these events). If so, the GPT HML may be exposed to $-\partial U(R_{m,t})$ (much more than it is exposed to $R_{m,t}$) even though the GPA HML is not, justifying their different risk premia.

The key challenge in exploring the non-linear CAPM empirically is that we do not know the utility function. So, following the prior literature, we start from a fourth-order polynomial approximation to the utility function, which implies the covariances with r_w, r_w^2, and r_w^3 are priced (see Harvey and Siddique (2000) and Dittmar (2002)). As shown in Dittmar (2002), if absolute risk aversion and prudence both decrease in wealth, which are sufficient conditions for "standard risk aversion" (Kimball (1993)), we have that r_m^2 has a negative risk price and r_m^3 has a positive risk price. So, investors' aversion to skewness induces them to accept low risk premia for assets with high covariance with r_m^2 whereas investors' aversion to kurtosis leads them to require high risk premia for assets with high covariance with r_m^3.

The first four columns of Table 8 explore this 4th order approximation to the utility function.[23] We have $\beta_{r_{m\psi}} = -0.08$ ($t_{stat} = 0.92$) and $\beta_{r^3_{m\psi}} = -4.68$ ($t_{stat} = -4.37$) for the GPT HML whereas the respective GPA betas are positive so that these two market risk factors would lead to a negative GPT risk premium that is lower than the GPA risk premium. So, aversion to variance and kurtosis does not help explain the geopolitical risk premia. In contrast, we have $\beta_{r^2_m} = -1.35$ ($t_{stat} = -2.85$) for the GPT HML and $\beta_{r^2_{m\psi}} = -0.22$

[23] In the models, r_m reflects real returns on the market portfolio. To be consistent with how we implement the standard CAPM, we proxy for r_m using the standard equity market factor, which is given by nominal equity market returns in excess of the nominal risk-free rate.

($t_{stat} = -0.77$) for the GPA HML, suggesting that aversion to skewness could help explain the geopolitical risk premia (given the resulting negative risk price for r_m^2). Verifying whether the quantitative e ect of skewness aversion is strong enough to induce a positive GPT risk premium requires taking a stand on the utility function. The fourth column in Table 8 shows betas relative to $-\partial U_t \approx const + \gamma \cdot r_{m,t} - (1/2) \cdot \gamma \cdot (1+\gamma) \cdot r_{m,t}^2 + (1/6) \cdot \gamma \cdot (\gamma+1) \cdot (\gamma+2) \cdot r_{m,t}^3$, which is an approximation that holds under constant relative risk aversion (CRRA). We use $\gamma = 10$, which is a relatively high risk aversion value. Since the GPT HML beta is negative (and lower than the GPA HML), we have that the skewness aversion e ect is not strong enough to explain our risk premia results under CRRA. It is possible that skewness aversion plays a larger role in some other utility functions, but it is unlikely that empirically plausible utility functions deviate that much from the quantitative results observed under CRRA.

To account for potential non-linearities beyond the 4th order, the next five columns consider CRRA without any approximation so that $-\partial U(R_{m,t}) = -R_{m,t}^{-\gamma}$. We consider five different γ values varying from 1 to 10. Similar to the results from the fourth-order polynomial approximation to the utility function, we have that the non-linear CAPM cannot explain a positive GPT risk premium that is higher than the GPA risk premium. In particular, for all risk aversion levels, the GPT HML beta on $-R_{m,t}^{-\gamma}$ is economically small and statistically insignificant (it is also lower than the respective GPA HML beta).

An alternative approach is to assume investors' utility functions incorporate disappointment aversion, which leads to the pricing of downside market beta (e.g., Ang, Chen, and Xing (2006) and Lettau, Maggiori, and Weber (2014)). Following Lettau, Maggiori, and Weber (2014), we estimate downside betas ($\beta_{r_m}^-$) of our GPT and GPA HML portfolios by regressing their returns onto r_m using only observations for which $r_m \leq \overline{r}_m - \sigma_m$, where $\overline{r}_m$ and σ_m are the average and standard deviation of r_m over our sample. The GPT HML $\beta_{r_{m\psi}}^-$and $\beta_{r_{m\psi}}$ are both lower than the respective GPA HML betas. So, downside market risk also does not explain the geopolitical risk premia.

Overall, we conclude that non-linear market risk exposures do not contribute to the geopolitical risk premia we uncover.

4.2 Time Variation in the Likelihood of Disasters

Geopolitical risks are naturally related to extreme events. In the context of static asset pricing models, the resulting non-normality of returns leads to the pricing of non-linear market risk exposures (which we explore in the prior subsection). In contrast, non-normality in intertemporal models leads to the pricing of long-term news to high order moments of the investors' endowment process. Internet Appendix C formalizes this statement by considering an Epstein-Zin investor (Epstein and Zin (1989, 1991) and Weil (1989)) with time discount factor δ, intertemporal elasticity of substitution ψ, and relative risk aversion $\gamma > 1$. Specifically, we show that the log Stochastic Discount Factor (SDF) of such an investor can be generally written as[24]

$$sdf_t = \lambda_{t-1} - \gamma \cdot \Delta c_t - \lambda_{\mathbb{E}} \cdot N_{\mathbb{E}c,t} + \lambda_{\mathbb{V}} \cdot N_{\mathbb{V},t} + \lambda_{\mathbb{H}} \cdot N_{\mathbb{H},t} \tag{1}$$

where $\lambda_{\mathbb{E}}$, $\lambda_{\mathbb{V}}$, and $\lambda_{\mathbb{H}}$ are positive if $\gamma > 1/\psi$ (i.e., if the investor prefers early resolution of uncertainty), $\widetilde{v}_t$ reflects shocks to the investor's log value function, Δc_t is log consumption growth, $N_{\mathbb{E}c,t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \delta^h \cdot \Delta c_{t+h}\right]$ is expected consumption growth news, $N_{\mathbb{V},t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \delta^h \cdot \mathbb{V}ar_{t+h-1}[\widetilde{v}_{t+h}]\right]$ is news about $\widetilde{v}_t$ volatility, and $N_{\mathbb{H},t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \delta^h \cdot \mathbb{H}_{t+h-1}[\widetilde{v}_{t+h}]\right]$ is news about $\widetilde{v}_t$ high order moments as we define

$$\mathbb{H}_t[\widetilde{v}] = \sum_{j=3}^{\infty} \frac{(1-\gamma)^{j-1}}{j!} \cdot \mathbb{K}_t^{(j)}[\widetilde{v}] \tag{2}$$

where $\mathbb{K}_t^{(j)}[\cdot]$ is the j-th cumulant (e.g., $\mathbb{K}_t^{(2)}[\widetilde{v}] = \mathbb{E}_t[\widetilde{v}^2]$ and $\mathbb{K}_t^{(3)}[\widetilde{v}] = \mathbb{E}_t[\widetilde{v}^3]$).

So, for an Epstein-Zin investor who prefers early resolution of uncertainty, negative shocks to Δc and $N_{\mathbb{E}c}$ and positive shocks to $N_{\mathbb{V}}$ and $N_{\mathbb{H}}$ reflect bad news. Note that we can always write $\widetilde{v}_t = \widetilde{vc}_t + \widetilde{c}_t$ and shocks to the value-consumption ratio ($\widetilde{vc}$) reflect shocks to the parameters of the future consumption distribution under an exogenous consumption endowment process, as standard in exchange economies (Lucas (1978)). As such, $\widetilde{v}_t$ is entirely

[24]Equation 1 is exact if $\ = 1$, but it still holds as an approximation if $\ \neq 1$ (in which case we replace $\delta\psi$ with $\bar{\delta}$, which is a log-linearization constant close to δ). See Internet Appendix C for details.

determined by shocks to consumption and its distribution so that $N_{\mathbb{V}}$ and $N_{\mathbb{H}}$ reflect news about the volatility and high order moments of the consumption distribution.

As demonstrated in Internet Appendix C, if the endowment process follows a conditionally normal distribution, then $N_{\mathbb{H}} = 0$ and and ICAPM of Campbell et al. (2018) and Chabi-Yo, Gonçalves, and Loudis (2025) captures the relevant risk factors. However, Subsection 2.2 shows that the GPT HML has a positive alpha relative to the intertemporal risk factor model of Chabi-Yo, Gonçalves, and Loudis (2025). So, we know that a standard intertemporal asset pricing model can only (potentially) explain the geopolitical risk premia under $N_{\mathbb{H}} \neq 0$ (i.e., a non-normal distribution for the endowment process).

The main way in which the prior literature explores $N_{\mathbb{H}} \neq 0$ empirically is by considering rare disasters that have a time-varying probability (see Tsai and Wachter (2015) for a review of the rare disasters literature). In this case, $N_{\mathbb{H}}$ captures news about the probability of disasters (see Internet Appendix C.6). Importantly, $N_{\mathbb{H}}$ reflects news about the long-run probability of disasters, not short-run. As we show below, GPA predicts cumulative consumption disasters over the short-term (next one or three years) whereas GPT predicts cumulative consumption disasters over the long-term (next five or ten years). This result is natural given the more forward looking nature of GPT and indicates variation in GPT better reflects variation in objective risk from the perspective of Epstein-Zin investors.

Table 9 reports regressions of the average frequency of consumption disasters (realized or expected) over the next H years onto lagged levels of GPT and GPA. For realized disasters, we use the dataset from Caldara and Iacoviello (2022), which is an updated version of the dataset of Nakamura et al. (2013). For expected disasters (i.e., disaster probabilities), we use the dataset from Marfè and Pénasse (2025). All specifications reflect panel regressions with country fixed e ects. Moreover, following the prior literature exploring disasters empirically (e.g., Nakamura et al. (2013) and Caldara and Iacoviello (2022)), they all control for structural changes in the expectation and variability of consumption growth using dummy variables for Pre-1946, 1946-1972, and Post-1972. The sample of our analysis covers from 1927 to 2019, with 26 countries for the analysis of realized disasters and 42 countries for the analysis of expected disasters.

Panel A shows that both GPT and GPA are linked to the average number of future consumption disasters over the next H years. However, the link between GPT and future disasters is weaker over the next 1 or 3 years and stronger over the next 10 years (being comparable over the next 5 years). In fact, in bivariate regressions, GPT is statistically insignificant for $H = 1$ and GPA is statistically insignificant for $H = 10$. Panel B shows similar (but stronger) results when we consider the average probability of future consumption disasters. Specifically, the link between GPT and future disasters is weaker only over the next 1 year, being comparable over the next 3 years and stronger over the next 5 and 10 years. For instance, in bivariate regressions, GPT is statistically insignificant for $H = 1$ and GPA is statistically insignificant for $H = 5, 10$.[25]

Overall, the results suggest that higher GPT and GPA levels are associated with higher likelihood of disasters going forward. However, the effect of GPA tends to dominate for cumulative disasters over the next 1 or 3 years while the effect of GPT tends to dominate for cumulative disasters over the next 5 or 10 years. These results align with the message (conveyed in Section 1) that GPT anticipates future adverse geopolitical events whereas GPA is more reflective of the realization of such events. Moreover, they indicate GPT is a more relevant risk factor (than GPA) in intertemporal asset pricing models given the log SDF in Equation 1, which is consistent with the fact (shown in Section 1.3) that GPT better aligns with the geopolitical risk perceptions of investors.

So, the evidence is consistent with the view that time variation in the likelihood disasters contributes to the geopolitical risk premia we uncover. Importantly, we do not build a full structural model to quantify the exact risk premia effect of exposure to rare disasters because other channels are also likely to contribute to the geopolitical risk premia. Even within a rare disasters model, features such as limited stock market participation may be important in fully teasing out the quantitative effect of rare disasters on geopolitical risk

[25] The prior literature finds that some of the risk indices explored in the prior sections also predict consumption disasters. Internet Appendix Section B.9 shows that the consumption disaster results from Table 9 continue to hold after controlling for these other risk indices.

premia. So, our conclusion is simply that time variation in the likelihood of disasters helps explain the geopolitical risk premia (i.e., we do not conclude that rare disasters fully explain the geopolitical risk premia).

4.3 Overreaction to Geopolitical Threats

Another potential channel for our findings is overreaction to geopolitical threats. That is, suppose geopolitical threats are signals about future adverse outcomes investors care about either because they are informative about expected growth (e.g., a war decreases expected output) or risk (e.g., the likelihood of disasters can be a priced variable as in the previous subsection). If investors overreact to geopolitical threats, then an increase in GPT implies undervaluation (due to overly pessimistic growth expectation or risk assessment), which leads to high expected returns going forward, explaining our findings on the time variation in the equity premium. Similarly, the underlying belief distortion would imply the SDF under the objective measure can be written as $SDF_t = X_t \cdot SDF_t^{Inv}$, where X_t captures the change of measure (from the objective measure to the investors' measure). As such, in the spirit of Cui, Delao, and Myers (2025), GPT would also appear as a priced factor in the realized return data through its effect on X_t even if GPT did not affect the SDF of investors (SDF_t^{Inv}). Under this overreaction view, GPA would not have a risk premium because the signal from geopolitical actions is less uncertain, minimizing the scope for overreaction to take place.

For the above mechanism to affect asset prices in equilibrium, we need to either assume that (i) there are no rational investors in the market or (ii) the rational investors face frictions that limit their ability to take advantage of the mispricing that is induced by the overreaction of other investors to geopolitical threats (i.e., rational investors face "limits to arbitrage" as in Shleifer and Vishny (1997)). We do not have a clean way to explore the proposed overreaction channel empirically under (i). So, we explore it under (ii), which is also the standard assumption in the behavioral finance literature. In this case, rational investors correctly perceive the mispricings in the market, but are unable to take full advantage of them due to limits to arbitrage. We further assume that global fund managers proxy for the rational investors in the market whereas retail investors proxy for the overreacting investors. So, under the overreaction to geopolitical threats story, GPT should be negatively correlated with perceptions of equity overvaluation by fund managers whereas GPA should not (at least after controlling for GPT). We find that this is not the case empirically, as detailed below.

The BofA surveys discussed in Subsection 1.3 directly ask fund managers about mispricing in equity markets (see Bastianello and Peng (2025) and Couts et al. (2024)). So, we measure perceived overvaluation of US equities (from 04-2001 to 12-2024) using the net fraction of fund managers who answer "yes" to the question of whether US equities are overvalued in the BofA surveys. We measure perceived overvaluation of global equities following an analogous approach (but in this case the variable is available from 01-1998 to 12-2024). Table 10 provides regressions of these two perceived overvaluation variables onto GPT and GPA. The results indicate that GPT is positively correlated with perceived overvaluation. So, when GPT is high fund managers tend to view equity markets are overvalued, not undervalued. This finding is the opposite of what we would expect if the GPT risk premium was driven by overreaction to geopolitical threats, which would lead to undervaluation of equities at time of high GPT. Moreover, we find that, in contrast to GPT, GPA is negatively correlated with perceived overvaluation, which also goes against the view that di erences in overreaction to GPT and GPA help explain di erences in risk premia between GPT and GPA.

So, the evidence is inconsistent with the view that overreaction to geopolitical threats is important to the geopolitical risk premia we uncover.

5 Conclusion

This paper examines the asset pricing implications of geopolitical tensions using nearly a century of data and a decomposition of geopolitical risks into threats (GPT) and acts (GPA). Our key insight is that GPT aligns closely with perceptions of geopolitical risk and decisions of investors and firms, and it explains variation in risk premia across assets and over time. In contrast, GPA shows weaker and less stable links to the beliefs and decisions of investors and firms as well as to risk premia. These results suggest that distinguishing between anticipated and realized geopolitical tensions is essential for understanding how geopolitical risks relate to investment decisions and asset prices.

Our findings have broader implications for macro-finance research and policy frameworks. From an asset pricing perspective, they underscore the importance of incorporating forward-looking measures of uncertainty when examining the interaction between such measures and risk premia. While we focus on the e ects of geopolitical risk, our results suggest that similar dynamics may apply to other forms of uncertainty, including climate, cybersecurity, or trade policy. More broadly, our findings indicate that expectations of geopolitical conflicts (rather than the conflicts themselves) can meaningfully influence both financial markets and real economic decisions. This distinction is particularly important in an era of rising geopolitical uncertainty and can help inform how investors, policymakers, and researchers interpret the economic consequences of global tensions.

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GPT Expressions (blue) vs GPA Expressions (orange)

Figure 1
GPT and GPA Expressions Sized based on Frequency

This figure plots expressions (bigrams and trigrams) used in the construction of the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022). The expressions associated with the GPT index are in blue (left side) whereas and the expressions associated with the GPA index are in orange (right side). The relative size of the expressions reflects the relative frequency of the word categories associated with the respective expressions. Section 1.1 provides measurement details for the GPT and GPR indices and covers the results from this figure.

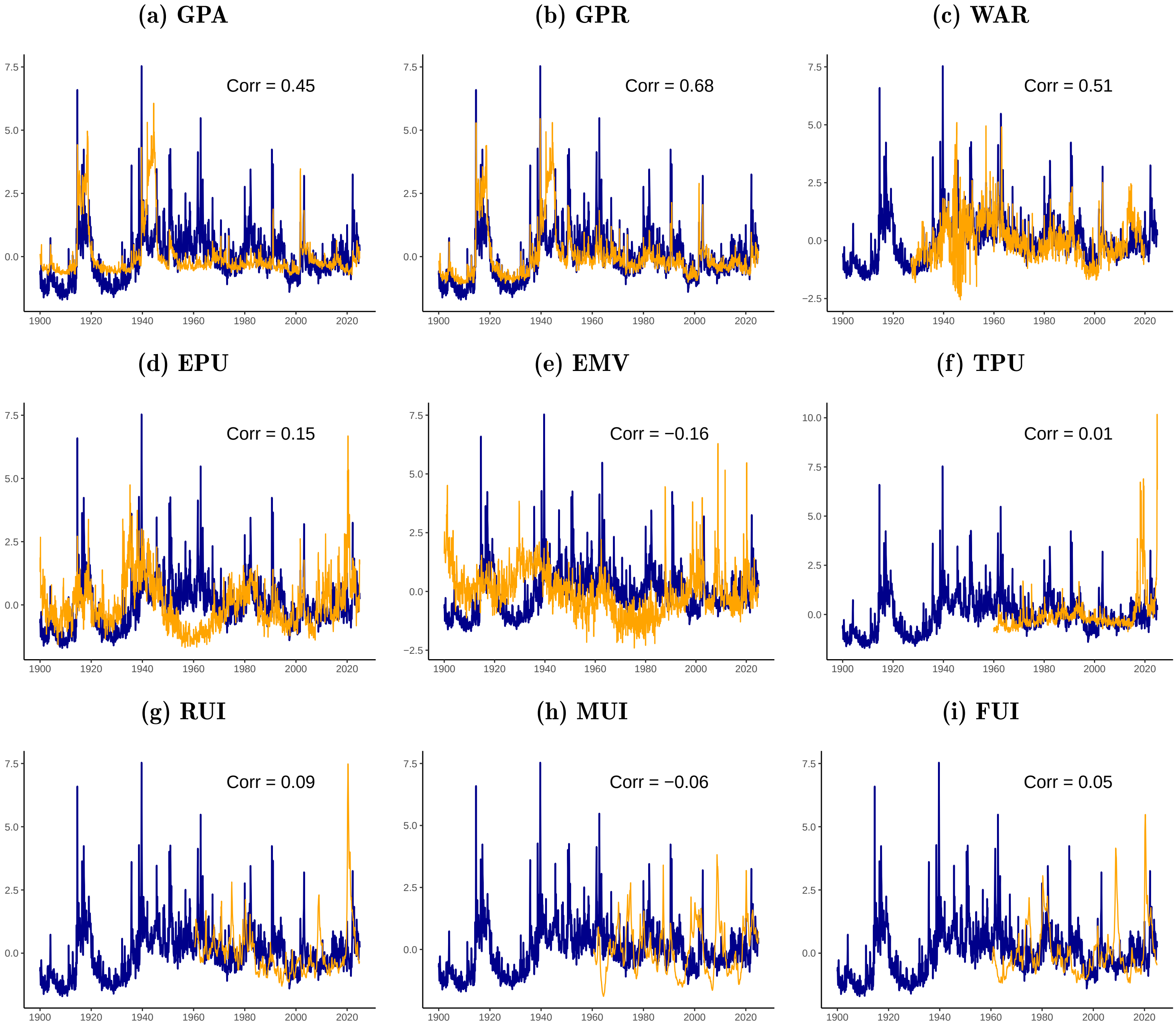


Figure 2
GPT (blue) vs Other Risk Indices (orange)

This figure plots the (z-scores of the) risk indices we use throughout the paper. We consider ten risk indices in total. The first three are the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). The other indices (detailed in Table 1) cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV), trade policy uncertainty (TPU), real uncertainty (RUI), macro uncertainty (MUI), and financial uncertainty (FUI). Each panel plots the index under the respective panel title (in orange) together with the GPT index (in blue), with the correlation between the two provided in the upper right of the graph. Section 1.1 provides measurement details for the geopolitical risk indices while Section 2.1 provides measurement details for the other risk indices.

(a) World War II (b) Cold War Crises in the 1960s

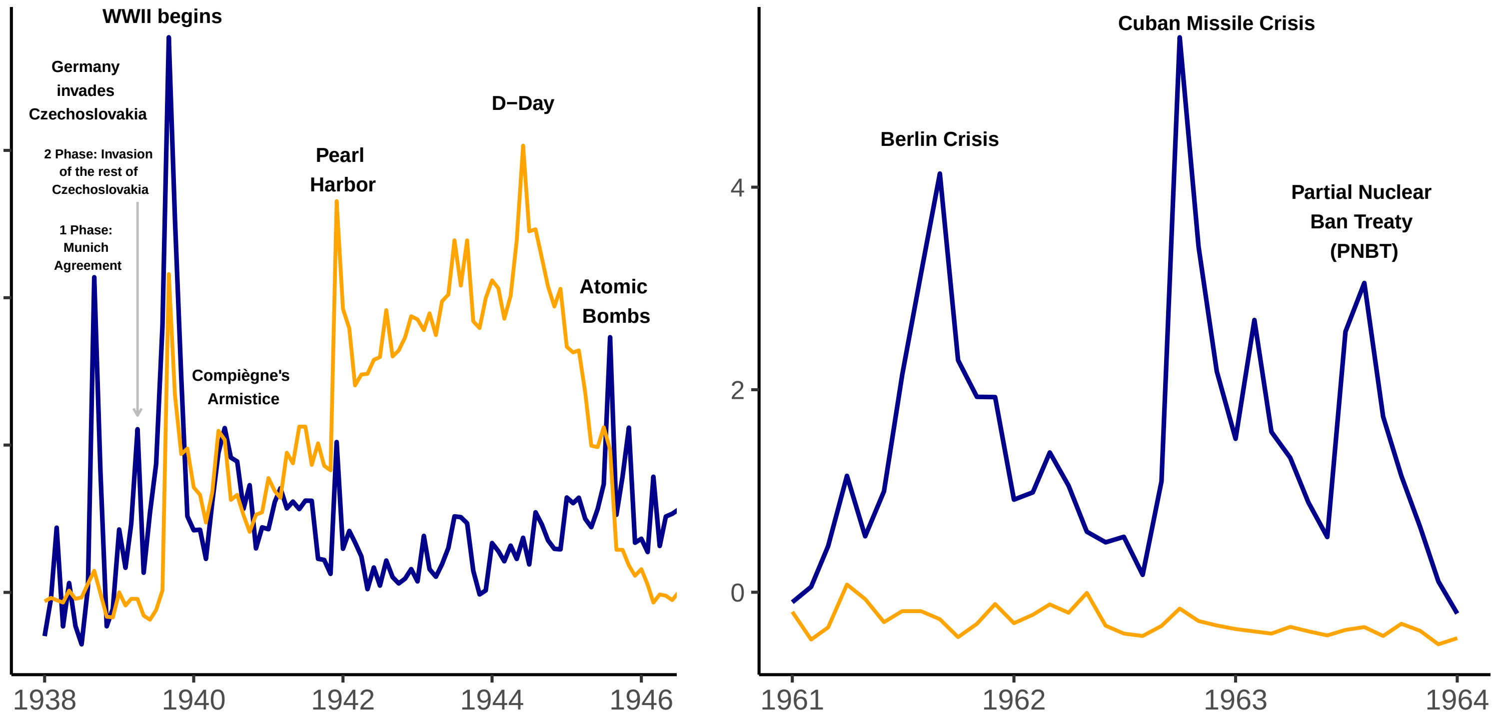
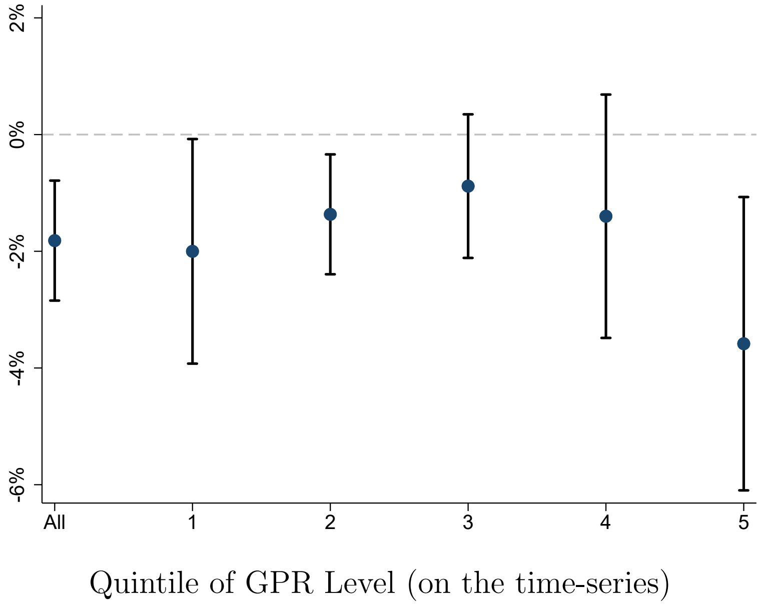


Figure 3

Historical Episodes: GPT (blue) vs GPA (orange)

This figure plots the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) over two of the historical periods highlighted in their figure 4: the second world war in Panel (a) and the early 1960s with important developments associated with the cold war in Panel (b). The GPT index is in blue and the GPA index is in orange. We also identify some relevant geopolitical events. Section 1.1 provides measurement details for these geopolitical risk indices while Section 1.2 covers the results from this figure.

(a) GPT Beta Effect on Investor Portfolio Allocations



(b) GPA Beta Effect on Investor Portfolio Allocations

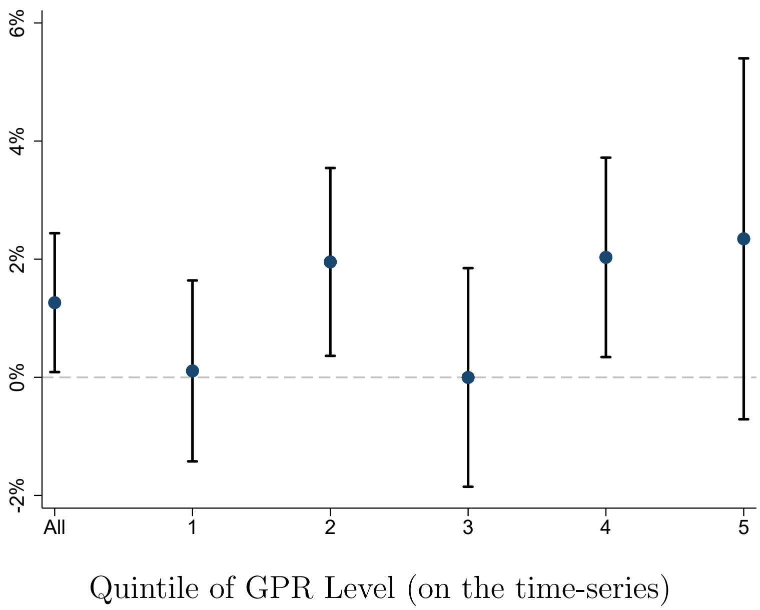
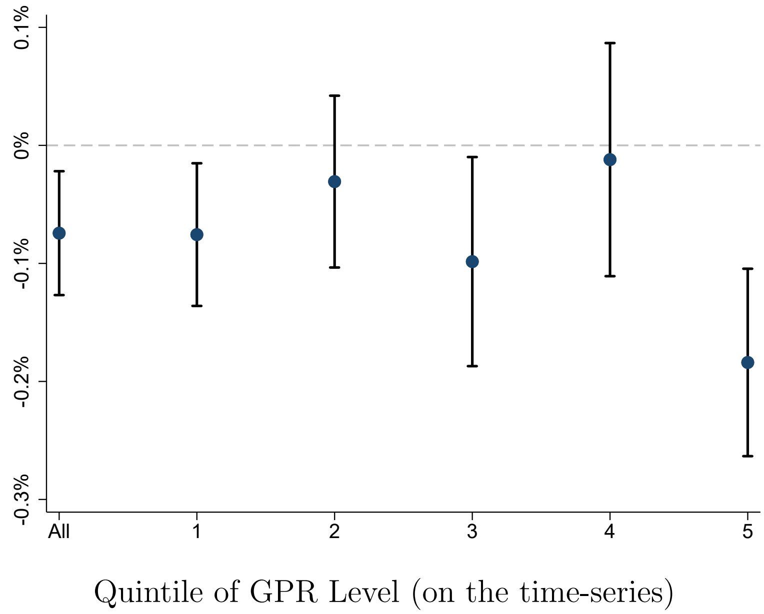


Figure 4

GPT vs GPA: Beta Effect on Investor Portfolio Allocations as a Function of GPR Level

This figure plots the average slope coefficients for the GPT and GPA betas on the demand functions of investors conditioned on different levels of GPR. We follow a two step approach. In the first step, we estimate logit demand functions for investor portfolio allocations using the same method as in Koijen and Yogo (2019) (using 13F data from 1980Q1 to 2024Q4). The only difference is that we add the GPT and GPA betas (from Section 2.2) as firm-level characteristics that can affect investor demand (beyond the ones they use). In the second step, we perform panel regressions of the slope coefficients of the logit demand function (θ_{GPT} and θ_{GPA}), which vary by investor and quarter, onto dummies for different quintiles of the (time-series of the) GPR index. We report the respective coefficients and 95% confidence intervals from Driscoll and Kraay (1998) (with lag selection from Newey and West (1994)), which is robust to residual correlation over time and across countries. The first value (under "All") reports the average effect without conditioning on the GPR level. Section 1.1 provides measurement details for the GPT and GPR indices while Section 1.3 covers the results from this figure.

(a) GPT Beta Effect on Firm Investment



(b) GPA Beta Effect on Firm Investment

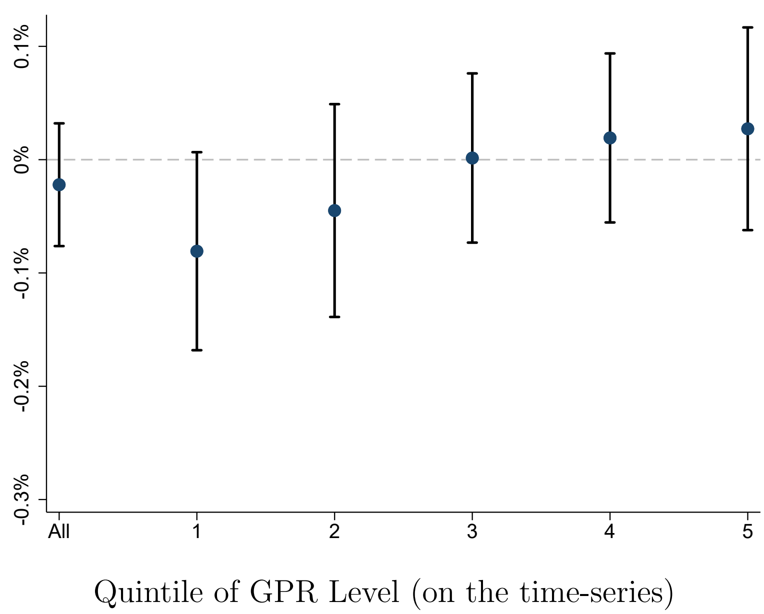


Figure 5

GPT vs GPA: Beta Effect on Firm Investment as a Function of GPR Level

This figure plots the effect of GPT and GPA betas on firm investment conditioned on different levels of GPR. For the first value (under "All"), we estimate panel regressions of firm-level quarterly investment (capital expenditures over lagged assets) onto lagged firm-level variables with fixed effects for firm, time, fiscal quarter, and calendar quarter (using data from 1990Q1 to 2024Q4). The specification (including control variables and initial quarter) follows Wang, Wu, and Xu (2024). We differ from them by replacing GPR as an independent variable with the GPT and GPA betas (from Section 2.2) and by adding time fixed effects (since betas vary by firm and time). The other reported values are analogous except that they interact the GPT and GPA betas with dummies for different quintiles of the (time-series of the) GPR index. The figure also provides 95% confidence intervals for the coefficient estimates based on Driscoll and Kraay (1998) (with lag selection from Newey and West (1994)), which is robust to residual correlation over time and across countries. Section 1.1 provides measurement details for the GPT and GPR indices while Section 1.4 covers the results from this figure.

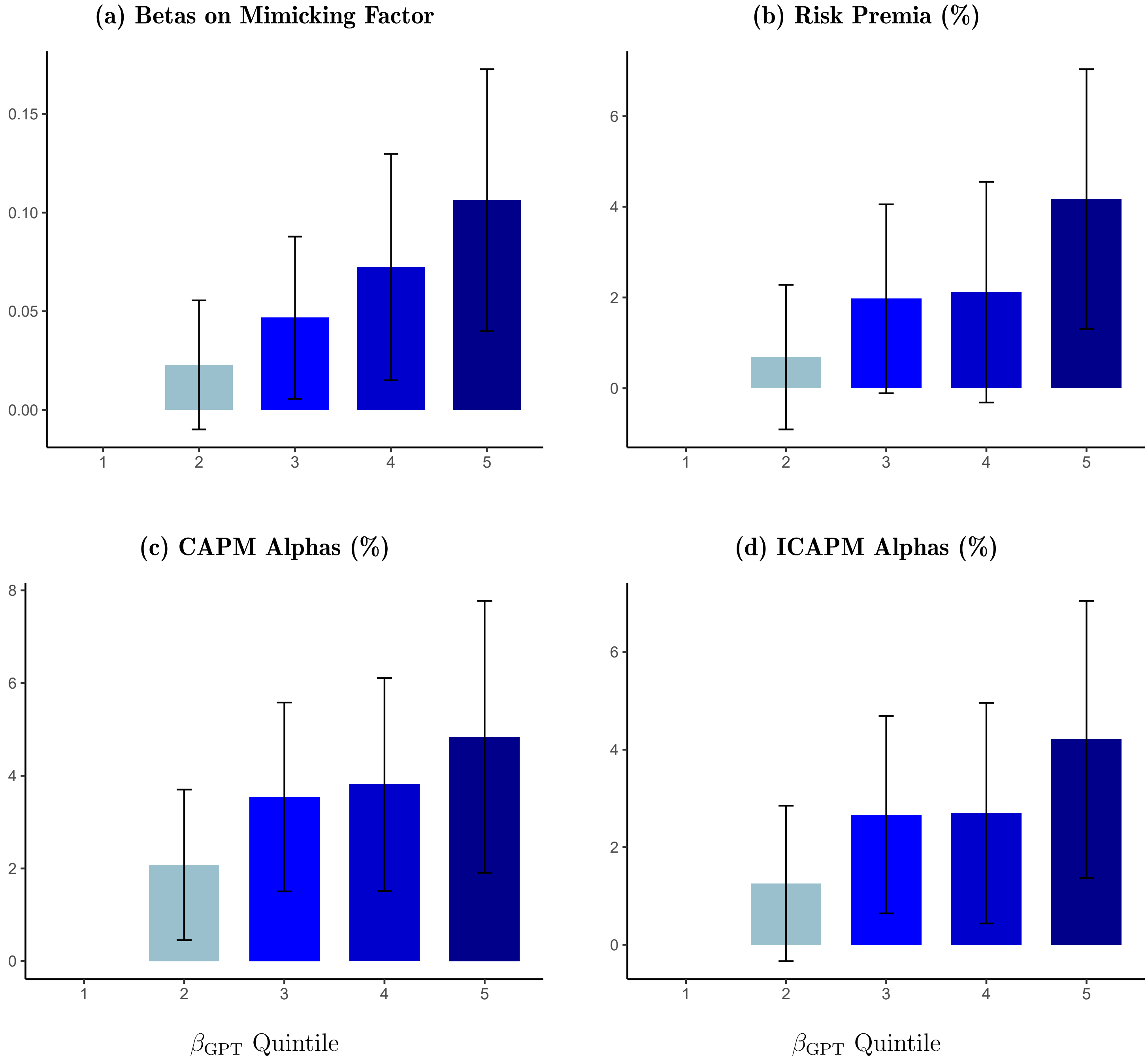


Figure 6
GPT Beta Quintile Portfolios: Betas, Risk Premia, and Alphas

This figure plots annualized risk premia, annualized alphas, and mimicking factor betas of value-weighted quintile portfolios sorted on stock-level betas on the news-based geopolitical threats (GPT) index of Caldara and Iacoviello (2022). The sample period is from 01-1930 to 12-2024. The GPT mimicking factor used to estimate betas (with risk premia summarized in Table 5) is constructed applying the Supervised Principal Component Analysis (SPCA) method proposed by Giglio, Xiu, and Zhang (2025) to anomaly portfolios (as described in Section 2.3). All statistics are reported relative to quintile 1 (so that the quintile 1 values are zero by construction). Panel (a) reports betas, Panel (b) reports risk premia, Panel (c) reports CAPM alphas, and Panel (d) reports ICAPM alphas from the model in Chabi-Yo, Gonçalves, and Loudis (2025). The graphs also provide 95% confidence intervals for the respective statistics based on Newey and West (1987, 1994) standard errors. Section 1.1 provides measurement details for the GPT index while Section 2.2 covers the results from this figure.

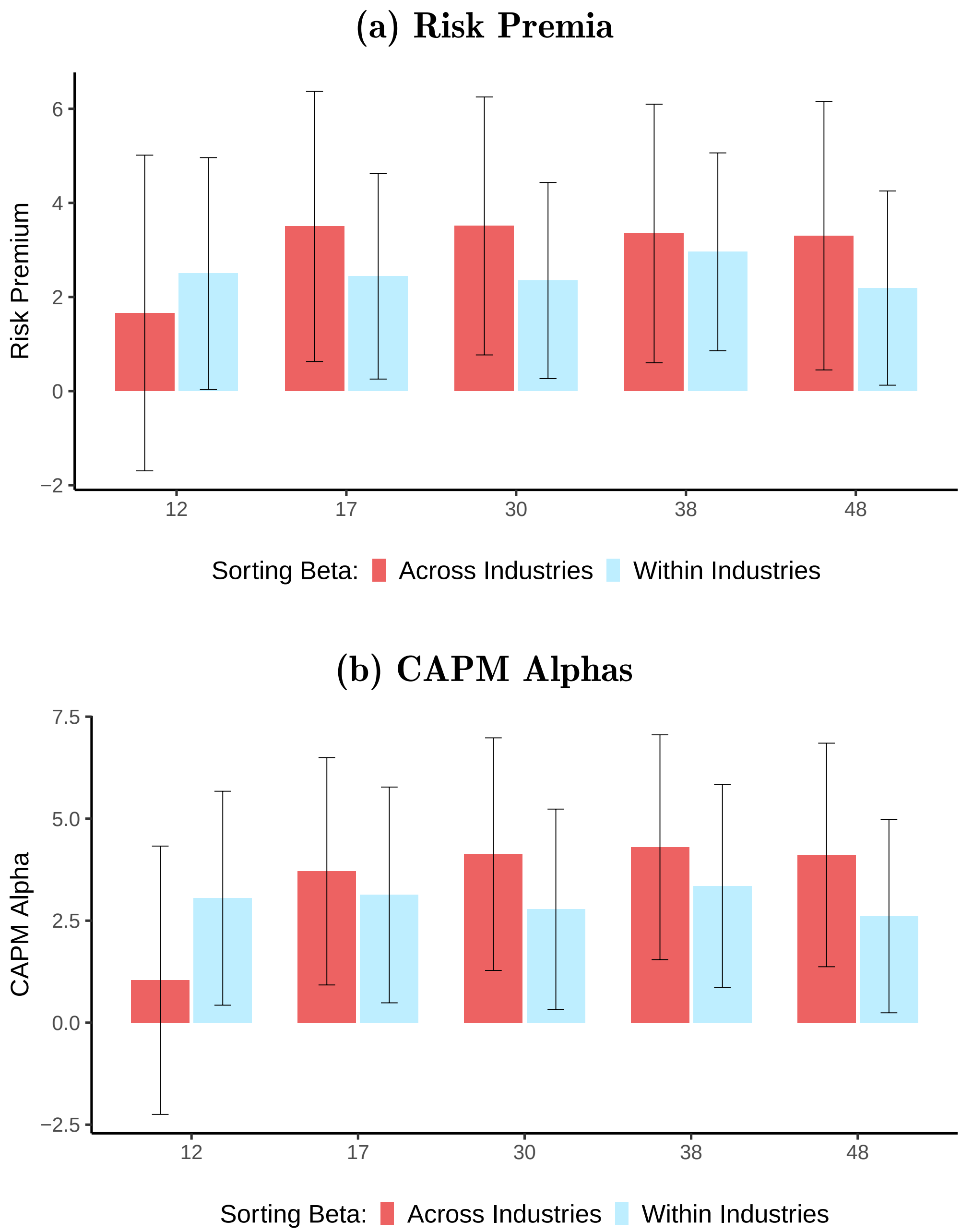
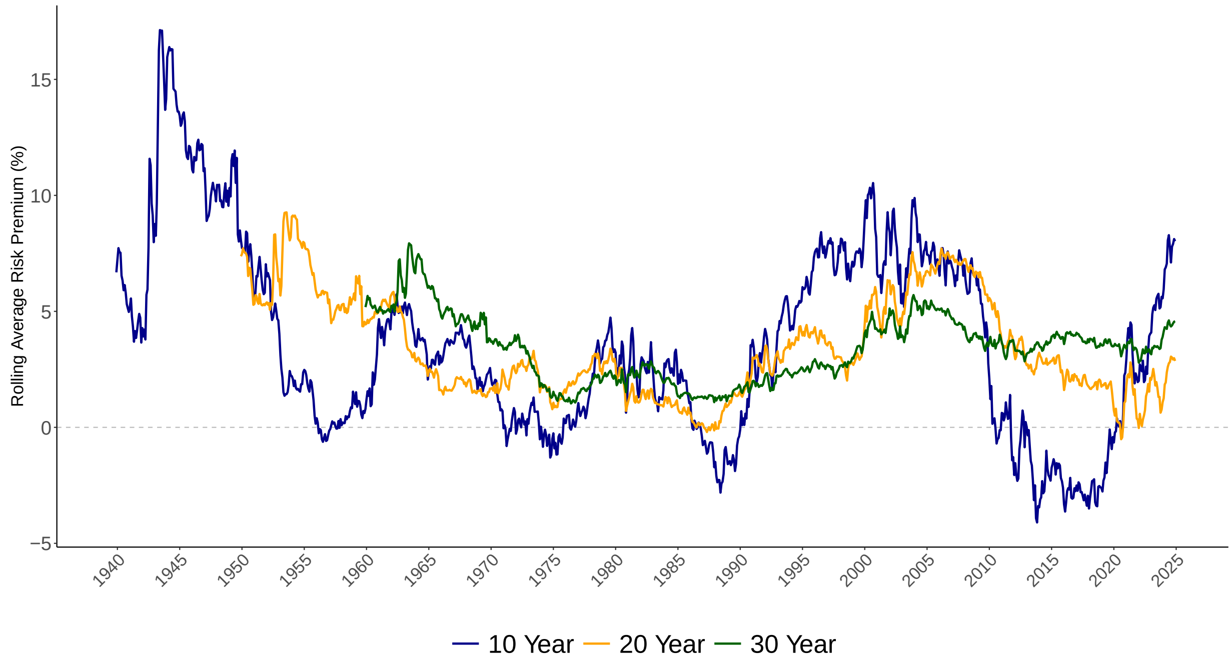


Figure 7

GPT Beta HML Risk Premia and CAPM Alphas: Across Industries vs Within Industries

This figure plots the annualized risk premia (Panel (a)) and CAPM alphas (Panel (b)) of alternative GPT HML portfolios. At each month t, we construct two beta measures for each stock n within each industry i: $\overline{\beta}^{GPT}_{n,t} = \beta^{GPT}_{i,t}$ and $\widetilde{\beta}^{GPT}_{n,t} = \beta^{GPT}_{n,t} - \beta^{GPT}_{i,t}$, where $\beta^{GPT}_{i,t}$ is the GPT beta of the industry stock n belongs to in month t. We use the (updated version of the) industry definitions from Fama and French (1997) and consider multiple specifications that di er based on the number of industries (varying from 12 industries to 48 industries). Given their construction, variation in $\overline{\beta}^{GPT}$ across stocks captures variation in geopolitical risk across industries whereas variation in $\widetilde{\beta}^{GPT}$ across stocks captures variation in geopolitical risk within industries. So, we construct the alternative GPT HML portfolios used in this figure analogously to the baseline GPT HML portfolio, but using these alternative beta measures. The figure also provides 95% confidence intervals for the risk premia and CAPM alpha estimates based on Newey and West (1987, 1994) standard errors. Section 1.1 provides measurement details for the GPT index while Section 2.2 covers the results from this figure.

(a) Realized Risk Premia on a Rolling Window (GPT Beta HML)



(b) Realized Risk Premia on a Rolling Window (Market Factor)

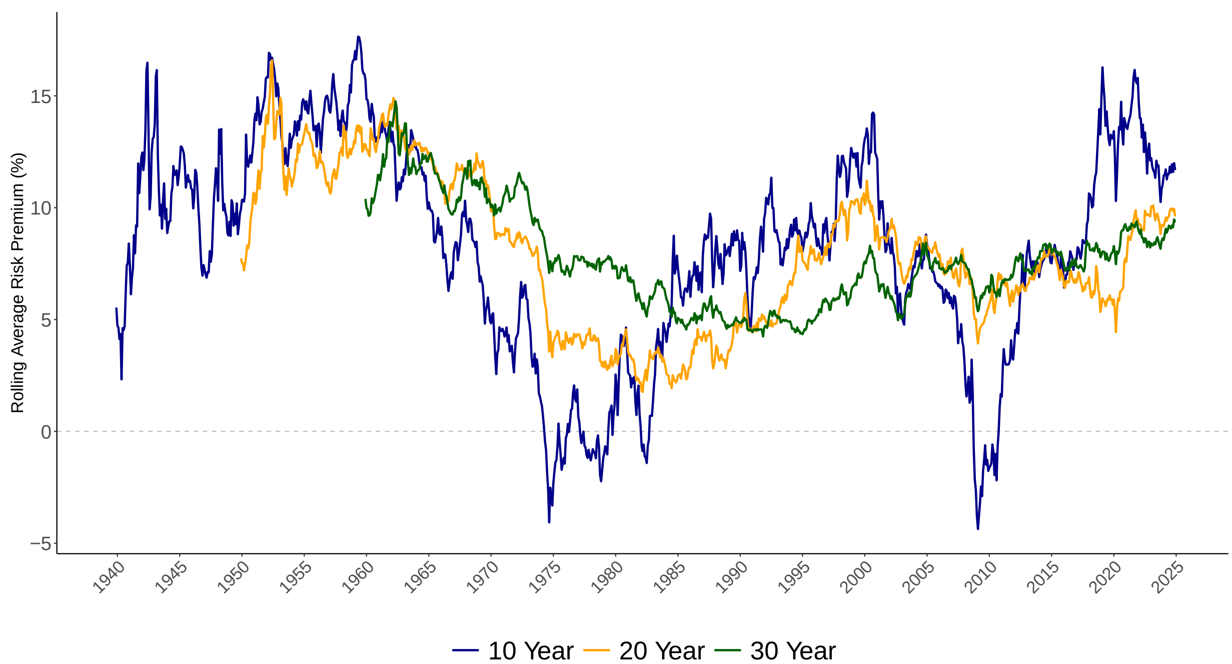
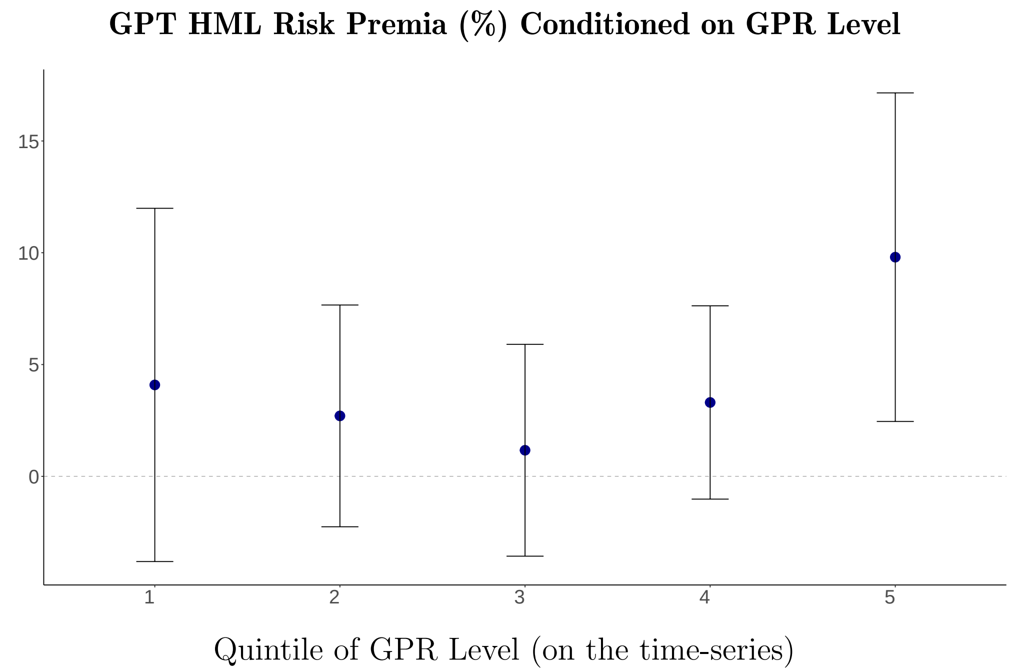


Figure 8
Realized Risk Premia on a Rolling Window: GPT Beta HML Portfolio and Market Factor

This figure plots annualized risk premia (i.e., average returns multiplied by twelve) realized over 10-year, 20-year and 30-year rolling windows. Panel (a) covers the GPT HML portfolio whereas Panel (b) focuses on the market factor for comparison. The GPT HML portfolio is constructed from value-weighted beta quintile portfolios, buying (selling) stocks with high (low) stock-level betas on the news-based geopolitical threats (GPT) index of Caldara and Iacoviello (2022). Section 1.1 provides measurement details for the GPT index while Section 2.2 covers the results from this figure.



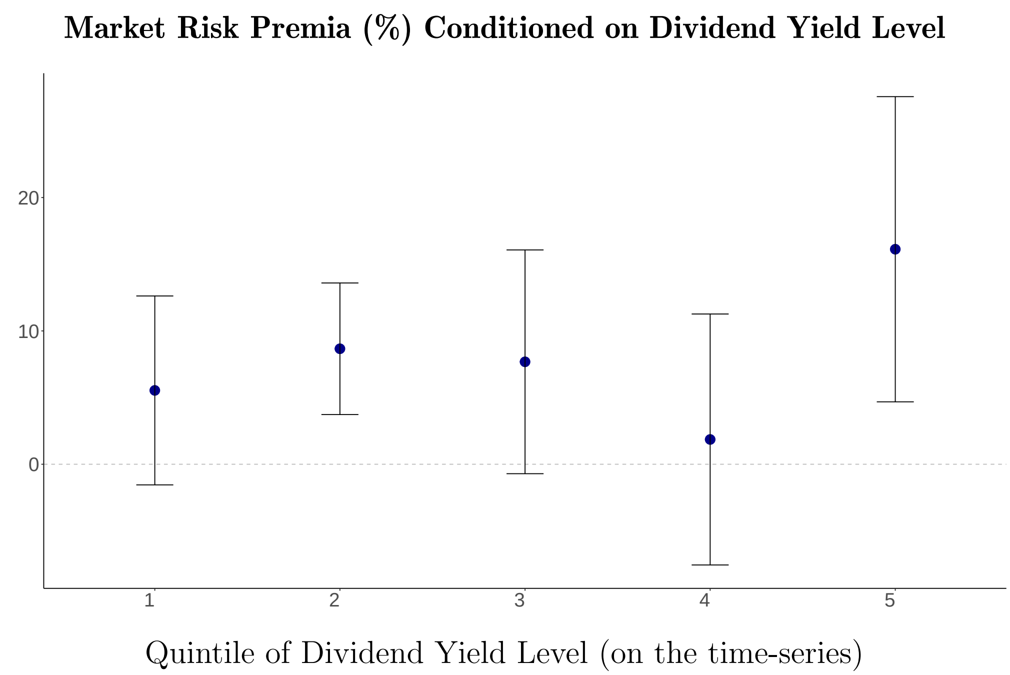


Figure 9
Conditional Risk Premia: GPT Beta HML Portfolio and Market Factor

This figure plots annualized risk premia conditioned on di erent levels of a given state variable. Panel (a) covers risk premia on the GPT HML portfolio, which is constructed from value-weighted beta quintile portfolios, buying (selling) stocks with high (low) stock-level betas on the news-based geopolitical threats (GPT) index of Caldara and Iacoviello (2022). The risk premia are conditioned on the level of GPR in the prior month (see Internet Appendix Figure IA.1 for conditioning on GPT). Specifically, we consider five quintiles of the (time-series of the) GPR index, with the quintile levels (in the x-axes) going from low to high levels of the GPR index. For comparison, Panel (b) covers the market factor and conditions on the level of the dividend yield (following a methodology analogous to the GPR conditioning). The figure also provides 95% confidence intervals for the conditional risk premia estimates based on Newey and West (1987, 1994) standard errors. Section 1.1 provides measurement details for the GPT and GPR indices while Section 2.2 covers the results from this figure.

Table 1

Correlations Between Risk Indices

This table reports information on the sample period for the ten risk indices we use throughout the paper. It also provides their pairwise correlations based on the longest sample available for each pair of indices. The first three indices are the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). The next three indices are also based on news articles: the war discourse (WAR) index from Hirshleifer, Mai, and Pukthuanthong (2025b), the historical economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), and an expected market volatility (EMV) index that splices the Manela and Moreira (2017) (until 1984) and Baker et al. (2025) (after 1984) indices, both in z-score units. The next index is the news-based trade policy uncertainty (TPU) index of Caldara et al. (2020), which is available since 01-1960. The last three indices (available since 07-1960) are the real uncertainty index (RUI), macro uncertainty index (MUI), and financial uncertainty index (FUI), all from Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021) and designed to summarize forecasting uncertainty in a large set of macro-finance variables. Section 1.1 provides measurement details for the geopolitical risk indices while Section 2.1 provides measurement details for the other risk indices.

	Sample Period			**Correlations**									
	First Month	**Last Month**	**# of Months**	**GPT**	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**TPU**	**RUI**	**MUI**	**FUI**
GPT	01-1900	12-2024	1500	1									
GPA	01-1900	12-2024	1500	0.45	1								
GPR	01-1900	12-2024	1500	0.68	0.96	1							
WAR	01-1927	10-2019	1114	0.51	0.22	0.36	1						
EPU	01-1900	12-2024	1500	0.15	0.26	0.25	-0.11	1					
EMV	01-1900	12-2024	1500	-0.16	0.06	-0.01	-0.10	0.31	1				
TPU	01-1960	12-2024	780	0.01	-0.09	-0.08	-0.04	0.35	0.09	1			
RUI	07-1960	12-2024	774	0.09	-0.11	0.00	0.10	0.50	0.12	0.06	1		
MUI	07-1960	12-2024	774	-0.06	0.03	-0.04	-0.15	0.41	0.34	0.09	0.46	1	
FUI	07-1960	12-2024	774	0.05	0.00	0.01	-0.09	0.57	0.15	0.03	0.80	0.62	1

GPT: Geopolitical Threats

GPA: Geopolitical Acts

GPR: Geopolitical Risk (includes threats and acts)

WAR: War Discourse

EPU: Economic Policy Uncertainty

EMV: Expected Market Volatility

TPU: Trading Policy Uncertainty

RUI: Real Uncertainty Index

MUI: Macroeconomic Uncertainty Index

FUI: Financial Uncertainty Index

Table 2

GPT vs GPA: Time Variation in Investors' Geopolitical Risk Perceptions

This table reports regressions of variables capturing investors' geopolitical risk perceptions onto the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022). The first and second measures are based on the International Country Risk Guide (ICRG) rating of the PRS Group, covering an unbalanced panel of annual observations for 138 countries over the period from 1984 to 2021. For the first measure, we use the negative of the ICRG country-level rating (resulting in a time-series of risk perception per country with high values indicating high risk). For the second measure, we use the component of the ICRG rating attributed only to the two categories that are more connected to geopolitical tensions, "internal conflicts" and "external conflicts". For each measure, we perform panel regressions (with country fixed e ects) of the risk perception measure onto the GPT and GPA indices. The third measure is the geopolitical risk perception from surveys of global fund managers conducted by the Bank of America (BofA), resulting in a single time series from 07-2007 to 12-2024. All variables are normalized to z-scores and t-statistics (in brackets) are based on Newey and West (1987, 1994) for time-series regressions and on Driscoll and Kraay (1998) (with lag selection from Newey and West (1994)) for panel regressions, which is robust to residual correlation over time and across countries. Section 1.1 provides measurement details for the GPT and GPA indices while Section 1.3 covers the measurement of geopolitical risk perception variables and the results from this table.

	ICRG (All Categories)			**ICRG (Internal+External Conflicts)**			**BofA Surveys of Fund Managers**		
	[1]	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**
GPT	0.30		0.36	0.31		0.35	1.07		1.01
	[3.61]		[5.17]	[2.46]		[2.64]	[6.64]		[5.42]
GPA		-0.10	-0.31		0.00	-0.20		1.31	0.33
		[-0.67]	[-2.37]		[0.01]	[-1.05]		[3.32]	[1.01]
$\boldsymbol{R^2_{within}}$	10%	0%	14%	14%	14%	25%	40%	11%	40%
$\mathbb{C}\boldsymbol{or}[\boldsymbol{Y_t}, \widehat{\boldsymbol{Y}}_t]$	0.16	0.03	0.19	0.19	0.19	0.25	0.63	0.33	0.63
# Obs	4,970	4,970	4,970	4,970	4,970	4,696	210	210	210

Table 3
GPT vs GPA: Time Variation in Firm Investment

This table reports regressions of variables capturing firm investment onto the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022). The first three columns reflect panel regressions (with country fixed e ects) of investment risk perceptions onto the GPT and GPA indices. Investment risk perception is based on the (negative of the) investment risk rating from the International Country Risk Guide (ICRG) rating of the PRS Group, covering an unbalanced panel of annual observations for 138 countries over the period from 1984 to 2021. The next three columns reflect regressions of log real investment per capita on a time trend and lagged risk indices (stochastic trend specifications using real GDP and aggregate stock prices, as in Caldara and Iacoviello (2022), yield similar results). Following Gennaioli, Ma, and Shleifer (2015), real investment is the U.S. real private nonresidential fixed investment from the FRED from 1947Q1 to 2024Q4 (using real private fixed investment as in Caldara and Iacoviello (2022) yields similar results). The last three columns reflect panel regressions (with industry fixed e ects) of industry-level real investment on lagged capital and lagged risk indices. Following Bai et al. (2022), industry-level investment is measured as real current-cost investments in private nonresidential equipment and structure and industry-level capital is current-cost capital stocks in private nonresidential equipment and structure (both obtained from the BEA from 1947 to 2024). For the last six columns, we report partial r-squared values, $(R^2 - R^2_{trend})/(1 - R^2_{trend})$, which capture the share of variance in detrended log investment explained by the lagged risk indices by comparing the r-squared values from regressions with (R^2) and without (R^2_{trend}) these indices. The perceived investment risk and the geopolitical risk indices are normalized to z-scores and t-statistics (in brackets) are based on Newey and West (1987, 1994) for time-series regressions and on Driscoll and Kraay (1998) (with lag selection from Newey and West (1994)) for panel regressions, which is robust to residual correlation over time and across countries or industries. Section 1.1 provides measurement details for the GPT and GPA indices while Section 1.4 covers the measurement of investment-related variables and the results from this table.

	Perceived Investment Risk			**Aggregate Investment**			**Industry-Level Investment**		
	[1]	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**
GPT	0.34		0.50	-0.03		-0.04	-0.03		-0.03
	[1.65]		[3.15]	[-1.61]		[-3.04]	[-1.83]		[-1.80]
GPA		-0.53	-0.83		0.03	0.06		-0.05	-0.03
		[-2.46]	[-2.97]		[0.58]	[1.91]		[-0.86]	[-0.50]
R^2_{within}	6%	5%	16%	5%	2%	10%	1%	0%	1%
# Obs	4,970	4,970	4,970	312	312	312	1,482	1,482	1,482

Table 4
Beta HML Portfolios Constructed from Single Stocks

This table reports annualized risk premia, annualized alphas, and mimicking factor betas of beta HML portfolios. Each beta HML portfolio is constructed from value-weighted beta quintile portfolios, buying (selling) stocks with high (low) stock-level betas on the given risk index. Stock-level betas are estimated from the three-year rolling window univariate beta on the (negative of the) given index growth rate. We consider ten risk indices in total. The first three are the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). The other indices (detailed in Table 1) cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV), trade policy uncertainty (TPU), real uncertainty (RUI), macro uncertainty (MUI), and financial uncertainty (FUI). The first six columns cover our long sample (01-1930 to 12-2024), except that WAR is only available until 10-2019. The last four columns cover our modern sample (08-1963 to 12-2024) due to the availability of the underlying risk indices. Internet Appendix Table IA.2 provides results using only our modern sample. Rows di er based on the statistic reported, with mimicking factors described in Table 5 (constructed following Giglio, Xiu, and Zhang (2025)) and ICAPM alphas based on the intertemporal factor model of Chabi-Yo, Gonçalves, and Loudis (2025). The t-statistics (in brackets) are based on Newey and West (1987, 1994). Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section 2.2 covers the return data and results from this table.

INDEX =	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Beta on Mimicking Factor	0.11	0.03	0.09	-0.03	0.22	0.10	0.04	0.90	1.40	1.18
	[3.14]	[1.02]	[3.04]	[-0.24]	[11.3]	[6.58]	[1.41]	[3.64]	[5.25]	[4.04]
Risk Premium (%)	4.17	1.69	2.71	1.22	2.99	0.68	-0.49	2.56	2.39	2.40
	[2.85]	[0.98]	[1.65]	[0.87]	[1.42]	[0.40]	[-0.30]	[1.36]	[1.22]	[1.05]
CAPM Alpha (%)	4.84	1.18	3.06	2.41	-1.08	0.15	-1.12	0.26	-0.11	-0.42
	[3.23]	[0.72]	[1.90]	[1.61]	[-0.59]	[0.09]	[-0.65]	[0.15]	[-0.06]	[-0.20]
ICAPM Alpha (%)	4.21	0.93	2.28	1.48	0.45	-1.27	-1.23	1.18	0.99	0.62
	[2.91]	[0.53]	[1.38]	[0.97]	[0.25]	[-0.86]	[-0.72]	[0.88]	[0.66]	[0.27]
GPT Alpha w.r.t INDEX		3.34	2.05	2.82	4.25	4.04	3.27	2.89	2.86	2.93
		[2.61]	[2.59]	[2.17]	[3.12]	[2.80]	[2.09]	[1.82]	[1.93]	[1.96]
INDEX Alpha w.r.t GPT		-0.37	-1.00	-0.68	3.15	-0.37	0.13	1.78	1.41	1.45
		[-0.25]	[-1.21]	[-0.50]	[1.25]	[-0.20]	[0.08]	[0.98]	[0.77]	[0.66]

Table 5
Mimicking Factors Constructed from Equity Anomaly Portfolios

This table reports annualized risk premia and annualized alphas from mimicking factors for the given risk indices. The first three risk indices are the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). The other risk indices (detailed in Table 1) cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV), trade policy uncertainty (TPU), real uncertainty (RUI), macro uncertainty (MUI), and financial uncertainty (FUI). Mimicking factors for these risk indices are constructed using the Supervised Principal Component Analysis (SPCA) method proposed by Giglio, Xiu, and Zhang (2025). The test assets are 2,620 anomaly portfolios. The first group of anomaly portfolios is from the Open Source Asset Pricing (OSAP) dataset of Chen and Zimmermann (2022), and comprises 2,344 decile portfolios from 115 anomaly signals (one set based on value-weights and one set based on equal-weights). The second group of anomaly portfolios is from the factor dataset of Jensen, Kelly, and Pedersen (2023), and comprises 276 long-short portfolios based on 138 anomaly signals (one set based on value-weights and another based on equal-weights). We use the same SPCA tuning parameters for all risk indices: 5 factors and 786 test assets (30% of the 2,620 test assets), with a sensitivity analysis provided in Internet Appendix Table IA.6. Each mimicking correlation reflects the correlation between the mimicking factor and the respective non-tradable index (defined as the negative of its growth rate). Due to the availability of anomaly portfolios, all columns in this table focus on the period from 08-1963 to 12-2024 (our modern sample), except that WAR is only available until 10-2019. Internet Appendix Table IA.5 provides results starting in 01-1930 (using 914 portfolios from a smaller set of anomaly signals). The t-statistics (in brackets) are based on Newey and West (1987, 1994) and each mimicking factor is normalized to have an annual volatility of 20%, which is similar to the market annual volatility. Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section 2.3 covers the return data and results from this table.

INDEX =	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Mimicking Correlation	0.32	0.38	0.42	0.31	0.41	0.33	0.28	0.38	0.45	0.47
Risk Premium (%)	3.03	1.83	1.86	2.79	2.55	1.82	2.23	2.29	1.27	2.81
	[4.11]	[2.74]	[2.65]	[3.63]	[3.99]	[2.40]	[2.94]	[2.61]	[1.33]	[3.13]
CAPM Alpha (%)	2.53	1.16	1.27	2.76	1.15	0.44	2.76	1.26	0.21	1.21
	[3.26]	[1.76]	[1.96]	[3.50]	[1.74]	[0.66]	[3.75]	[1.60]	[0.24]	[1.72]
ICAPM Alpha (%)	2.41	1.15	1.20	2.56	1.27	0.76	2.65	1.16	0.18	1.11
	[3.08]	[1.62]	[1.68]	[3.10]	[2.12]	[1.15]	[3.86]	[1.31]	[0.18]	[1.43]
GPT Alpha w.r.t INDEX		1.80	1.50	1.73	2.04	2.64	3.75	3.06	3.12	2.47
		[3.03]	[3.16]	[2.76]	[2.67]	[3.58]	[4.96]	[4.06]	[4.08]	[3.11]
INDEX Alpha w.r.t GPT		-0.22	-0.65	1.72	1.37	1.16	3.21	2.32	1.47	2.20
		[-0.35]	[-1.32]	[2.43]	[1.94]	[1.58]	[4.53]	[2.52]	[1.58]	[2.52]

Table 6

Mimicking Factors Constructed from Country-Level Equity and Bond Portfolios

This table reports annualized risk premia and annualized alphas from mimicking factors for the given risk indices. The first three risk indices are the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). The other risk indices (detailed in Table 1) cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV), trade policy uncertainty (TPU), real uncertainty (RUI), macro uncertainty (MUI), and financial uncertainty (FUI). Mimicking factors are constructed from the slope coefficients of annual Fama and MacBeth (1973) regressions of returns on full sample univariate betas on the (negative of the) respective index growth rate. These regressions use annual returns from the 16 country-level equity and bond portfolios of developed countries from the Jordà et al. (2019) dataset. The first six columns cover the period from 1930 to 2020 (most of our long sample), except that the last full year over which WAR is available is 2018. The last four columns cover from 1961 to 2020 (most of our our modern sample) due to the availability of the underlying risk indices. Internet Appendix Table IA.7 provides results using only this 1961 to 2020 sample. The world market portfolio (used for the world CAPM alphas) is constructed as the GDP-weighted average return on the same 16 countries. Each mimicking correlation reflects the correlation between the mimicking factor and the respective non-tradable index (defined as the negative of its growth rate). The t-statistics (in brackets) are based on Newey and West (1987, 1994) and each mimicking factor is normalized to have an annual volatility of 20%, which is similar to the market annual volatility. Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section 2.4 covers the return data and results from this table.

PANEL A - Only Equities

	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Mimicking Correlation	0.23	0.19	0.20	0.24	0.43	0.40	0.39	0.17	0.32	0.47
Risk Premium (%)	8.84	9.81	10.05	-7.58	9.47	8.78	6.69	8.18	7.94	7.86
	[4.33]	[4.17]	[4.66]	[-3.86]	[4.78]	[5.41]	[2.72]	[3.86]	[5.38]	[4.78]
World CAPM Alpha (%)	2.73	3.82	3.78	-2.09	2.77	2.38	2.65	2.16	2.56	1.96
	[1.92]	[2.14]	[2.44]	[-1.14]	[1.91]	[1.72]	[1.13]	[1.40]	[2.04]	[1.65]

PANEL B - Only Bonds

	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Mimicking Correlation	0.25	0.14	0.18	0.25	0.28	0.32	0.34	0.27	0.32	0.39
Risk Premium (%)	6.90	6.21	6.74	7.09	-5.75	-2.75	-5.44	-1.04	6.38	0.11
	[3.61]	[3.05]	[3.36]	[3.60]	[-3.16]	[-1.55]	[-2.93]	[-0.33]	[3.33]	[0.04]
World CAPM Alpha (%)	5.85	5.78	5.96	7.04	-6.14	-4.22	-5.16	0.08	5.72	-0.88
	[2.60]	[2.77]	[2.78]	[3.34]	[-2.77]	[-2.19]	[-1.82]	[0.03]	[2.10]	[-0.33]

PANEL C - Equities and Bonds

	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Mimicking Correlation	0.26	0.21	0.22	0.27	0.44	0.41	0.42	0.19	0.34	0.48
Risk Premium (%)	9.49	10.33	10.77	-6.89	9.14	8.60	7.80	8.15	8.34	7.80
	[4.49]	[4.31]	[4.77]	[-3.56]	[4.65]	[5.30]	[2.45]	[4.02]	[5.26]	[4.75]
World CAPM Alpha (%)	3.44	4.34	4.52	-1.39	2.45	2.21	1.67	2.18	3.09	1.92
	[2.49]	[2.46]	[3.04]	[-0.82]	[1.68]	[1.61]	[0.74]	[1.39]	[2.36]	[1.58]

Table 7
Predicting the Equity Risk Premia over Time

This table reports regressions of equity excess returns (relative to the risk-free asset) over the next 1 or 5 years onto current values of the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). Some columns control for the other three risk indices that are available since the beginning of our full sample, which are detailed in Table 1 and cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV). We estimate panel regressions with country fixed e ects and observations at the country-year level (from 1927 to 2019). The predicted returns are based on the 16 country-level equity indices of developed countries from the Jordà et al. (2019) dataset. Predictive variables are normalized to z-scores and t-statistics (in brackets) are based on Driscoll and Kraay (1998) (with lag selection from Newey and West (1994)), which is robust to residual correlation over time and across countries. Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section 3.1 covers the results from this table. Internet Appendix Tables IA.9 and IA.11 replicate this table using, respectively, the WAR index of Hirshleifer, Mai, and Pukthuanthong (2025a) (instead of the one from Hirshleifer, Mai, and Pukthuanthong (2025b)) and only monthly observations for the US equity index (instead of an annual panel of 16 countries).

PANEL A - Next 1 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	3.17						3.00	2.87	4.62	3.08	3.22	3.99
	[1.52]						[1.37]	[1.25]	[2.37]	[1.57]	[1.62]	[2.11]
GPA		1.46					0.48					-0.29
		[1.35]					[0.53]					[-0.33]
GPR			2.18					0.51				
			[1.44]					[0.50]				
WAR				0.73					-1.91			-1.21
				[0.39]					[-1.06]			[-0.56]
EPU					1.93					1.84		1.80
					[1.51]					[1.42]		[0.99]
EMV						-0.43					0.19	-0.47
						[-0.22]					[0.12]	[-0.26]
R^2_{within}	1%	0%	1%	0%	1%	0%	1%	1%	1%	2%	1%	2%
# Obs	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472

PANEL B - Next 5 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	25.77						29.00	32.39	33.25	25.07	26.25	31.89
	[2.79]						[2.71]	[2.71]	[2.80]	[3.08]	[2.78]	[2.57]
GPA		0.33					-9.16					-17.16
		[0.06]					[-1.60]					[-3.61]
GPR			7.53					-11.34				
			[0.81]					[-1.76]				
WAR				9.88					-9.77			-2.22
				[1.23]					[-1.00]			[-0.21]
EPU					14.50					13.65		18.75
					[2.16]					[2.13]		[2.29]
EMV						-3.23					1.82	-2.55
						[-0.39]					[0.26]	[-0.33]
R^2_{within}	6%	0%	0%	1%	3%	0%	6%	6%	6%	8%	6%	10%
# Obs	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408

Table 8
Potential Channel for Geopolitical Risk Premia: Non-Linear Market Risk Exposures

This table reports time-series slope coefficients from univariate regressions of the GPT and GPA beta HML portfolios onto several risk factors that capture non-linear market risk exposures. GPT and GPA reflect the news-based geopolitical threats and acts indices from Caldara and Iacoviello (2022), respectively. The market risk factor (r_m) is the same one used to obtain CAPM alphas in other tables, with $R_m = 1 + r_m$. The first four columns consider a 4th order Taylor expansion for the (unknown) utility function so that r_m, r_m^2, and r_m^3 are priced (as in Dittmar (2002)). Under the "standard risk aversion" definition of Kimball (1993), these risk factors would have positive, negative, and positive risk price, respectively. The $-\partial U$ column considers the (negative of the) marginal utility under the same 4th order approximation, but imposing constant relative risk aversion (CRRA) utility with a relative risk aversion of ten ($\gamma = 10$). The next five columns consider the exact $-\partial U$ under CRRA with $\gamma = 1, 3, 5, 7, 10$. The last column considers a disappointment aversion utility function, which would lead to a stronger price of risk for declines in r_m in comparison to general variation in r_m (see Ang, Chen, and Xing (2006)). We use the specification in Lettau, Maggiori, and Weber (2014) so that two betas are priced: the usual r_m beta (reported in the column r_m) and the beta on r_m conditioned on observations with an r_m below one standard deviation from its mean (reported in the last column). The t-statistics (in brackets) are based on Newey and West (1987, 1994). Sections 1.1 provides measurement details for GPT and GPA while Section 4.1 covers the results from this table.

Utility Function =	**4th Order Approximation**				**CRRA**					**Disappointment Aversion**
Risk Factor =	r_m	r_m^2	r_m^3	$-\partial U$	$-R_m^{-1}$	$-R_m^{-3}$	$-R_m^{-5}$	$-R_m^{-7}$	$-R_m^{-10}$	$r_m \mid r_m \leq \overline{r}_m - \sigma_m$
GPT Beta HML	-0.08	-1.35	-4.68	-0.01	-0.05	-0.01	-0.00	-0.00	0.000	0.03
	[-0.92]	[-2.85]	[-4.37]	[-1.10]	[-0.56]	[-0.47]	[-0.35]	[-0.08]	[0.32]	[0.34]
GPA Beta HML	0.06	-0.22	0.42	0.00	0.07	0.02	0.01	0.01	0.004	0.27
	[0.95]	[-0.77]	[0.40]	[1.15]	[1.23]	[1.34]	[1.46]	[1.66]	[2.18]	[2.12]
# Obs	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140	141

Table 9
Potential Channel for Geopolitical Risk Premia: Time Variation in Likelihood of Disasters

This table reports panel regressions of disaster-related outcomes onto the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022). Observations are at the country-year level and all specifications consider an unbalanced panel from 1927 to 2019, with country fixed e ects and 26 (42) countries when predicting realized disasters (disaster probabilities). Panel A predicts the average number of disasters over the next 1, 3, 5, and 10 years. Panel B predicts the average probability of disasters materializing over the next 1, 3, 5, and 10 years. The realized disasters and disaster probability levels are from Nakamura et al. (2013) and Marfè and Pénasse (2025), respectively. Following the prior literature exploring disasters empirically (e.g., Nakamura et al. (2013) and Caldara and Iacoviello (2022)), all specifications control for structural changes in the expectation and variability of consumption growth using dummy variables for Pre-1946, 1946-1972, and Post-1972. Predictive variables are always normalized to z-scores and t-statistics (in brackets) are based on Driscoll and Kraay (1998) (with lag selection from Newey and West (1994)), which is robust to residual correlation over time and across countries. Section 1.1 provides measurement details for GPT and GPA while Section 4.2 covers the results from this table.

PANEL A - Realized Disasters: $\mathbf{Y_t = 1/H \cdot \sum_{h=1}^{H} Disaster_{t+h}}$

	H = 1 Year			**H = 3 Years**			**H = 5 Years**			**H = 10 Years**		
	[1]	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**
GPT	9.34		3.72	8.63		4.24	8.36		5.37	5.98		5.63
	[3.16]		[1.45]	[3.27]		[1.55]	[3.79]		[2.27]	[4.17]		[3.56]
GPA		13.18	11.56		10.86	9.02		8.47	6.14		3.17	0.73
		[6.63]	[6.56]		[5.49]	[4.58]		[4.21]	[3.32]		[1.82]	[0.56]
R^2_{within}	21%	26%	26%	25%	28%	28%	29%	29%	31%	36%	34%	36%
# Obs	2,418	2,418	2,418	2,366	2,366	2,366	2,314	2,314	2,314	2,184	2,184	2,184

PANEL B - Probability of Disasters: $\mathbf{Y_t = 1/H \cdot \sum_{h=1}^{H} Prob_{t+h-1}[Disaster_{t+h}]}$

	H = 1 Year			**H = 3 Years**			**H = 5 Years**			**H = 10 Years**		
	[1]	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**
GPT	1.41		0.42	1.53		0.99	1.32		1.15	0.57		0.74
	[2.98]		[1.58]	[3.09]		[2.44]	[2.69]		[2.41]	[2.03]		[2.85]
GPA		2.63	2.44		1.78	1.33		0.92	0.40		-0.09	-0.42
		[5.14]	[5.12]		[2.68]	[2.37]		[1.57]	[0.85]		[-0.26]	[-1.56]
R^2_{within}	24%	36%	37%	34%	36%	39%	40%	35%	40%	50%	48%	51%
# Obs	3,666	3,666	3,666	3,576	3,576	3,576	3,486	3,486	3,486	3,261	3,261	3,261

Table 10

Potential Channel for Geopolitical Risk Premia: Overreaction to Geopolitical Threats

This table reports time-series regressions of perceived equity market overvaluation onto the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022). The overvaluation variables come from the Bank of America (BofA) survey of global fund managers. The first reflects perceived overvaluation of US equities (from 04-2001 to 12-2024) based on the net fraction of fund managers who answer "yes" to the question of whether US equities are overvalued in the BofA surveys. The second reflects perceived overvaluation of global equities and is measured analogously (from 01-1998 to 12-2024). The t-statistics (in brackets) are based on Newey and West (1987, 1994). Sections 1.1 provides measurement details for GPT and GPA while Section 4.3 covers the results from this table.

	Perceived Overvaluation (US Equities)			**Perceived Overvaluation (Global Equities)**		
	[1]	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**
GPT	0.55		0.76	0.34		0.68
	[2.82]		[4.43]	[1.28]		[3.52]
GPA		-0.20	-0.62		-0.48	-0.91
		[-0.86]	[-3.67]		[-2.10]	[-3.51]
R^2_{within}	12%	1%	19%	5%	5%	19%
$\mathbb{C}or[Y_t, \widehat{Y}_t]$	0.34	0.10	0.43	0.21	0.23	0.43
# Obs	285	285	285	324	324	324

Internet Appendix

"The Pricing of Geopolitical Tensions over a Century"

By Andrei S. Gonçalves, Alessandro Melone, and Andrea Ricciardi

Contents

A Data Sources

This section provides the data sources for the risk indices (Section A.1), asset returns (Section A.2), and factor models (Section A.3) used throughout the paper.

A.1 Risk Indices

- **GPT:** we obtain the geopolitical threats (GPT) index of Caldara and Iacoviello (2022) (updated to 12-2024) from https://www.matteoiacoviello.com/gpr.htm.

- **GPA:** we obtain the geopolitical acts (GPA) index of Caldara and Iacoviello (2022) (updated to 12-2024) from https://www.matteoiacoviello.com/gpr.htm.

- **GPR:** we obtain the geopolitical risk (GPR) index of Caldara and Iacoviello (2022) (updated to 12-2024) from https://www.matteoiacoviello.com/gpr.htm.

- **WAR:** we obtain the war discourse (WAR) indices of Hirshleifer, Mai, and Pukthuanthong (2025a,b) from https://www.kuntara.net/.

- **EPU:** we obtain the economic policy uncertainty (EPU) index of Baker et al. (2025) (updated to 12-2024) by splicing the (z-scores of the) US historical EPU (until 12-1984) with the US EPU (starting on 01-1985). Both of these indices are available under https://www.policyuncertainty.com/us_monthly.html.

- **EMV:** we obtain the expected market volatility (EMV) index (updated to 12-2024) by splicing the (z-scores of the) news-implied volatility index of Manela and Moreira (2017) (until 12-1984) and the expected market volatility index of Baker et al. (2025) (starting on 12-1985). These indices are available, respectively, under https://apps.olin.wustl.edu/faculty/manela/data.html and https://www.policyuncertainty.com/EMV_monthly.html.

- **TPU:** we obtain the trade policy uncertainty (TPU) index of Caldara et al. (2020) (updated to 12-2024) from https://www.matteoiacoviello.com/tpu.htm.

- **RUI:** we obtain the real uncertainty index (RUI) of Ludvigson, Ma, and Ng (2021) (updated to 12-2024) from https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

- **MUI:** we obtain the macroeconomic uncertainty index (MUI) of Jurado, Ludvigson, and Ng (2015) (updated to 12-2024) from https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

- **FUI:** we obtain the financial uncertainty index (FUI) of Jurado, Ludvigson, and Ng (2015) (updated to 12-2024) from https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

A.2 Asset Returns

- **Individual Stock Returns:** we obtain monthly stock returns for US individual stocks using the Center for Research in Security Prices (CRSP) dataset (available starting on 12-1925). We access CRSP through the Wharton Research Data Services (WRDS).

- **Anomaly Portfolio Returns:** we obtain anomaly portfolio returns from two sources. The first is the Open Source Asset Pricing (OSAP) dataset of Chen and Zimmermann (2022) (updated to 12-2024), available under https://www.openassetpricing.com/. The second is the factor dataset of Jensen, Kelly, and Pedersen (2023) (updated to 12-2024), available under https://jkpfactors.com/.

- **International Country-Level Equity and Bond Returns:** we obtain the annual returns on the international panel of country-level equity and bond indices of Jordà et al. (2019) (updated to 2020) from https://www.macrohistory.net/database/.

- **Risk-Free Returns to Calculate Excess Returns:** for monthly excess returns on US equities and anomaly decile portfolios, we the 1-month treasury bill rate from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. For annual excess returns on the international panel of country-level equity and bond indices, we use the country-specific government bill rate (code "bill_rate") variable from the Jordà et al. (2019) dataset.

A.3 Factor Models

- **CAPM:** we obtain the data for the equity market factor from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
- **ICAPM:** we obtain the factor data for the ICAPM of Chabi-Yo, Gonçalves, and Loudis (2025) from https://andreigoncalves.com/published-papers/
- **FF3:** we obtain the factor data for the 3-Factor model of Fama and French (1993) from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
- **FF5:** we obtain the factor data for the 5-Factor model of Fama and French (2015) from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
- **MOM:** we obtain the data for the momentum factor (used in the FF3+MOM and FF5+MOM factor models) from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
- **q4:** we obtain the factor data for the q–theory 4-Factor model of Hou, Xue, and Zhang (2015) from https://global-q.org/factors.html
- **q5:** we obtain the factor data for the q–theory 5-Factor model of Hou et al. (2021) from https://global-q.org/factors.html
- **DHS:** we obtain the factor data for the 3-Factor model of Daniel, Hirshleifer, and Sun (2020) from https://sites.google.com/view/linsunhome

B Supplementary Empirical Results

This section covers empirical results that supplement the findings reported in the main text.

B.1 Geopolitical Threats vs Acts: Link to Investors' Risk Perceptions

The results in Section 1.3 (reported in Table 2) are based on time-series regressions of investors' geopolitical risk perceptions onto GPT and GPA. One of the geopolitical risk perception measures we use is from the Bank of America (BofA) surveys of global fund managers. Table IA.1 explores analogous time-series regressions, but using the other six subjective risk measures present in the BofA surveys. We order these subjective risk measures (from high to low) by their correlation with the BofA subjective geopolitical risk measure. The key finding is that for subjective monetary risk, emerging market risk, and protectionist risk (which are related to subjective geopolitical risk), we see significant (sometimes marginally) connection with GPT, but not GPA. In contrast, for subjective business cycle risk, credit risk, and counterparty risk (which are not related to subjective geopolitical risk), we see no significant connection with GPT or GPA.

The key finding is that for subjective monetary risk, emerging market risk, and protectionist risk (which we show are positively related to subjective geopolitical risk), we see significant (sometimes marginally) connection with GPT, but not GPA. In contrast, for subjective business cycle risk, credit risk, and counterparty risk (which we show are negatively related to subjective geopolitical risk), we see no significant connection with GPT or GPA.

B.2 Beta HML Portfolios (Modern Sample)

The results in Section 2.2 are based on standard portfolios sorts for each risk index applied over our long sample (01-1930 to 12-2024) for some indices and, due to data availability, over our modern sample (08-1963 to 12-2024) for other indices (see Table 4). In this section, we consider an analysis that focuses entirely on our modern sample. In particular, Table IA.2 replicates our main results for the beta HML portfolios using only our modern sample instead of using our long sample for the first six risk indices. The results are very similar to the ones we present in the main text (in Table 4). One exception is that the GPT alpha relative to GPR is small and statistically insignificant over the modern sample. However, the GPR index contains GPT and GPA information simultaneously so that it can partially reflect GPT in some periods by construction. In fact, the GPR alpha relative to GPT over the modern sample is even smaller (and also statistically insignificant). Moreover, the GPT alpha relative to GPR is strong and statistically significant over the long sample (as reported in Table 4) whereas the GPR alpha relative to GPT over the long sample is negative (and statistically insignificant). So, the GPT HML portfolio dominates the GPR HML portfolio over both the long and modern samples.

B.3 Beta HML Portfolios (Alternative Specifications)

The results in Section 2.2 are based on standard portfolios sorts (see Table 4). Each month, we compute the univariate beta coefficient for each stock's excess return relative to the (negative of the) growth rate in each index using a 3-year rolling window. We then sort the stocks into value-weighted quintile portfolios (with NYSE breakpoints) based on these beta estimates. This section provides a comprehensive sensitivity analysis that considers alternative definitions of index shocks (instead of the index growth rate), alternative number of portfolios (instead of quintiles), alternative portfolio weights (instead of value-weights), and alternative sorting betas (instead of monthly betas on a 3-year rolling window). The results are provided in Table IA.3, which replicates the core results in Table 4 under the different specifications, showing that our findings are broadly consistent across specifications. That is, the results get somewhat stronger under some specifications and somewhat weaker under some others, but overall the message is very similar: the GPT HML produces strong risk premia (especially over the long sample) whereas the HML of other risk indices do not (with the exception of GPR, which is a hybrid between GPT and GPA).

In terms of the index shocks, our baseline analysis uses the growth rate because it is similar to the log growth rate commonly used in the literature (e.g., Adrian, Etula, and

Muir (2014), Herskovic, Moreira, and Muir (2019), and etc), but accounts for the fact that uncertainty indices display large spikes so that in some periods log growth is not a good proxy for the growth rate. Table IA.3 considers three alternatives. The first is the log growth rate (as in Adrian, Etula, and Muir (2014)). The second is the first difference (as in Ang et al. (2006)). The third is the index level (as in Bali, Brown, and Tang (2017)). An alternative approach would be to use residuals from autoregressive processes as in Hirshleifer, Mai, and Pukthuanthong (2025b). The problem with this approach is that different indices have di erent sample periods to estimate the autoregressive processes, and thus we do not take this approach. However, the results for WAR index using the autoregressive shocks made available directly by Hirshleifer, Mai, and Pukthuanthong (2025b) are similar to (in fact, slightly weaker than) the results we report for the WAR variable in our baseline analysis.

In terms of portfolio formation, while our baseline analysis uses quintile portfolios, our sensitivity checks explore decile and tercile portfolios. Also, while our baseline analysis uses value-weighted portfolios with NYSE breakpoints (as suggested by Hou, Xue, and Zhang (2019)), our sensitivity analysis considers equal-weighted portfolios excluding microcaps.

In terms of the sorting betas, our baseline analysis uses 3-year rolling window betas. However, Frazzini and Pedersen (2014) propose using daily returns and decoupling the estimation of correlations and volatilities so that volatilities can be measured over short windows (since they are more dynamic) even if correlations are measured over long windows (since they are less dynamic). In the context of our analysis, their beta would be given by $\beta = -\mathbb{C}orr[r, F] \cdot \mathbb{V}ol[r]$.[IA.1] Moreover, while they observe their F (market returns) daily, we observe our F monthly. So, we consider a hybrid method that estimates $\mathbb{V}ol[r]$ using daily returns over a one-year rolling window (as in Frazzini and Pedersen (2014)) and $\mathbb{C}orr[r, F]$ using monthly returns over a 3-year rolling window (as in our baseline analysis). Using this hybrid method, we can also consider longer windows for $\mathbb{C}orr[r, F]$ without sacrificing on the $\mathbb{V}ol[r]$ measurement. So, we also consider an alternative specification that uses a 10-year

[IA.1] Note that, technically, $= -\mathbb{C}orr[r, F] \cdot \mathbb{V}ol[r]/\mathbb{V}ol[F]$. However, $\mathbb{V}ol[F]$ is common across assets, and thus normalizing it to one (as we implicitly do) has no e ect on our portfolio sorts.

rolling window for $\mathbb{C}orr[r, F]$ (as in Herskovic, Moreira, and Muir (2019), who also observe F monthly). To ensure comparability, we require a minimum of 3 years of monthly returns available when computing this 10-year $\mathbb{C}orr[r, F]$.

The final specification we consider addresses the fact that the CRSP dataset contains only a limited number of stocks in its early years. Specifically, we begin our analysis in 1934 (the first full year in which our sample includes at least 500 stocks with three years of prior return data available).

B.4 GPT Beta HML Portfolio (Controlling for Factor Models)

The alphas studied in Section 2.2 control for the factors in the CAPM and ICAPM (of Chabi-Yo, Gonçalves, and Loudis (2025)), or for the risk indices we study (see Table 4). This section reproduces the CAPM and ICAPM alphas for the GPT HML portfolio (for comparability) and also presents GPT HML alphas based on other widely used factor models in the literature. They are the Fama-French 3-Factor (FF3) and 5-Factor (FF5) models from Fama and French (1993, 2015), the Fama-French models augmented with the momentum factor (FF3+MOM and FF5+MOM), similar to Fama and French (2018), the q–theory 4-Factor (q4) model from Hou, Xue, and Zhang (2015), the q-theory 5-Factor (q5) model from Hou et al. (2021), and the behavioral 3-Factor model (DHS) from Daniel, Hirshleifer, and Sun (2020).

The results are provided in Table IA.4. Since the data for di erent factor models (detailed in Section A.3) are available over di erent periods, the table also provides information on the risk premia over the respective periods. In all cases, the GPT alphas are higher than the GPT risk premia over the matched periods. The only exception is the Fama and French (2015) factor model, which leads to an annualized GPT alpha that is 0.12% lower than the GPT risk premium over the same period (a small e ect).

Note that there is some variation in the level of risk premia and their statistical significance across the columns of Table IA.4. However, that variation is mainly a function of sample size (since factors are available over di erent periods), with stronger t-statistics associated with longer sample periods. While this mechanical pattern gives the impression that the strength of the GPT risk premium is declining over time, this is not the case. In particular, the green line in Figure 8(a) provides the realized GPT risk premia on a 30-year rolling window, showing that the GPT risk premium has not declined over time.

B.5 Equity Anomaly Portfolios (Long Sample)

The results in Section 2.3 are based on the Supervised Principal Component Analysis (SPCA) of Giglio, Xiu, and Zhang (2025) applied to anomalies over our modern sample covering from 08-1963 to 12-2024 (see Table 5). In this section, we consider an analysis covering our long sample (01-1930 to 12-2024), at the cost of a lower number of anomaly portfolios. We keep the tuning parameters the same as in Section 2.3 and use the same data sources for anomaly portfolios. However, the overall number of anomalies is lower. In particular, we have a total of 914 anomaly portfolios from two sources. The first source is the Open Source Asset Pricing (OSAP) dataset of Chen and Zimmermann (2022), which yields 834 decile portfolios from 41 anomaly signals (one set based on value-weights and another based on equal-weights). The second source is the factor dataset of Jensen, Kelly, and Pedersen (2023), which yields 80 long-short portfolios based on 40 anomaly signals (one set based on value-weights and another based on equal-weights).

The results are provided in Table IA.5. For comparability, we still normalize the mimicking factors of each index to have an annualized volatility of 20%, which is similar to the market annual volatility. As in the modern sample, the GPT mimicking factor provides an economically and statistically significant risk premium that remains present after controlling for the CAPM and ICAPM factors as well as for the other risk indices in our analysis. Also as in the modern sample, these results are equally valid for many the other risk indices analyzed as they also produce economically and statistically significant risk premia. Two important exceptions (as in the modern sample) are that the alphas of the GPA and GPR mimicking factors are statistically insignificant after controlling for the GPT mimicking factor.

B.6 Equity Anomaly Portfolios (Varying SPCA Parameters)

The results in Section 2.3 are based on the Supervised Principal Component Analysis (SPCA) of Giglio, Xiu, and Zhang (2025) using 5 factors and 786 test portfolios (30% of all test portfolios) as SPCA tuning parameters (see Table 5). In this section, we provide a sensitivity analysis on these tuning parameters. Specifically, Table IA.6 considers 4 and 6 factors (as an alternative to 5 factors) as well as 20% and 40% of the total number of test portfolios (as an alternative to 30%). Overall, the results are broadly consistent across the tuning parameters explored.

B.7 Country-Level Equity and Bond Portfolios (1961-2020)

The results in Section 2.4 rely on country-level equity and bond annual returns from 1930 to 2020, which covers most of our long sample (see Table 6). In this section, we consider an analysis that focuses entirely on the period from 1961 to 2020, which covers most of our modern sample. Table IA.7 provides the results, which effectively replicate Table 6 using data from 1961 to 2020. Overall, the findings are very similar to the ones we report in the main text. In particular, GPT has strong and statistically significant risk premia and world CAPM alphas. In contrast, other indices have more mixed results. For instance, the risk premia and WCAPM alphas are negative for WAR when equity indices are included in the analysis.

Note that, as discussed in the main text, the GPA world CAPM alphas are weak and statistically insignificant over the modern sample (whenever equity portfolios are included in the analysis). As such, GPT provides a more stable risk premia than GPA even in the cross-section of country-level equity and bond portfolios.

B.8 The Time-Series of Risk Premia (Alternative Specifications)

The results in Section 3 are based on panel regressions of country-level returns onto the risk indices we study with country fixed effects (see Tables 7 and IA.8). This section considers two alternative specifications relative to what we report in the main text.

First, Tables IA.9 and IA.10 replicate Tables 7 and IA.8 after replacing the WAR index from Hirshleifer, Mai, and Pukthuanthong (2025b) (which is a cross-sectional paper) with the WAR index from Hirshleifer, Mai, and Pukthuanthong (2025a) (which is a time-series paper). The overall results are similar to the ones we report in the main text.

Second, Tables IA.11 and IA.12 replicate Tables 7 and IA.8 after replacing the excess returns on a panel of 16 countries observed annually (from Jordà et al. (2019)) with US excess returns observed monthly (from the updated version of the Goyal and Welch (2008) dataset). This allows us to replace one year return predictions with one month return predictions. The key findings are similar to the ones we report in the main text.

B.9 Geopolitical Risks and Disasters (Controlling for other Risk Indices)

The results in Section 4.2 show that GPA and GPT are associated with the probability of consumption disasters over the short- and long-term, respectively (see Table 9). This section shows that these results also hold while controlling for the other risk indices available over our long sample (WAR, EPU, and EMV), some of which have been previously linked to disaster risks in the literature. Table IA.13 provides the relevant results (with specifications analogous to Table 9). Panel A shows that both GPT and GPA are linked to consumption disasters in the subsequent year. However, GPA has a stronger e ect, with GPT being only marginally linked to next year consumption disasters after controlling for GPA. Panel B considers consumption disasters over the next three years, showing that in this case GPA continues to dominate for realized disasters, but GPT is comparable to GPA for disaster probabilities. Panel C further considers consumption disasters over the next five years, showing that in this case GPA and GPT have comparable e ects on realized disasters while GPT subsumes GPA for disaster probabilities. Finally, Panel D considers consumption disasters over the next ten years, in which case GPA is entirely subsumed by GPT for both realized disasters and disaster probabilities (becoming even negative in the latter case).

C Deriving the General Epstein-Zin SDF

This section derives the general Stochastic Discount Factor (SDF) under Epstein-Zin preferences (i.e., Equations 1 in the main text). To simplify notation, we define $r_w \equiv log(R_w)$, use tilde to represent shocks (e.g., $\widetilde{x}_t \equiv x_t - \mathbb{E}_{t-1}[x_t]$), and suppress time subscripts inside first and second moments when convenient (e.g., $\mathbb{E}_t[x] \equiv \mathbb{E}_t[x_{t+1}]$ and $\mathbb{V}ar_t[x] \equiv \mathbb{V}ar_t[x_{t+1}]$).

A long-term (i.e., infinitely lived) investor has Epstein-Zin recursive preferences (Epstein and Zin (1989, 1991) and Weil (1989)) with time discount factor δ, intertemporal elasticity of substitution ψ, and relative risk aversion γ. The investor chooses consumption, C_t, and portfolio allocation, ϖ_t, to maximize lifetime utility subject to the budget constraint $W_{t+1} = (W_t - C_t) \cdot R_{w,t+1}$, with $R_{w,t} = \varpi_t' R_t$ representing the investor's wealth portfolio.

C.1 The Budget Constraint

It is instructive to start by rewriting the budget constraint as

$$R_{w,t} \ = \left(\frac{C_{t-1}}{W_{t-1} - C_{t-1}}\right) \cdot \left(\frac{C_t}{C_{t-1}}\right) \cdot \left(\frac{W_t}{C_t}\right), \tag{IA.1}$$

or in logs,

$$r_{w,t} \ = crw_{t-1} + \Delta c_t - cw_t, \tag{IA.2}$$

where $crw_t = -log(e^{-cw_t \psi} - 1)$ is consumption over reinvested wealth.

This alternative way to write the budget constraint demonstrates that shocks to returns on the wealth portfolio can be written as

$$\widetilde{r}_{w,t} \ = \widetilde{\Delta c}_t - \widetilde{cw}_t \ = \ \widetilde{\Delta w}_t. \tag{IA.3}$$

In parts of the derivations, we rely on a log-linear approximation to the consumption-wealth ratio,

$$cw_t \ \approx k \ + \ \overline{\delta} \cdot crw_t \tag{IA.4}$$

which yields the log-linearized budget constraint

$$r_{w,t} \;\approx\; -\frac{k}{\overline{\delta}} + \frac{1}{\overline{\delta}} \cdot cw_{t-1} + \Delta c_t - cw_t, \tag{IA.5}$$

where $\overline{\delta} = e^{-\overline{crw}}/(e^{-\overline{crw}} + 1)$ and $k = \overline{\delta} \cdot log(\overline{\delta}) + (1 - \overline{\delta}) \cdot log(1 - \overline{\delta})$ are log-linearization coefficients.[IA.2]

C.2 A Quick Derivation for Epstein-Zin SDF Shocks

Start from the well-known form of the Epstein-Zin SDF,

$$SDF_{t+1} \;= \delta \cdot \left(\frac{C_{t+1}}{C_t}\right)^{-1/\psi} \cdot \quad \left. \frac{V_{t+1}}{\mathbb{E}_t[V_{t+1}^{1-\gamma}]^{1/(1-\gamma)}} \right)^{-(\gamma-1/\psi)}$$

$$\Downarrow$$

$$\widetilde{sdf}_{t+1} \;=\; -\,1/\psi \cdot \widetilde{\Delta c}_{t+1} \;-\; (\gamma - 1/\psi) \cdot \widetilde{v}_{t+1}, \tag{IA.6}$$

and note that Hansen, Heaton, and Li (2008) provide a link between consumption, wealth, and the continuation value function (henceforth "value"),

$$\widetilde{c}_t \;= \psi \cdot \widetilde{w}_t + (1 - \psi) \cdot \widetilde{v}_t. \tag{IA.7}$$

$$\Downarrow$$

$$\widetilde{cw}_t \;=\; (1 - \psi) \cdot \widetilde{vw}_t \tag{IA.8}$$

so that the budget constraint shocks (Equation IA.3) can be alternatively written as

$$\widetilde{r}_{w,t} \;= \widetilde{\Delta c}_t - (1 - \psi) \cdot \widetilde{vw}_t. \tag{IA.9}$$

Substituting Equations IA.7 and IA.3 into the SDF Equation IA.6, we have

$$\widetilde{sdf}_t \;=\; -\,\gamma \cdot \widetilde{r}_{w,t} \;-\; (\gamma - 1) \cdot \widetilde{vw}_t \tag{IA.10}$$

In addition, Substituting Equation IA.9 into Equation IA.10, we have

$$\widetilde{sdf}_t \;=\; -\,\gamma \cdot \widetilde{\Delta c}_t \;-\; \psi \cdot (\gamma - 1/\psi) \cdot \widetilde{vw}_t \tag{IA.11}$$

[IA.2] As we demonstrate below (in Equation IA.22), the optimality conditions yield $cw_t = log(1 - \delta)$ and $crw_t = log((1 - \delta)/\delta)$ if $\quad = 1$, which implies that this log-linear approximation is exact with $\overline{\delta}\psi = \delta\psi$ and $r_{w,t} = \Delta c_t - log(\delta)$ in this case.

In the rest of this section, we formalize this quick exposition by directly deriving these two versions of the SDF based on the investor's optimality conditions. More importantly, we show that

$$\widetilde{vw}_t \;= N_{\mathbb{E}r,t} \;-\; 0.5 \cdot (\gamma - 1) \cdot N_{\mathbb{V},t} \;-\; N_{\mathbb{H},t} \tag{IA.12}$$

$$= N_{\mathbb{E}c,t} \;-\; \frac{0.5}{\psi} \cdot (\gamma - 1) \cdot N_{\mathbb{V},t} \;-\; \frac{1}{\psi} \cdot N_{\mathbb{H},t} \tag{IA.13}$$

so that the SDF shocks can be written in the Intertemporal CAPM form,

$$\widetilde{sdf}_t = -\,\gamma \cdot \widetilde{r}_{w,t} - (\gamma - 1) \cdot N_{\mathbb{E}r,t} + 0.5 \cdot (\gamma - 1)^2 \cdot N_{\mathbb{V},t} + (\gamma - 1) \cdot N_{\mathbb{H},t}, \tag{IA.14}$$

or the Consumption CAPM form,

$$\widetilde{sdf}_t = -\,\gamma \cdot \widetilde{\Delta c}_t - (\gamma - 1/\psi) \cdot N_{\mathbb{E}c,t} + 0.5 \cdot (\gamma - 1/\psi) \cdot (\gamma - 1) \cdot N_{\mathbb{V},t} + (\gamma - 1/\psi) \cdot N_{\mathbb{H},t}, \tag{IA.15}$$

where

$N_{\mathbb{E}r,t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \overline{\delta}^h \cdot r_{w,t+h} \right.$ is expected return news

$N_{\mathbb{E}c,t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \overline{\delta}^h \cdot \Delta c_{t+h} \right.$ is expected consumption growth news

$N_{\mathbb{V},t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{V}ar_{t+h-1}[\widetilde{v}_{t+h}] \right.$ is news about $\widetilde{v}_t$ volatility

$N_{\mathbb{H},t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{H}_{t+h-1}[\widetilde{v}_{t+h}] \right.$ is news about $\widetilde{v}_t$ high order moments

C.3 Deriving the Epstein-Zin SDF with $vw\psi$

This subsection derives the Epstein-Zin SDF with vw as a risk factor. We assume $\gamma \neq 1$ throughout this section as this is the empirically relevant case. However, the SDF expressions we derive also hold under $\gamma = 1$, with simpler derivations in this case give the (intratemporal) log utility.

C.3.1 Deriving the Epstein-Zin SDF with vw under $\psi = 1$

With $\psi = 1$, the investor's value function can be written as

$$V(W_t) \;=\; \underset{\{C_t,\varpi_t\}}{Max}\; C_t^{1-\delta} \cdot \left(\mathbb{E}_t \;\; V(W_{t+1})^{1-\gamma}]\right)^{\delta/(1-\gamma)}, \tag{IA.16}$$

or in log terms,

$$log(V_t) \;=\; \underset{\{C_t,\varpi_t\}}{Max}\; (1-\delta)\cdot log(C_t) \;+\; \frac{\delta}{(1-\gamma)} \cdot log\left(\mathbb{E}_t \;\; V_{t+1}^{1-\gamma}]\right), \tag{IA.17}$$

where the second equation simplifies the notation by suppressing the dependence of the value function on wealth.

The consumption first order condition (FOC) then yields:

$$\frac{(1-\delta)}{C_t} \;=\; \frac{\delta}{\mathbb{E}_t[V_{t+1}^{1-\gamma}]} \cdot \mathbb{E}_t[V_{t+1}^{-\gamma} \cdot \partial_W V_{t+1} \cdot R_{w,t+1}], \tag{IA.18}$$

and the Benveniste and Scheinkman (1979) condition relative to wealth implies

$$\partial_W log(V_t) \;=\; \frac{\partial_W V_t}{V_t} \;=\; \frac{\delta}{\mathbb{E}_t[V_{t+1}^{1-\gamma}]} \cdot \mathbb{E}_t[V_{t+1}^{-\gamma} \cdot \partial_W V_{t+1} \cdot R_{w,t+1}], \tag{IA.19}$$

so that combining the two optimality conditions gives

$$\partial_W V_t \;=(1-\delta)\cdot \frac{V_t}{C_t}. \tag{IA.20}$$

Equation IA.20 is the main optimality condition we need to derive the Epstein-Zin SDF. To do so, start by conjecturing that $V(W_t)$ is homogeneous of degree one (i.e., V_t/W_t is not a function of wealth). This conjecture implies that $\partial_W V_t = V_t/W_t$, which, after substituting into Equation IA.20 and using $crw_t = -log(e^{-cw_t\psi} - 1)$, yields

$$C_t/W_t \;= (1-\delta), \tag{IA.21}$$

$$cw_t = log(1-\delta), \qquad \text{and} \qquad crw_t = log((1-\delta)/\delta), \tag{IA.22}$$

so that Equation IA.8 holds when $\psi = 1$. Note that Equation IA.22 allows us to rewrite the budget constraint (Equation IA.2) as

$$r_{w,t} \;=\Delta c_t - log(\delta) \;=\; \Delta w_t - log(\delta). \tag{IA.23}$$

Now, rewrite the objective function (i.e., Equation IA.17) as

$$
\begin{aligned}
vw_t \;&= (1-\delta)\cdot cw_t \;-\; \delta\cdot w_t \;+\; \frac{\delta}{(1-\gamma)}\cdot log\left(\mathbb{E}_t \;\; e^{(1-\gamma)\cdot v_{t+1}}\big]\right) \\
&= (1-\delta)\cdot cw_t \;+\; \frac{\delta}{(1-\gamma)}\cdot log\left(\mathbb{E}_t \;\; e^{(1-\gamma)\cdot v_{t+1}-(1-\gamma)\cdot w_t}\big]\right) \\
&= (1-\delta)\cdot cw_t \;+\; \frac{\delta}{(1-\gamma)}\cdot log\left(\mathbb{E}_t \;\; e^{(1-\gamma)\cdot(log(\delta)+vw_{t+1}+r_{w,t+1})}\big]\right) \\
&= (1-\delta)\cdot log(1-\delta) \;+\; \frac{\delta}{(1-\gamma)}\cdot log\left(\mathbb{E}_t \;\; e^{(1-\gamma)\cdot(log(\delta)+vw_{t+1}+r_{w,t+1})}\big]\right),
\end{aligned}
\tag{IA.24}
$$

where the third equality relies on Equation IA.23 and the last equality uses Equation IA.22.

Equation IA.24 represents a recursion for vw_t that shows that if vw_{t+1} does not depend on wealth, then vw_t also does not. As such, the conjecture that $V(W_t)$ is homogeneous of degree one is valid.

We can further work on Equation IA.24 to get

$$
\begin{aligned}
log(e^{vw_t}) \;&= log\left((1-\delta)^{(1-\delta)}\right) \;+\; log\left(\mathbb{E}_t \;\; e^{(1-\gamma)\cdot(log(\delta)+vw_{t+1}+r_{w,t+1})}\big]^{\delta/(1-\gamma)}\right) \\
&= log\left(\mathbb{E}_t\left[e^{(1-\gamma)\cdot(\frac{1-\delta\psi}{\delta\psi}log(1-\delta)+log(\delta)+vw_{t+1}+r_{w,t+1})} \quad {}^{\delta/(1-\gamma)}\right.\right) \\
&\Downarrow \\
1 \;&= \mathbb{E}_t\left[e^{(1-\gamma)\cdot(\frac{1-\delta\psi}{\delta\psi}log(1-\delta)+log(\delta)-\frac{1}{\delta\psi}vw_t+vw_{t+1}+r_{w,t+1})}\right. \\
&= \mathbb{E}_t\left[e^{\frac{(\;\;-1)}{\delta\psi}\cdot[vw_t-f_0(\delta,\delta)]\;-\;\gamma\cdot r_{w,t+1}\;-\;(\gamma-1)\cdot vw_{t+1}}\cdot R_{w,t+1}\right.\quad,
\end{aligned}
\tag{IA.25}
$$

where $f_0(z,y) = (1-y)\cdot log(1-z) + y\cdot log(z)$.

Now, rewrite the budget constraint as $W_{t+1} = (W_t - C_t)\cdot(R_{f,t+1} + \varpi_t'(R_{t+1} - R_{f,t+1}))$

and substitute it in $V(W_{t+1})$ so that the FOC with respect to ϖ_t yields

$$
\begin{aligned}
0 &= \mathbb{E}_t\left[\delta \cdot \left(\frac{C_{t+1}}{C_t}\right)^{-1} \cdot \quad \frac{V_{t+1}}{E_t[V_{t+1}^{1-\gamma}]^{1/(1-\gamma)}}\right)^{-(\gamma-1)} \cdot (R_{t+1} - R_{f,t+1})\Bigg] \\
&= \mathbb{E}_t\left[e^{-\widetilde{\Delta c}_{t+1} \,-\, (\gamma-1)\cdot \widetilde{v}_{t+1}} \cdot (R_{t+1} - R_{f,t+1})\right) \\
&= \mathbb{E}_t \;\; e^{-\gamma\cdot \widetilde{r}_{w,t+1} \,-\, (\gamma-1)\cdot \widetilde{vw}_{t+1}} \cdot (R_{t+1} - R_{f,t+1})\big] \\
&= \mathbb{E}_t\left[e^{\frac{(\;-1)}{\delta\psi}\cdot[vw_t - f_0(\delta,\delta)] \,-\gamma\cdot r_{w,t+1} \,-\, (\gamma-1)\cdot vw_{t+1}} \cdot (R_{t+1} - R_{f,t+1})\right) \quad ,
\end{aligned}
\tag{IA.26}
$$

where the third equality is based on the same derivation as in Equation IA.10 and the second and fourth equalities use the fact that we can multiply any arbitrary variable known as of time t on both sides of this FOC.

Equations IA.25 and IA.26 jointly imply that the SDF, given by

$$
sdf_{t+1} \;=\; \frac{(\gamma-1)}{\delta} \cdot [vw_t - f_0(\delta,\delta)] \;-\; \gamma \cdot r_{w,t+1} \;-\; (\gamma-1) \cdot vw_{t+1}, \tag{IA.27}
$$

prices all assets available to the Epstein-Zin investor.

C.3.2 Deriving the Epstein-Zin SDF with vw under $\psi \neq 1$

With $\psi \neq 1$, the investor's value function can be written as

$$
\underset{\{C_t,\varpi_t\}}{Max}\left\{(1-\delta)\cdot C_t^{1-1/\psi} \;+\; \delta \cdot \mathbb{E}_t \;\; V(W_{t+1})^{1-\gamma}\big]^{\frac{1-1/\psi}{1-}}\right\}^{1/(1-1/\psi)} . \tag{IA.28}
$$

The consumption FOC then yields

$$
(1-\delta)\cdot C_t^{-1/\psi} \;= \delta \cdot \mathbb{E}_t[V_{t+1}^{1-\gamma}]^{\frac{-1/\psi}{1-}} \cdot \mathbb{E}_t[V_{t+1}^{-\gamma} \cdot \partial_W V_{t+1} \cdot R_{w,t+1}], \tag{IA.29}
$$

and the Benveniste and Scheinkman (1979) condition relative to wealth implies

$$
\partial_W V_t \;= V_t^{1/\psi} \cdot \delta \cdot \mathbb{E}_t[V_{t+1}^{1-\gamma}]^{\frac{-1/\psi}{1-}} \cdot \mathbb{E}_t[V_{t+1}^{-\gamma} \cdot \partial_W V_{t+1} \cdot R_{w,t+1}], \tag{IA.30}
$$

so that combining the two optimality conditions gives

$$
\partial_W V_t \;= (1-\delta) \cdot \left(\frac{V_t}{C_t}\right)^{1/\psi} \tag{IA.31}
$$

Equation IA.31 is the main optimality condition we need to derive the ICAPM SDF. To do so, start by conjecturing that $V(W_t)$ is homogeneous of degree one (i.e., V_t/W_t is not a function of wealth). This conjecture implies that $\partial_W V_t = V_t/W_t$, which, after substituting into Equation IA.31, yields:

$$
\begin{aligned}
(V_t/W_t)^{1-1/\psi} \;&=\; (1-\delta)\cdot(C_t/W_t)^{-1/\psi} && \text{(IA.32)}\\
&\Downarrow \\
cw_t \;&=\; \psi\cdot log(1-\delta) \;+\; (1-\psi)\cdot vw_t, && \text{(IA.33)}
\end{aligned}
$$

so that Equation IA.8 also holds when $\psi \neq 1$.

Now, rewrite the objective function (i.e., Equation IA.28) as:

$$
\begin{aligned}
(W_t \cdot V_t/W_t)^{1-1/\psi} \;&= (1-\delta)\cdot W_t^{1-1/\psi}\cdot(C_t/W_t)^{1-1/\psi} \;+\; \delta\cdot\mathbb{E}_t \;\; W_{t+1}^{1-\gamma}\left(\frac{V_{t+1}}{W_{t+1}}\right)^{1-\gamma}\Bigg]^{\frac{1-1/\psi}{1-}}\\
&\Downarrow\\
(V_t/W_t)^{1-1/\psi} \;&= (1-\delta)\cdot(C_t/W_t)^{1-1/\psi} \;+\; \delta\cdot\mathbb{E}_t \;\; \left(\frac{W_{t+1}}{W_t}\right)^{1-\gamma}\left(\frac{V_{t+1}}{W_{t+1}}\right)^{1-\gamma}\Bigg]^{\frac{1-1/\psi}{1-}}\\
&= C_t/W_t\cdot(V_t/W_t)^{1-1/\psi} \;+\; \delta\cdot\mathbb{E}_t \;\; \left(1-\frac{C_t}{W_t}\right)^{1-\gamma}\left(\frac{V_{t+1}}{W_{t+1}}\right)^{1-\gamma} R_{w,t+1}^{1-\gamma}\Bigg]^{\frac{1-1/\psi}{1-}}\\
&= \delta\cdot\mathbb{E}_t \;\; (1-C_t/W_t)^{\frac{1-}{1-}}\left(\frac{V_{t+1}}{W_{t+1}}\right)^{1-\gamma} R_{w,t+1}^{1-\gamma}\Bigg]^{\frac{1-1/\psi}{1-}}, \qquad \text{(IA.34)}
\end{aligned}
$$

where the third equality relies on Equation IA.32 and the budget constraint (Equation IA.1).

Equation IA.34 represents a recursion for V_t/W_t that shows that if V_{t+1}/W_{t+1} does not depend on wealth, then V_t/W_t also does not.[IA.3] As such, the conjecture that $V(W_t)$ is homogeneous of degree one is valid.

[IA.3] The recursion in Equation IA.34 also depends on C_t/W_t. However, Equation IA.32 shows that C_t/W_t is a function of V_t/W_t, and thus the recursion implies that V_t/W_t is a function of the distribution of $[V_{t+1}/W_{t+1}, R_{w,t+1}]$, which does not depend on the wealth level from the perspective of the Epstein-Zin investor.

We can further work on Equation IA.34 to get

$$\begin{aligned}
1 \; &= \mathbb{E}_t \; \left\{ \delta^{\frac{1-}{1-1/\psi}} \cdot (1 - C_t/W_t)^{\frac{1-}{1-}} \cdot R_{w,t+1}^{-\gamma} \cdot \left(\frac{V_{t+1}/W_{t+1}}{V_t/W_t} \right)^{-(\gamma-1)} \right\} \cdot R_{w,t+1} \Big] \\
&= \mathbb{E}_t \; e^{f_{sdf}(\psi,\delta,\gamma,cw_t) \, - \, \gamma \cdot r_{w,t+1} \, - \, (\gamma-1) \cdot vw_{t+1}} \cdot R_{w,t+1} \Big] \,, \qquad \text{(IA.35)}
\end{aligned}$$

where $f_{sdf}(\psi, \delta, \gamma, cw_t) \; = \; (\gamma - 1) \cdot \left(vw_t + \frac{1}{\psi-1} \cdot [cw_t - crw_t] - \frac{1}{1-1/\psi} \cdot log(\delta) \right)$ is implicitly defined in Equation IA.35.

Now, rewrite the budget constraint as $W_{t+1} = (W_t - C_t) \cdot (R_{f,t+1} + \varpi_t'(R_{t+1} - R_{f,t+1}))$ and substitute it in $V(W_{t+1})$ so that the FOC with respect to ϖ_t yields

$$\begin{aligned}
0 \; &= \mathbb{E}_t \left[\delta \cdot \left(\frac{C_{t+1}}{C_t} \right)^{-1/\psi} \cdot \quad \frac{V_{t+1}}{E_t[V_{t+1}^{1-\gamma}]^{1/(1-\gamma)}} \right)^{-(\gamma-1/\psi)} \cdot (R_{t+1} - R_{f,t+1}) \right] \\
&= \mathbb{E}_t \left[e^{-1/\psi \cdot \widetilde{\Delta c}_{t+1} \, - \, (\gamma-1/\psi) \cdot \tilde{v}_{t+1}} \cdot (R_{t+1} - R_{f,t+1}) \right. \\
&= \mathbb{E}_t \; e^{-\gamma \cdot \tilde{r}_{w,t+1} \, - \, (\gamma-1) \cdot \widetilde{vw}_{t+1}} \cdot (R_{t+1} - R_{f,t+1}) \Big] \\
&= \mathbb{E}_t \; e^{f_{sdf}(\psi,\delta,\gamma,cw_t) \, - \gamma \cdot r_{w,t+1} \, - \, (\gamma-1) \cdot vw_{t+1}} \cdot (R_{t+1} - R_{f,t+1}) \Big] \,, \qquad \text{(IA.36)}
\end{aligned}$$

where the third equality is based on the same derivation as in Equation IA.10 and the second and fourth equalities use the fact that we can multiply any arbitrary variable known as of time t on both sides of this FOC.

Equations IA.35 and IA.36 jointly imply that the SDF, given by

$$sdf_{t+1} \; = f_{sdf}(\psi, \delta, \gamma, cw_t) \; - \; \gamma \cdot r_{w,t+1} \; - \; (\gamma - 1) \cdot vw_{t+1}, \qquad \text{(IA.37)}$$

prices all assets available to the Epstein-Zin investor.

C.3.3 Summarizing the Epstein-Zin SDF with $vw\psi$

As Equations IA.27 and IA.37 demonstrate, the SDF shocks with Epstein-Zin preferences can be written as

$$\widetilde{sdf}_{t+1} \; = \; - \; \gamma \cdot \tilde{r}_{w,t+1} \; - \; (\gamma - 1) \cdot \widetilde{vw}_{t+1}. \qquad \text{(IA.38)}$$

The SDF level is more complicated due to the nonlinear $f_{sdf}(\psi, \delta, \gamma, cw_t)$ function. However, we can simplify this function to

$$
\begin{aligned}
f_{sdf}(\psi, \delta, \gamma, cw_t) &= (\gamma - 1) \cdot \left(vw_t + \frac{1}{\psi - 1} \cdot [cw_t - crw_t] - \frac{1}{1 - 1/\psi} \cdot log(\delta) \right) \\
&\approx (\gamma - 1) \cdot \left(vw_t + \frac{1}{\psi - 1} \cdot \quad cw_t - \left(-\frac{k}{\bar{\bar{\delta}}} + \frac{1}{\bar{\bar{\delta}}} \cdot cw_t \right) \right] - \frac{1}{1 - 1/\psi} \cdot log(\delta) \right) \\
&= \frac{\gamma - 1}{\bar{\delta}} \cdot \left(vw_t - \frac{1}{\psi - 1} \quad \psi \cdot f_0(\delta, \bar{\delta}) - f_0(\bar{\delta}, \bar{\delta})] \right) \\
&= \frac{\gamma - 1}{\bar{\delta}} \cdot \left(vw_t - f_0(\delta, \bar{\delta}) - \frac{1}{\psi - 1} \cdot \quad f_0(\delta, \bar{\delta}) - f_0(\bar{\delta}, \bar{\delta})] \right), \qquad \text{(IA.39)}
\end{aligned}
$$

where $f_0(z, y) = (1 - y) \cdot log(1 - z) + y \cdot log(z)$, with the second equality relying on the log-linear approximation to cw_t in Campbell (1993) (Equation IA.4), which is exact if $\psi = 1$, and the third equality using Equation IA.33.

As such, the Epstein-Zin log SDF can be summarized by

$$
\begin{aligned}
sdf_{t+1} &= \frac{\gamma - 1}{\bar{\delta}} \cdot \left(vw_t - f(\psi, \delta, \bar{\delta}) \right) \; - \; \gamma \cdot r_{w,t+1} \; - \; (\gamma - 1) \cdot vw_{t+1} \\
&= \kappa_t \; - \; \gamma \cdot r_{w,t+1} \; - \; (\gamma - 1) \cdot \widetilde{vw}_{t+1} \qquad \text{(IA.40)}
\end{aligned}
$$

where

$$
\kappa_t = (\gamma - 1) \cdot \left(vw_t/\bar{\delta} - \mathbb{E}_t[vw] - f(\psi, \delta, \bar{\delta})/\bar{\delta} \right) \qquad \text{(IA.41)}
$$

and

$$
f(\psi, \delta, \bar{\delta}) = \begin{cases} f_0(\delta, \delta) & if \ \psi = 1 \\ f_0(\delta, \bar{\delta}) + \frac{1}{\psi - 1} \cdot \quad f_0(\delta, \bar{\delta}) - f_0(\bar{\delta}, \bar{\delta})] & if \ \psi \neq 1. \end{cases} \qquad \text{(IA.42)}
$$

C.4 Deriving the Recursive Equation for $vw\psi$

The wealth portfolio pricing equation, $\mathbb{E}_t[SDF_{t+1} \cdot R_{w,t+1}] = 1$, can be written as

$$\begin{aligned} 0 \ &= \mathbb{E}_t\left[sdf_{t+1} + r_{w,t+1}\right] \ + \ log\left(\mathbb{E}_t\left[e^{\widetilde{sdf}_{t+1}+\widetilde{r}_{w,t+1}}\right.\right) \\ &= \mathbb{E}_t\left[sdf_{t+1} + r_{w,t+1}\right] \ + \ (1-\gamma) \cdot log\left(\mathbb{E}_t \ \ e^{(1-\gamma)\cdot\widetilde{v}_{t+1}}\right]^{1/(1-\gamma)}\right) \\ &= \mathbb{E}_t\left[sdf_{t+1} + r_{w,t+1}\right] \ + \ (1-\gamma) \cdot \mathbb{CE}_t[\widetilde{v}_{t+1}], \end{aligned} \tag{IA.43}$$

with $\mathbb{CE}_t[\widetilde{v}] = log(\mathbb{E}_t[e^{(1-\gamma)\cdot\widetilde{v}_{t+1}}]^{1/(1-\gamma)})$ reflecting the certainty equivalent function, which satisfies

$$\mathbb{CE}_t\left[\widetilde{v}\right] \ = \sum_{j=2}^{\infty} \frac{(1-\gamma)^{j-1}}{j!} \cdot \mathbb{K}_t^{(j)}[\widetilde{v}] \ = \ \frac{(1-\gamma)}{2} \cdot \mathbb{V}ar_t[\widetilde{v}] + \underbrace{\sum_{j=3}^{\infty} \frac{(1-\gamma)^{j-1}}{j!} \cdot \mathbb{K}_t^{(j)}[\widetilde{v}]}_{\mathbb{H}_t[\widetilde{v}]} \tag{IA.44}$$

where $\mathbb{K}_t^{(j)}[\cdot]$ is the j-th cumulant (e.g., $\mathbb{K}_t^{(2)}[\widetilde{v}] = \mathbb{E}[\widetilde{v}^2]$ and $\mathbb{K}_t^{(3)}[\widetilde{v}] = \mathbb{E}_t[\widetilde{v}^3]$). Note that $\mathbb{H}_t[\cdot]$ captures high order terms of the $\widetilde{v}_t$ distribution and it would be zero if $\widetilde{v}_t$ was normally distributed.

Substituting Equation IA.44 into IA.43, we have

$$0 \ = \mathbb{E}_t\left[sdf_{t+1} + r_{w,t+1}\right] \ + \ \frac{(1-\gamma)^2}{2} \cdot \mathbb{V}ar_t[\widetilde{v}_{t+1}] \ + \ (1-\gamma) \cdot \mathbb{H}_t[\widetilde{v}_{t+1}], \tag{IA.45}$$

so that further substituting the sdf_t from Equation IA.40 into Equation IA.45 results in

$$vw_t \ = f(\psi, \delta, \overline{\delta}) \ + \overline{\delta} \cdot \mathbb{E}_t\left[r_w\right] + \overline{\delta} \cdot \mathbb{E}_t\left[vw\right] \ - \ \overline{\delta} \cdot \frac{(\gamma-1)}{2} \cdot \mathbb{V}ar_t\left[\widetilde{v}\right] \ - \ \overline{\delta} \cdot \mathbb{H}_t\left[\widetilde{v}\right], \tag{IA.46}$$

which is a recursive equation for vw_t.

Note that combining the approximate budget constraint (Equation IA.5) with the optimal relation between cw and vw (Equation IA.33) yields

$$\overline{\delta} \cdot r_{w,t} \ = (\psi - 1) \cdot (1-\overline{\delta}) \cdot log(1-\overline{\delta}) - \overline{\delta} \cdot log(\overline{\delta}) + \overline{\delta} \cdot \Delta c_t + (1-\psi) \cdot vw_{t-1} - \overline{\delta} \cdot (1-\psi) \cdot vw_t, \tag{IA.47}$$

which we can substitute into Equation IA.46 to obtain an alternative form of the recursive equation for vw_t:

$$\psi \cdot vw_t \; = g(\psi,\delta,\overline{\delta}) \; + \overline{\delta} \cdot \mathbb{E}_t\left[\Delta c\right] \; + \overline{\delta} \cdot \mathbb{E}_t\left[\psi \cdot vw\right] \; - \overline{\delta} \cdot \frac{(\gamma-1)}{2} \cdot \mathbb{V}ar_t\left[\widetilde{v}\right] \; - \overline{\delta} \cdot \mathbb{H}_t\left[\widetilde{v}\right], \tag{IA.48}$$

where $g(\psi,\delta,\overline{\delta}) = f(\psi,\delta,\overline{\delta}) + (\psi-1)\cdot(1-\overline{\delta})\cdot log(1-\overline{\delta}) - \overline{\delta}\cdot log(\overline{\delta})$.

C.5 Deriving the Epstein-Zin SDF with News

This subsection derives the Epstein-Zin SDF with news as a risk factor.

C.5.1 Epstein-Zin SDF in Intertemporal CAPM Format

Solving the vw_t recursive Equation IA.46 forward yields

$$\begin{aligned} vw_t \; &= \frac{f(\psi,\delta,\overline{\delta})}{1-\overline{\delta}} \; + \mathbb{E}_t \left. \sum_{h=1}^{\infty} \overline{\delta}^h \cdot r_{w,t+h} \right] \\ &\quad - \frac{(\gamma-1)}{2} \cdot \mathbb{E}_t \left. \sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{V}ar_{t+h-1}\left[\widetilde{v}_{t+h}\right] \right] \\ &\quad - \mathbb{E}_t \left. \sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{H}_{t+h-1}\left[\widetilde{v}_{t+h}\right] \right] \end{aligned} \tag{IA.49}$$

which implies

$$\widetilde{vw}_t \; = N_{\mathbb{E}r,t} \; - \; 0.5\cdot(\gamma-1)\cdot N_{\mathbb{V},t} \; - \; N_{\mathbb{H},t} \tag{IA.50}$$

where
$N_{\mathbb{E}r,t} = (\mathbb{E}_t - \mathbb{E}_{t-1})\left[\sum_{h=1}^{\infty} \overline{\delta}^h \cdot r_{w,t+h}\right.$ is expected return news
$N_{\mathbb{V},t} = (\mathbb{E}_t - \mathbb{E}_{t-1})\left[\sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{V}ar_{t+h-1}[\widetilde{v}_{t+h}]\right.$ is news about $\widetilde{v}_t$ volatility
$N_{\mathbb{H},t} = (\mathbb{E}_t - \mathbb{E}_{t-1})\left[\sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{H}_{t+h-1}[\widetilde{v}_{t+h}]\right.$ is news about $\widetilde{v}_t$ high order moments

Then, substituting Equation IA.50 back into the log SDF in Equation IA.40, we have

$$sdf_t = \kappa_{t-1} - \gamma\cdot r_{w,t} - (\gamma-1)\cdot N_{\mathbb{E}r,t} + 0.5\cdot(\gamma-1)^2\cdot N_{\mathbb{V},t} + (\gamma-1)\cdot N_{\mathbb{H},t} \tag{IA.51}$$

where $\kappa_t = (\gamma-1)\cdot(vw_t/\overline{\delta} - \mathbb{E}_t[vw] - f(\psi,\delta,\overline{\delta})/\overline{\delta})$.

Equation IA.51 is the Intertemporal CAPM equivalent of the Consumption CAPM log SDF in Equation 1, with $\kappa_{\mathbb{E}} = (\gamma - 1)$, $\kappa_{\mathbb{V}} = 0.5 \cdot (\gamma - 1)^2$, and $\kappa_{\mathbb{H}} = (\gamma - 1)$. Note that, if $N_{\mathbb{H},t} = 0$, this log SDF is identical to the one in the Intertemporal CAPM of Campbell et al. (2018) and Chabi-Yo, Gonçalves, and Loudis (2025).

C.5.2 Epstein-Zin SDF in Consumption CAPM Format

Solving the vw_t recursive Equation IA.48 forward yields

$$
\begin{aligned}
\psi \cdot vw_t \; &= \frac{g(\psi, \delta, \overline{\delta})}{1 - \overline{\delta}} \; + \; \mathbb{E}_t \left. \sum_{h=1}^{\infty} \overline{\delta}^h \cdot \Delta c_{t+h} \right] \\
&\quad - \frac{(\gamma - 1)}{2} \cdot \mathbb{E}_t \left. \sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{V}ar_{t+h-1} \left[\widetilde{v}_{t+h} \right] \right] \\
&\quad - \mathbb{E}_t \left. \sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{H}_{t+h-1} \left[\widetilde{v}_{t+h} \right] \right]
\end{aligned}
\tag{IA.52}
$$

which implies

$$
\widetilde{vw}_t \; = \frac{1}{\psi} \cdot N_{\mathbb{E}c,t} \; - \; \frac{0.5}{\psi} \cdot (\gamma - 1) \cdot N_{\mathbb{V},t} \; - \; \frac{1}{\psi} \cdot N_{\mathbb{H},t} \tag{IA.53}
$$

where

$N_{\mathbb{E}c,t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \overline{\delta}^h \cdot \Delta c_{t+h} \right.$ is expected consumption growth news

$N_{\mathbb{V},t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{V}ar_{t+h-1}[\widetilde{v}_{t+h}] \right.$ is news about $\widetilde{v}_t$ volatility

$N_{\mathbb{H},t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{H}_{t+h-1}[\widetilde{v}_{t+h}] \right.$ is news about $\widetilde{v}_t$ high order moments

Moreover, substituting Equation IA.47 into the log SDF Equation IA.40 yields

$$
sdf_t \; = \lambda_{t-1} \; - \; \gamma \cdot \Delta c_t \; - \; \psi \cdot (\gamma - 1/\psi) \cdot \widetilde{vw}_t \tag{IA.54}
$$

so that further substituting Equation IA.53 results in

$$
sdf_t = \lambda_{t-1} - \gamma \cdot \Delta c_t - (\gamma - 1/\psi) \cdot N_{\mathbb{E}c,t} + 0.5 \cdot (\gamma - 1/\psi) \cdot (\gamma - 1) \cdot N_{\mathbb{V},t} + (\gamma - 1/\psi) \cdot N_{\mathbb{H},t} \tag{IA.55}
$$

where $\lambda_t = \; \kappa_t - \frac{\gamma}{\delta} \cdot (\psi - 1) \cdot (1 - \overline{\delta}) \cdot log(1 - \overline{\delta}) + \gamma \cdot log(\overline{\delta}) - \gamma \cdot (1 - \psi) \cdot (vw_t / \overline{\delta} - \mathbb{E}_t[vw])$.

Equation IA.55 is the Consumption CAPM log SDF in Equation 1, with $\lambda_{\mathbb{E}} = (\gamma - 1/\psi)$,

$\lambda_{\mathbb{V}} = 0.5 \cdot (\gamma - 1/\psi) \cdot (\gamma - 1)$, and $\lambda_{\mathbb{H}} = (\gamma - 1/\psi)$.

C.6 The E ect of Consumption Disasters on the Epstein-Zin SDF

The log SDF in Equation IA.54 can be written as Equation 1 in the main text:

$$sdf_t \ = \lambda_{t-1} \ - \ \gamma \cdot \Delta c_t \ - \ \lambda_{\mathbb{E}} \cdot N_{\mathbb{E}c,t} \ + \ \lambda_{\mathbb{V}} \cdot N_{\mathbb{V},t} \ + \ \lambda_{\mathbb{H}} \cdot N_{\mathbb{H},t} \tag{IA.56}$$

where $\lambda_{\mathbb{E}}$, $\lambda_{\mathbb{V}}$, and $\lambda_{\mathbb{H}}$ are positive if $\gamma > 1/\psi$ (i.e., if the investor prefers early resolution of uncertainty) since $\gamma > 1$ in the main text.

So, for an Epstein-Zin investor who prefers early resolution of uncertainty, negative shocks to Δc and $N_{\mathbb{E}c}$ and positive shocks to $N_{\mathbb{V}}$ and $N_{\mathbb{H}}$ reflect bad news. Note that we can always write $\widetilde{v}_t = \widetilde{vc}_t + \widetilde{c}_t$ and shocks to the value-consumption ratio ($\widetilde{vc}$) reflect shocks to the parameters of the future consumption distribution under an exogenous consumption process, as standard in endowment economies. As such, $\widetilde{v}_t$ is entirely determined by shocks to consumption and its distribution so that $N_{\mathbb{V}}$ and $N_{\mathbb{H}}$ reflect news about the volatility and high order moments of the consumption distribution.

For instance, suppose the consumption growth process is as in Bansal and Yaron (2004):

$$\Delta c_{t+1} \ = g_t \ + \ \sigma_t \cdot \epsilon_{c,t+1} \tag{IA.57}$$

$$g_{t+1} \ = g \ + \ \phi_g \cdot (g_t - g) \ + \ \varphi_g \cdot \sigma_t \cdot \epsilon_{g,t+1} \tag{IA.58}$$

$$\sigma^2_{t+1} \ = \sigma^2 \ + \ \phi_\sigma \cdot \left(\sigma^2_t - \sigma^2\right) \ + \ \sigma_\sigma \cdot \epsilon_{\sigma,t+1} \tag{IA.59}$$

where $(\epsilon_{c,t}, \epsilon_{g,t}, \epsilon_{\sigma,t}) \overset{iid}{\sim} \mathcal{N}(0, \mathrm{I})$. In this case, we have that $vc_t = a_{vc} + b_g \cdot g_t + b_\sigma \cdot \sigma^2_t$ because cw_t is linear in g_t and σ^2_t (as derived in Bansal and Yaron (2004)) and vc_t is linear in cw_t.[IA.4] As such, $\widetilde{v}_{t+1} = \widetilde{vc}_{t+1} + \widetilde{c}_{t+1} = b_\sigma \cdot \sigma_\sigma \cdot \epsilon_{\sigma,t+1} + \sigma_t \cdot (b_g \cdot \epsilon_{g,t+1} + \epsilon_{c,t+1})$, which is normally distributed. Consequently, $\mathbb{H}_t[\widetilde{v}_{t+1}] = 0$, which implies $N_{\mathbb{H},t} = 0$. So, Δc, $N_{\mathbb{E}c}$, and $N_{\mathbb{V}}$ are present in the

[IA.4] The fact that vc_t is linear in cw_t follows directly from Equation IA.33, which can be written as

$$vc_t \ = \ \frac{}{1-} \cdot cw_t \psi - \frac{}{1-} \cdot log(1-\delta)$$

long-run risks model, but $N_{\mathbb{H}}$ is not as it reflects news about high order moments of the consumption shock distribution, which are zero given the normal shocks.

Now, suppose instead that Δc_t is given by

$$\Delta c_{t+1} = g + \sigma_c \cdot \epsilon_{c,t+1} - \sigma_\eta \cdot \eta_{t+1} \quad \text{(IA.60)}$$

$$\pi_{t+1} = \pi + \phi_\pi \cdot (\pi_t - \pi) + \sigma_\pi \cdot \epsilon_{\pi,t+1} \quad \text{(IA.61)}$$

where $\epsilon_{\pi,t} \overset{iid}{\sim} \mathcal{N}(0,1)$ and $\eta_{t+1} = 1$ with probability π_t (and 0 otherwise). In this case, vc_t is a non-linear function of π_t (since this is the only state variable driving the consumption growth distribution). As such, $\widetilde{v}_{t+1} = (vc(\pi_{t+1}) - \mathbb{E}_t[vc(\pi_{t+1})]) + \sigma_c \cdot \epsilon_{c,t+1} - \sigma_\eta \cdot \eta_{t+1}$. Clearly, $\mathbb{H}_t[\widetilde{v}_{t+1}] \neq 0$ because of η_{t+1} and the non-linearity of the $vc(\pi_{t+1})$ function. In turn, $\mathbb{H}_t[\widetilde{v}_{t+1}]$ is also a non-linear function of π_t as this is the only state variable driving the π_{t+1} and η_{t+1} distributions. So, $N_{\mathbb{H}} \neq 0$ is a non-linear function of shocks to the probability of disasters in this model.[IA.5]

In a more general model, the dynamics of disasters (e.g., time-varying disaster severity) can also a ect $N_{\mathbb{H}}$ so that we should think of $N_{\mathbb{H}}$ as a general risk factor that captures news about the prospects of disasters (i.e., shocks to the parameters of the distribution of potential future consumption disasters). The probability of disasters is the most obvious parameter, but not the only possible one. Importantly for our argument, $N_{\mathbb{H},t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \sum_{h=1}^{\infty} \overline{\delta}^h \cdot \mathbb{H}_{t+h-1}[\widetilde{v}_{t+h}]$ reflects news about long-term prospects of disasters, not short-term. So, GPT (which predicts cumulative disasters over long periods) is more relevant for asset pricing from the perspective of disaster risk models than GPA (which only predicts cumulative disasters over short periods).

[IA.5] Note that shocks to π_t also affect $N_{\mathbb{E}}$ and $N_{\mathbb{V}}$, but the main e ect of π_t shocks is on $N_{\mathbb{H}}$. Moreover, we can have the g_t, σ_t^2, and π_t state variables operating simultaneously so that the e ect of π_t shocks on $N_{\mathbb{E}}$ and $N_{\mathbb{V}}$ would be minor relative to the e ect of g_t and σ_t^2 shocks on these news. In any case, only π_t shocks affect $N_{\mathbb{H}}$ in this model.

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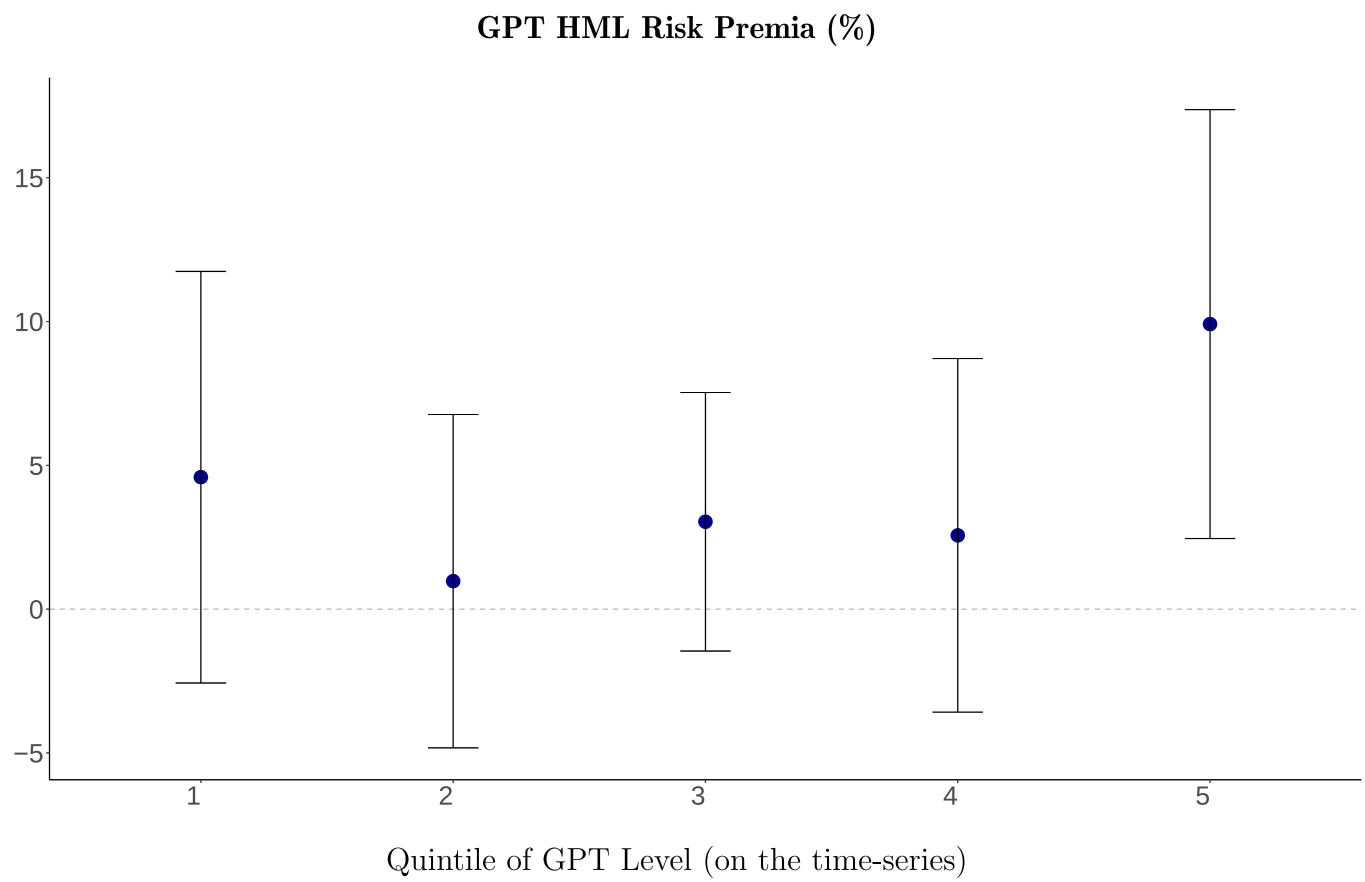

Figure IA.1

GPT Beta HML Portfolio Risk Premia Conditional on GPT Level

This figure is analogous to Figure 9(a), but it uses GPT levels. Specifically, it plots the GPT HML portfolio annualized risk premia conditioned on di erent levels of GPT. The GPT HML portfolio is constructed from value-weighted beta quintile portfolios, buying (selling) stocks with high (low) stock-level betas on the news-based geopolitical threats (GPT) index of Caldara and Iacoviello (2022). Specifically, we consider five quintiles of the (time-series of the) GPT index, with the quintile levels (in the x-axes) going from low to high levels of the GPT index. The figure also provides 95% confidence intervals for the conditional risk premia estimates based on Newey and West (1987, 1994) standard errors. Section 1.1 provides measurement details for the GPT and GPR indices while Section 2.2 covers the results from this figure.

Table IA.1

GPT vs GPA: Investors' Perceptions of Other Risks

This table reports panel regressions of investors' perceptions of risks beyond geopolitical risk onto the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022). All risk perception measures are based on the surveys of global fund managers conducted by the Bank of America (BofA), each resulting in a time series from 07-2007 to 12-2024. The construction of each of these measures is analogous to that of the BofA geopolitical risk perception measure explored in Table 2. We order these risk perception measures by the most correlated with the BofA geopolitical risk measure to the least correlated (with correlations provided in the header of each panel block). All variables are normalized to z-scores and t-statistics (in brackets) are based on Newey and West (1987, 1994). Section 1.1 provides measurement details for the GPT and GPA indices while Section B.1 covers the results from this table.

BofA =	**Monetary Risk (Corr = 0.44)**			**Emerging Market Risk (Corr = 0.31)**			**Protectionist Risk (Corr = 0.23)**		
	[1]	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**
GPT	0.8		0.72	0.36		0.36	0.18		0.34
	[5.65]		[4.07]	[1.85]		[1.54]	[1.2]		[1.75]
GPA		1.16	0.46		0.33	-0.02		-0.56	-0.89
		[2.29]	[0.73]		[0.61]	[-0.03]		[-0.78]	[-1.2]
R^2_{within}	22%	8%	23%	4%	1%	4%	1%	2%	5%
$\mathbb{C}or[Y_t, \widehat{Y}_t]$	0.47	0.29	0.48	0.21	0.08	0.21	0.11	0.14	0.23
# Obs	210	210	210	210	210	210	210	210	210
BofA =	**Business Cycle Risk (Corr = -0.04)**			**Credit Risk (Corr = -0.31)**			**Counterparty Risk (Corr = -0.49)**		
	[1]	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**
GPT	0.13		0.06	-0.09		-0.21	-0.39		-0.47
	[0.47]		[0.20]	[-0.32]		[-0.73]	[-1.21]		[-1.23]
GPA		0.45	0.39		0.50	0.70		-0.01	0.44
		[0.83]	[0.64]		[1.10]	[1.36]		[-0.02]	[0.76]
R^2_{within}	1%	1%	1%	0%	2%	3%	5%	0%	6%
$\mathbb{C}or[Y_t, \widehat{Y}_t]$	0.07	0.11	0.12	0.05	0.12	0.17	0.23	0.00	0.25
# Obs	210	210	210	210	210	210	210	210	210

Table IA.2

Beta HML Portfolios Constructed from Single Stocks (Modern Sample)

This table reports annualized risk premia, annualized alphas, and mimicking factor betas of beta HML portfolios. Each beta HML portfolio is constructed from value-weighted beta quintile portfolios, buying (selling) stocks with high (low) stock-level betas on the given risk index. Stock-level betas are estimated from the three-year rolling window univariate beta on the (negative of the) given index growth rate. We consider ten risk indices in total. The first three are the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). The other indices (detailed in Table 1) cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV), trade policy uncertainty (TPU), real uncertainty (RUI), macro uncertainty (MUI), and financial uncertainty (FUI). All columns cover our modern sample (08-1963 to 12-2024), except that WAR is only available until 10-2019. Rows differ based on the statistic reported, with mimicking factors described in Table 5 (constructed following Giglio, Xiu, and Zhang (2025)) and ICAPM alphas based on the intertemporal factor model of Chabi-Yo, Gonçalves, and Loudis (2025). The t-statistics (in brackets) are based on Newey and West (1987, 1994). Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section B.2 covers the return data and results from this table.

INDEX =	**GPT**	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**TPU**	**RUI**	**MUI**	**FUI**
Beta on Mimicking Factor	0.11	0.07	0.10	0.18	0.21	0.11	0.04	0.90	1.40	1.18
	[3.56]	[3.24]	[4.41]	[2.53]	[11.81]	[6.66]	[1.41]	[3.64]	[5.25]	[4.04]
Risk Premium (%)	3.36	2.33	3.51	-0.46	1.15	1.21	-0.49	2.56	2.39	2.40
	[1.99]	[1.14]	[1.87]	[-0.28]	[0.50]	[0.60]	[-0.30]	[1.36]	[1.22]	[1.05]
CAPM Alpha (%)	3.00	1.75	3.02	-0.39	-2.44	-1.77	-1.12	0.26	-0.11	-0.42
	[1.80]	[0.85]	[1.69]	[-0.24]	[-1.14]	[-0.95]	[-0.65]	[0.15]	[-0.06]	[-0.20]
ICAPM Alpha (%)	3.24	2.01	3.44	-0.32	-1.57	-1.50	-1.23	1.18	0.99	0.62
	[1.90]	[0.96]	[1.87]	[-0.19]	[-0.81]	[-1.05]	[-0.72]	[0.88]	[0.66]	[0.27]
GPT Alpha w.r.t INDEX		2.19	0.60	2.40	3.16	3.16	3.27	2.89	2.86	2.93
		[1.78]	[0.81]	[1.73]	[1.97]	[2.00]	[2.09]	[1.82]	[1.93]	[1.96]
INDEX Alpha w.r.t GPT		0.19	0.38	-1.29	0.09	0.33	0.13	1.78	1.41	1.45
		[0.12]	[0.46]	[-0.93]	[0.04]	[0.17]	[0.08]	[0.98]	[0.77]	[0.66]

Table IA.3
Beta HML Portfolios Constructed from Single Stocks (Alternative Specifications)

This table reports annualized risk premia and annualized alphas of beta HML portfolios. Each beta HML portfolio is constructed from beta sorted portfolios, buying (selling) stocks with high (low) stock-level betas on F_t. Unless otherwise noted, F_t reflects the growth rate of the given risk index (i.e., $F_t = IND_t/IND_{t-1} - 1$), portfolios are value-weighted quintiles with NYSE breakpoints (as suggested by Hou, Xue, and Zhang (2019)), and stock-level betas are estimated from the three-year rolling window univariate beta on (the negative of) F_t. We consider ten risk indices in total. The first three are the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). The other indices (detailed in Table 1) cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV), trade policy uncertainty (TPU), real uncertainty (RUI), macro uncertainty (MUI), and financial uncertainty (FUI). Rows di er based on the specification used, with our baseline specification results reproduced in the first row. While our baseline analysis uses $F_t = IND_t/IND_{t-1} - 1$, rows 2 to 4 use $F_t = log(IND_t/IND_{t-1})$ (as in Adrian, Etula, and Muir (2014)), $F_t = IND_t - IND_{t-1}$ (as in Ang et al. (2006)), and $F_t = IND_t$ (as in Bali, Brown, and Tang (2017)). In turn, rows 5 and 6 replace quintile portfolios with decile or tercile portfolios and row 7 uses equal-weighted portfolios and excludes microcaps (defined as stocks below the 20% quantile of market equity from NYSE stocks). Rows 8 and 9 replace 3-year rolling window betas with $\beta = -\mathbb{C}orr[r, F] \cdot \mathbb{V}ol[r]$, where $\mathbb{V}ol[r]$ is estimated from one year of daily stock returns (as in Frazzini and Pedersen (2014)) and $\mathbb{C}orr[r, F]$ is estimated from a 3-year (as in our baseline analysis) or 10-year (as in Herskovic, Moreira, and Muir (2019)) rolling window of monthly observations. Finally, row 10 starts the sample in the first year with at least 500 firms (01-1934). The t-statistics (in brackets) are based on Newey and West (1987, 1994). Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section B.3 covers the results from this table.

PANEL A - Risk Premia (%)

$IND_t =$	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Baseline	4.17	1.69	2.71	1.22	2.99	0.68	-0.49	2.56	2.39	2.40
	[2.85]	[0.98]	[1.65]	[0.87]	[1.42]	[0.40]	[-0.30]	[1.36]	[1.22]	[1.05]
$F_t = log(IND_t/IND_{t-1})$	3.23	1.81	2.74	1.15	3.05	-0.11	-0.82	2.52	2.28	2.34
	[1.92]	[1.07]	[1.70]	[0.81]	[1.48]	[-0.07]	[-0.52]	[1.34]	[1.17]	[1.02]
$F_t = IND_t - IND_{t-1}$	3.35	1.65	2.62	1.17	3.37	-0.97	-0.45	2.64	2.32	2.34
	[2.16]	[0.95]	[1.63]	[0.82]	[1.66]	[-0.58]	[-0.28]	[1.37]	[1.17]	[0.99]
$F_t = IND_t$	4.21	1.84	3.37	-0.35	2.57	1.53	1.50	1.22	0.47	4.69
	[2.50]	[1.04]	[1.79]	[-0.23]	[1.55]	[0.82]	[0.85]	[0.63]	[0.24]	[2.20]
Decile Portfolios	4.41	2.53	3.47	0.27	2.85	2.07	-1.17	3.63	3.09	2.72
	[2.38]	[1.13]	[1.63]	[0.13]	[1.18]	[1.04]	[-0.56]	[1.58]	[1.21]	[0.93]
Tercile Portfolios	2.95	1.06	2.29	0.74	2.06	1.03	-0.18	1.14	2.26	2.30
	[2.55]	[0.78]	[1.67]	[0.55]	[1.26]	[0.75]	[-0.14]	[0.78]	[1.43]	[1.24]
Equal Weighted Portfolios	2.37	1.80	2.46	1.48	1.15	0.71	-0.63	1.86	2.02	2.32
	[2.08]	[1.41]	[1.96]	[1.39]	[0.77]	[0.54]	[-0.59]	[1.36]	[1.30]	[1.40]
$= -\mathbb{C}orr_{3y}[r, F] \cdot \mathbb{V}ol_{1y}[r]$	4.47	2.28	3.47	1.14	3.90	1.34	-0.62	2.14	1.77	1.80
	[2.70]	[1.28]	[1.99]	[0.64]	[1.83]	[0.73]	[-0.36]	[1.11]	[0.88]	[0.75]
$= -\mathbb{C}orr_{10y}[r, F] \cdot \mathbb{V}ol_{1y}[r]$	3.28	1.13	2.06	0.30	2.53	0.44	-2.51	1.76	0.89	2.07
	[1.82]	[0.69]	[1.22]	[0.19]	[1.17]	[0.30]	[-1.55]	[0.95]	[0.43]	[0.89]
At Least 500 Firms (01-1934)	4.52	1.87	3.57	1.49	2.08	1.73	-0.49	2.56	2.39	2.40
	[3.20]	[1.07]	[2.38]	[1.13]	[1.10]	[1.12]	[-0.30]	[1.36]	[1.22]	[1.05]

Table IA.3
Beta HML Portfolios Constructed from Single Stocks (Alternative Specifications)
(Continued)

PANEL B - CAPM Alphas (%)

$IND \Downarrow$	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Baseline	4.84	1.18	3.06	2.41	-1.08	0.15	-1.12	0.26	-0.11	-0.42
	[3.23]	[0.72]	[1.90]	[1.61]	[-0.59]	[0.09]	[-0.65]	[0.15]	[-0.06]	[-0.20]
$F_t = log(IND_t/IND_{t-1})$	4.42	1.23	3.10	2.43	-0.99	-0.39	-1.61	0.21	-0.21	-0.40
	[3.01]	[0.77]	[1.97]	[1.65]	[-0.54]	[-0.25]	[-0.98]	[0.12]	[-0.12]	[-0.19]
$F_t = IND_t - IND_{t-1}$	4.31	1.26	3.42	2.49	-0.72	-1.48	-1.39	0.29	-0.26	-0.51
	[2.91]	[0.75]	[2.13]	[1.67]	[-0.39]	[-0.95]	[-0.83]	[0.17]	[-0.14]	[-0.24]
$F_t = IND_t$	4.72	1.51	3.44	1.00	1.16	0.49	1.70	0.48	-0.29	2.81
	[2.91]	[0.93]	[1.92]	[0.71]	[0.63]	[0.30]	[0.95]	[0.23]	[-0.14]	[1.45]
Decile Portfolios	5.06	2.43	4.02	1.76	-1.72	1.72	-2.09	1.06	-0.01	-0.78
	[2.69]	[1.07]	[1.95]	[0.91]	[-0.78]	[0.90]	[-0.95]	[0.49]	[-0.01]	[-0.30]
Tercile Portfolios	3.52	0.63	2.56	1.99	-1.20	0.62	-0.69	-0.68	0.27	0.18
	[2.83]	[0.48]	[1.98]	[1.63]	[-0.74]	[0.48]	[-0.48]	[-0.49]	[0.19]	[0.11]
Equal Weighted Portfolios	2.94	1.51	2.63	2.58	-1.93	0.52	-0.76	0.19	0.28	0.38
	[2.58]	[1.23]	[2.13]	[2.31]	[-1.43]	[0.42]	[-0.68]	[0.16]	[0.19]	[0.22]
$= -\mathbb{C}orr_{3y}[r,F] \cdot \mathbb{V}ol_{1y}[r]$	5.70	2.21	4.30	2.76	-0.71	1.25	-1.52	-0.41	-1.05	-1.14
	[3.80]	[1.18]	[2.56]	[1.82]	[-0.37]	[0.69]	[-0.82]	[-0.23]	[-0.58]	[-0.53]
$= -\mathbb{C}orr_{10y}[r,F] \cdot \mathbb{V}ol_{1y}[r]$	4.29	0.95	2.88	2.02	-2.39	-0.12	-2.57	-1.13	-2.76	-1.90
	[2.51]	[0.58]	[1.70]	[1.45]	[-1.07]	[-0.07]	[-1.44]	[-0.71]	[-1.54]	[-0.99]
At Least 500 Firms (01-1934)	3.75	1.65	3.15	0.91	-2.03	-0.33	-1.12	0.26	-0.11	-0.42
	[2.83]	[1.01]	[2.18]	[0.73]	[-1.14]	[-0.22]	[-0.65]	[0.15]	[-0.06]	[-0.20]

PANEL C - ICAPM Alphas (%)

$IND \Downarrow$	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Baseline	4.21	0.93	2.28	1.48	0.45	-1.27	-1.23	1.18	0.99	0.62
	[2.91]	[0.53]	[1.38]	[0.97]	[0.25]	[-0.86]	[-0.72]	[0.88]	[0.66]	[0.27]
$F_t = log(IND_t/IND_{t-1})$	3.47	1.25	2.55	1.49	0.58	-1.82	-2.09	1.14	0.91	0.66
	[2.25]	[0.74]	[1.58]	[0.99]	[0.32]	[-1.30]	[-1.31]	[0.86]	[0.6]	[0.28]
$F_t = IND_t - IND_{t-1}$	3.31	1.07	2.47	1.55	0.88	-2.85	-1.92	1.20	0.87	0.51
	[2.19]	[0.62]	[1.53]	[1.04]	[0.54]	[-1.95]	[-1.18]	[0.87]	[0.58]	[0.22]
$F_t = IND_t$	4.38	1.29	2.97	0.57	0.86	-0.97	1.16	-0.80	-1.08	2.36
	[2.59]	[0.76]	[1.60]	[0.39]	[0.49]	[-0.58]	[0.63]	[-0.38]	[-0.53]	[1.21]
Decile Portfolios	4.02	1.99	3.02	0.78	-0.57	0.23	-2.37	1.87	1.67	0.55
	[2.15]	[0.83]	[1.44]	[0.38]	[-0.29]	[0.13]	[-1.05]	[1.04]	[0.81]	[0.20]
Tercile Portfolios	3.02	0.41	2.05	1.08	-0.05	-0.42	-0.92	-0.07	1.16	0.99
	[2.59]	[0.30]	[1.54]	[0.84]	[-0.04]	[-0.36]	[-0.64]	[-0.06]	[0.96]	[0.50]
Equal Weighted Portfolios	2.32	0.89	1.95	1.72	-0.77	-0.53	-0.93	0.66	1.08	0.93
	[2.14]	[0.72]	[1.63]	[1.49]	[-0.68]	[-0.48]	[-0.85]	[0.60]	[0.85]	[0.53]
$= -\mathbb{C}orr_{3y}[r,F] \cdot \mathbb{V}ol_{1y}[r]$	4.93	1.80	3.65	1.66	0.94	-0.05	-1.66	0.54	0.04	0.01
	[3.33]	[0.96]	[2.11]	[1.01]	[0.55]	[-0.03]	[-0.90]	[0.40]	[0.02]	[0.00]
$= -\mathbb{C}orr_{10y}[r,F] \cdot \mathbb{V}ol_{1y}[r]$	3.37	-0.20	1.49	0.86	0.03	-0.99	-1.91	-0.97	-2.44	-0.83
	[1.93]	[-0.11]	[0.86]	[0.61]	[0.01]	[-0.61]	[-1.07]	[-0.67]	[-1.52]	[-0.37]
At Least 500 Firms (01-1934)	4.25	1.66	3.45	1.18	-0.86	-0.43	-1.23	1.18	0.99	0.62
	[3.11]	[0.94]	[2.21]	[0.84]	[-0.54]	[-0.33]	[-0.72]	[0.88]	[0.66]	[0.27]

Table IA.4

GPT Beta HML Portfolio: Risk Premia and Alphas Controlling for Factor Models

This table reports annualized risk premia and annualized alphas for long-short quintile portfolios that buy (sell) stocks with high (low) exposure to the news-based geopolitical threats (GPT) index. The risk exposures are estimated from the three-year rolling window univariate beta on the (negative of the) GPT index growth rate. Alphas are relative to the factor model under each column. We consider eight factor models. The standard CAPM with only the equity market index (proxied with the market factor from Fama and French (1993)), the ICAPM from Chabi-Yo, Gonçalves, and Loudis (2025), the Fama-French 3-Factor (FF3) and 5-Factor (FF5) models from Fama and French (1993, 2015), the Fama-French models augmented with the momentum factor (FF3+MOM and FF5+MOM), the q–theory 4-Factor (q4) model from Hou, Xue, and Zhang (2015), the q-theory 5-Factor (q5) model from Hou et al. (2021), and the behavioral 3-Factor model (DHS) from Daniel, Hirshleifer, and Sun (2020). The t-statistics (in brackets) are based on Newey and West (1987, 1994). Sections 1.1 and A.3 provide measurement details for GPT index and the tradable factors in the factor models considered while Section B.4 covers the results from this table.

Factor Model =	**CAPM**	**ICAPM**	**FF3**	**FF5**	**FF3+MOM**	**FF5+MOM**	**q4**	**q5**	**DHS**
Risk Premia (%)	4.17	4.17	4.17	3.34	4.17	3.34	3.61	3.61	3.57
	[2.85]	[2.85]	[2.85]	[1.98]	[2.85]	[1.98]	[2.05]	[2.05]	[1.86]
Alphas (%)	4.84	4.21	5.16	3.22	5.17	3.75	4.87	4.86	3.79
	[3.36]	[2.90]	[3.36]	[1.94]	[3.20]	[2.11]	[2.56]	[2.55]	[1.74]
First Month	01-1930	01-1930	01-1930	07-1963	01-1930	07-1963	01-1967	01-1967	07-1972
Last Month	12-2024	12-2024	12-2024	12-2024	12-2024	12-2024	12-2024	12-2024	12-2023

Table IA.5
Mimicking Factors Constructed from Equity Anomaly Portfolios (Long Sample)

This table reports annualized risk premia and annualized alphas from mimicking factors for the given risk indices. The first three risk indices are the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). The other risk indices (detailed in Table 1) cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV), trade policy uncertainty (TPU), real uncertainty (RUI), macro uncertainty (MUI), and financial uncertainty (FUI). Mimicking factors for these risk indices are constructed using the Supervised Principal Component Analysis (SPCA) method proposed by Giglio, Xiu, and Zhang (2025). The test assets are 914 anomaly portfolios. The first group of anomaly portfolios is from the Open Source Asset Pricing (OSAP) dataset of Chen and Zimmermann (2022), and comprises 834 decile portfolios from 41 anomaly signals (one set based on value-weights and another based on equal-weights). The second group of anomaly portfolios is from the factor dataset of Jensen, Kelly, and Pedersen (2023), and comprises 80 long-short portfolios based on 40 anomaly signals (one set based on value-weights and another based on equal-weights). Consistent with our baseline analysis, we use 5 factors and 786 test assets as SPCA tuning parameters. Each mimicking correlation reflects the correlation between the mimicking factor and the respective non-tradable index (defined as the negative of its growth rate). All columns in this table focus on the period from 01-1930 to 12-2024 (our long sample), except that WAR is only available until 10-2019. The t-statistics (in brackets) are based on Newey and West (1987, 1994) and each mimicking factor is normalized to have an annual volatility of 20%, which is similar to the market annual volatility. Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section B.5 covers the results from this table.

INDEX =	GPT	GPA	GPR	WAR	EPU	EMV
Mimicking Correlation	0.26	0.38	0.37	0.15	0.33	0.31
Risk Premium (%)	2.79	1.87	1.90	2.06	2.43	1.48
	[4.50]	[3.35]	[3.43]	[3.28]	[4.42]	[2.39]
CAPM Alpha (%)	2.26	1.67	1.51	2.25	1.19	0.57
	[3.76]	[3.25]	[3.00]	[3.42]	[2.50]	[0.91]
ICAPM Alpha (%)	1.94	1.11	1.15	1.67	1.01	0.67
	[3.16]	[1.89]	[2.02]	[2.54]	[2.08]	[1.09]
GPT Alpha w.r.t INDEX		1.56	1.20	2.08	1.81	2.45
		[3.15]	[2.88]	[3.55]	[2.90]	[3.87]
INDEX Alpha w.r.t GPT		0.05	-0.41	1.43	1.31	0.85
		[0.09]	[-1.02]	[2.35]	[2.35]	[1.43]

Table IA.6

Mimicking Factors Constructed from Equity Anomaly Portfolios (Varying SPCA Parameters)

This table reports annualized risk premia and annualized alphas from mimicking factors for the given risk indices. These mimicking factors are constructed using the Supervised Principal Component Analysis (SPCA) method proposed by Giglio, Xiu, and Zhang (2025) (with details provided in Section 2.3). We consider ten risk indices in total and test assets based on anomaly portfolios over the period from 08-1963 to 12-2024 (see the header of Table 5 for details). The first three rows reproduce the results from our baseline specification. The other rows consider alternative values for the SPCA tuning parameters. Specifically, our baseline analysis uses 5 factors and selects 30% of the total number of test assets in the construction of each factor. This table considers 4 and 6 factors instead of 5 as well as 20% and 40% of test assets instead of 30%. Each mimicking correlation reflects the correlation between the mimicking factor and the respective non-tradable index (defined as the negative of its growth rate). The t-statistics (in brackets) are based on Newey and West (1987, 1994) and each mimicking factor is normalized to have an annual volatility of 20%, which is similar to the market annual volatility. Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section B.6 covers the results from this table.

# of Factors	% of Test Assets	Statistic	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
5	30%	Mimicking Correlation	0.32	0.38	0.42	0.31	0.41	0.33	0.28	0.38	0.45	0.47
		Risk Premium (%)	3.03	1.83	1.86	2.79	2.55	1.82	2.23	2.29	1.27	2.81
		[t-stat]	[4.11]	[2.74]	[2.65]	[3.63]	[3.99]	[2.40]	[2.94]	[2.61]	[1.33]	[3.13]
4	30%	Mimicking Correlation	0.32	0.37	0.39	0.15	0.34	0.31	0.26	0.25	0.33	0.42
		Risk Premium (%)	2.49	0.99	0.15	3.52	3.33	1.03	3.25	2.24	2.21	1.13
		[t-stat]	[3.40]	[1.54]	[0.24]	[4.26]	[4.31]	[1.40]	[4.59]	[2.60]	[2.47]	[1.38]
6	30%	Mimicking Correlation	0.39	0.50	0.48	0.34	0.45	0.41	0.28	0.40	0.54	0.49
		Risk Premium (%)	3.39	2.13	2.08	2.85	2.82	1.55	2.74	1.82	1.16	2.69
		[t-stat]	[4.65]	[3.17]	[3.07]	[4.04]	[3.90]	[2.04]	[3.80]	[2.13]	[1.18]	[3.14]
5	20%	Mimicking Correlation	0.40	0.46	0.53	0.32	0.44	0.45	0.32	0.43	0.51	0.49
		Risk Premium (%)	2.74	2.08	2.98	1.93	3.35	1.61	2.43	2.69	2.23	1.12
		[t-stat]	[3.84]	[3.15]	[4.44]	[2.59]	[4.92]	[2.16]	[3.49]	[3.01]	[2.44]	[1.32]
5	40%	Mimicking Correlation	0.28	0.36	0.36	0.27	0.36	0.28	0.25	0.33	0.37	0.44
		Risk Premium (%)	2.55	2.08	1.81	3.43	2.61	1.90	2.19	2.02	1.40	2.97
		[t-stat]	[3.38]	[3.14]	[2.75]	[4.20]	[3.26]	[2.50]	[2.98]	[2.33]	[1.49]	[3.53]

Table IA.7

Mimicking Factors Constructed from Country-Level Equity and Bond Portfolios (1961-2020)

This table reports annualized risk premia and annualized alphas from mimicking factors for the given risk indices. The first three risk indices are the news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). The other risk indices (detailed in Table 1) cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV), trade policy uncertainty (TPU), real uncertainty (RUI), macro uncertainty (MUI), and financial uncertainty (FUI). Mimicking factors are constructed from the slope coefficients of annual Fama and MacBeth (1973) regressions of returns on full sample univariate betas on the (negative of the) respective index growth rate. These regressions use annual returns from the 16 country-level equity and bond portfolios of developed countries from the Jordà et al. (2019) dataset. All columns cover the period from 1961 to 2020 (most of our modern sample), except that the last full year over which WAR is available is 2018. The world market portfolio (used for the world CAPM alphas) is constructed as the GDP-weighted average return on the same 16 countries. Each mimicking correlation reflects the correlation between the mimicking factor and the respective non-tradable index (defined as the negative of its growth rate). The t-statistics (in brackets) are based on Newey and West (1987, 1994) and each mimicking factor is normalized to have an annual volatility of 20%, which is similar to the market annual volatility. Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section B.7 covers the return data and results from this table.

PANEL A - Only Equities

	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Mimicking Correlation	0.17	0.17	0.17	0.23	0.47	0.49	0.39	0.17	0.32	0.47
Risk Premium (%)	8.45	7.70	8.09	-6.96	7.57	7.55	6.69	8.18	7.94	7.86
	[3.90]	[2.74]	[3.15]	[-4.20]	[3.20]	[4.02]	[2.72]	[3.86]	[5.38]	[4.78]
World CAPM Alpha (%)	3.30	1.98	2.48	-0.97	1.17	1.55	2.65	2.16	2.56	1.96
	[1.78]	[0.88]	[1.14]	[-0.68]	[0.73]	[1.18]	[1.13]	[1.40]	[2.04]	[1.65]

PANEL B - Only Bonds

	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Mimicking Correlation	0.20	0.12	0.11	0.21	0.30	0.47	0.34	0.27	0.32	0.39
Risk Premium (%)	7.06	6.31	7.15	7.44	-3.36	-0.33	-5.44	-1.04	6.38	0.11
	[3.00]	[2.68]	[2.83]	[3.02]	[-1.74]	[-0.23]	[-2.93]	[-0.33]	[3.33]	[0.04]
World CAPM Alpha (%)	6.42	6.57	6.61	7.68	-5.48	-2.66	-5.16	0.08	5.72	-0.88
	[2.29]	[2.57]	[2.32]	[3.14]	[-2.14]	[-1.56]	[-1.82]	[0.03]	[2.10]	[-0.33]

PANEL C - Equities and Bonds

	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Mimicking Correlation	0.20	0.17	0.18	0.25	0.47	0.50	0.42	0.19	0.34	0.48
Risk Premium (%)	9.64	7.93	8.78	-6.33	7.44	7.42	7.80	8.15	8.34	7.80
	[3.82]	[2.78]	[3.21]	[-4.19]	[3.15]	[3.99]	[2.45]	[4.02]	[5.26]	[4.75]
World CAPM Alpha (%)	4.52	2.22	3.14	-0.33	1.05	1.43	1.67	2.18	3.09	1.92
	[2.51]	[0.98]	[1.47]	[-0.23]	[0.69]	[1.19]	[0.74]	[1.39]	[2.36]	[1.58]

Table IA.8
Predicting the Bond Risk Premia over Time

This table reports regressions of government bond excess returns (relative to the risk-free asset) over the next 1 or 5 years onto current values of the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). Some columns control for the other three risk indices that are available since the beginning of our full sample, which are detailed in Table 1 and cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV). We estimate panel regressions with country fixed e ects and observations at the country-year level (from 1927 to 2019). The predicted returns are based on the 16 country-level government bond indices of developed countries from the Jordà et al. (2019) dataset. Predictive variables are normalized to z-scores and t-statistics (in brackets) are based on Driscoll and Kraay (1998) (with lag selection from Newey and West (1994)), which is robust to residual correlation over time and across countries. Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section 3.2 covers the results from this table. Tables IA.10 and IA.12 replicate this table using, respectively, the WAR index of Hirshleifer, Mai, and Pukthuanthong (2025a) (instead of the one from Hirshleifer, Mai, and Pukthuanthong (2025b)) and only monthly observations for the US government bond index (instead of an annual panel of 16 developed countries).

PANEL A - Next 1 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	-0.30						-0.43	-0.50	-0.26	-0.32	-0.03	-0.20
	[-0.51]						[-0.72]	[-0.79]	[-0.24]	[-0.57]	[-0.05]	[-0.17]
GPA		0.25					0.39					0.15
		[0.84]					[1.37]					[0.39]
GPR			0.06					0.35				
			[0.15]					[1.11]				
WAR				-0.19					-0.04			0.13
				[-0.33]					[-0.04]			[0.11]
EPU					0.43					0.44		0.14
					[1.01]					[1.04]		[0.20]
EMV						1.02					1.02	0.96
						[1.83]					[1.77]	[1.52]
R^2_{within}	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	1%	1%
# Obs	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472

PANEL B - Next 5 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	-2.42						-1.73	-0.82	-0.54	-2.49	-1.00	1.80
	[-0.96]						[-0.64]	[-0.28]	[-0.14]	[-1.02]	[-0.42]	[0.42]
GPA		-2.53					-1.96					-3.22
		[-1.96]					[-1.41]					[-1.69]
GPR			-3.22					-2.75				
			[-2.01]					[-1.65]				
WAR				-2.78					-2.46			-2.07
				[-1.58]					[-0.84]			[-0.62]
EPU					1.33					1.41		0.11
					[0.78]					[0.83]		[0.04]
EMV						5.58					5.39	5.70
						[2.30]					[2.14]	[1.99]
R^2_{within}	1%	1%	1%	1%	0%	5%	1%	1%	1%	1%	5%	6%
# Obs	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408

Table IA.9
Predicting the Equity Risk Premia over Time (Alternative WAR Index)

This table reports regressions of equity excess returns (relative to the risk-free asset) over the next 1 or 5 years onto current values of the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). Some columns control for the other three risk indices that are available since the beginning of our full sample, which are detailed in Table 1 and cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV). We use the version of the WAR variable from Hirshleifer, Mai, and Pukthuanthong (2025a). We estimate panel regressions with country fixed e ects and observations at the country-year level (from 1927 to 2019). The predicted returns are based on the 16 country-level equity indices of developed countries from the Jordà et al. (2019) dataset. Predictive variables are normalized to z-scores and t-statistics (in brackets) are based on Driscoll and Kraay (1998) (with lag selection from Newey and West (1994)), which is robust to residual correlation over time and across countries. Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section B.8 covers the results from this table.

PANEL A - Next 1 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	3.17						3.00	2.87	4.04	3.08	3.22	3.31
	[1.52]						[1.37]	[1.25]	[1.75]	[1.57]	[1.62]	[1.48]
GPA		1.46					0.48					-0.28
		[1.35]					[0.53]					[-0.25]
GPR			2.18					0.51				
			[1.44]					[0.50]				
WAR				2.33					-1.52			-0.45
				[0.81]					[-0.47]			[-0.11]
EPU					1.93					1.84		2.02
					[1.51]					[1.42]		[1.10]
EMV						-0.43					0.19	-0.47
						[-0.22]					[0.12]	[-0.26]
R^2_{within}	1%	0%	1%	0%	1%	0%	1%	1%	1%	2%	1%	2%
# Obs	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472

PANEL B - Next 5 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	25.77						29.00	32.39	36.93	25.07	26.25	32.48
	[2.79]						[2.71]	[2.71]	[2.69]	[3.08]	[2.78]	[2.42]
GPA		0.33					-9.16					-16.70
		[0.06]					[-1.60]					[-3.34]
GPR			7.53					-11.34				
			[0.81]					[-1.76]				
WAR				16.55					-19.36			-4.20
				[1.40]					[-1.14]			[-0.24]
EPU					14.50					13.65		18.69
					[2.16]					[2.13]		[2.27]
EMV						-3.23					1.82	-2.45
						[-0.39]					[0.26]	[-0.31]
R^2_{within}	6%	0%	0%	1%	3%	0%	6%	6%	6%	8%	6%	10%
# Obs	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408

Table IA.10
Predicting the Bond Risk Premia over Time (Alternative WAR Index)

This table reports regressions of government bond excess returns (relative to the risk-free asset) over the next 1 or 5 years onto current values of the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). Some columns control for the other three risk indices that are available since the beginning of our full sample, which are detailed in Table 1 and cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV). We use the version of the WAR variable from Hirshleifer, Mai, and Pukthuanthong (2025a). We estimate panel regressions with country fixed e ects and observations at the country-year level (from 1927 to 2019). The predicted returns are based on the 16 country-level government bond indices of developed countries from the Jordà et al. (2019) dataset. Predictive variables are normalized to z-scores and t-statistics (in brackets) are based on Driscoll and Kraay (1998) (with lag selection from Newey and West (1994)), which is robust to residual correlation over time and across countries. Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section 3.2 covers the results from this table.

PANEL A - Next 1 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	-0.30						-0.43	-0.50	-0.60	-0.32	-0.03	-0.42
	[-0.51]						[-0.72]	[-0.79]	[-0.51]	[-0.57]	[-0.05]	[-0.34]
GPA		0.25					0.39					0.08
		[0.84]					[1.37]					[0.18]
GPR			0.06					0.35				
			[0.15]					[1.11]				
WAR				-0.05					0.52			0.59
				[-0.05]					[0.32]			[0.32]
EPU					0.43					0.44		0.19
					[1.01]					[1.04]		[0.28]
EMV						1.02					1.02	0.94
						[1.83]					[1.77]	[1.49]
R^2_{within}	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	1%	1%
# Obs	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472

PANEL B - Next 5 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	-2.42						-1.73	-0.82	0.08	-2.49	-1.00	2.20
	[-0.96]						[-0.64]	[-0.28]	[0.02]	[-1.02]	[-0.42]	[0.49]
GPA		-2.53					-1.96					-2.83
		[-1.96]					[-1.41]					[-1.52]
GPR			-3.22					-2.75				
			[-2.01]					[-1.65]				
WAR				-4.26					-4.34			-3.65
				[-1.63]					[-0.89]			[-0.73]
EPU					1.33					1.41		0.10
					[0.78]					[0.83]		[0.04]
EMV						5.58					5.39	5.78
						[2.30]					[2.14]	[2.02]
R^2_{within}	1%	1%	1%	1%	0%	5%	1%	1%	1%	1%	5%	6%
# Obs	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408

Table IA.11
Predicting the Equity Risk Premia over Time (Only US)

This table reports regressions of equity excess returns (relative to the risk-free asset) over the next 1 or 5 years onto current values of the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). Some columns control for the other three risk indices that are available since the beginning of our full sample, which are detailed in Table 1 and cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV). We estimate time-series regressions with monthly observations (from 01-1927 to 12-2024). The predicted returns are based on the value-weighted index of US stocks from the Goyal and Welch (2008) dataset. Predictive variables are always normalized to z-scores and t-statistics (in brackets) are based on Newey and West (1987, 1994). Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section B.8 covers the results from this table.

PANEL A - Next 1 Month Returns

	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[9]**	**[10]**	**[11]**	**[12]**
GPT	0.35						0.32	0.28	0.38	0.31	0.36	0.30
	[1.75]						[1.53]	[1.27]	[1.81]	[1.65]	[2.02]	[1.43]
GPA		0.19					0.08					-0.05
		[1.33]					[0.55]					[-0.27]
GPR			0.29					0.11				
			[1.77]					[0.61]				
WAR				0.19					0.01			0.09
				[1.45]					[0.08]			[0.56]
EPU					0.41					0.38		0.41
					[2.29]					[2.15]		[1.80]
EMV						0.06					0.10	-0.10
						[0.27]					[0.44]	[-0.46]
R^2_{within}	0.3%	0.0%	0.1%	0.0%	0.6%	-0.1%	0.2%	0.2%	0.3%	0.7%	0.2%	0.4%
# Obs	1,175	1,175	1,175	1,114	1,175	1,175	1,175	1,175	1,114	1,175	1,175	1,114

PANEL B - Next 5 Year Returns

	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[9]**	**[10]**	**[11]**	**[12]**
GPT	20.48						21.72	22.60	17.79	19.87	19.47	16.14
	[3.22]						[3.29]	[3.16]	[2.66]	[3.04]	[3.20]	[2.46]
GPA		4.27					-3.53					-6.60
		[0.71]					[-0.82]					[-1.54]
GPR			11.18					-3.48				
			[1.60]					[-0.65]				
WAR				13.40					4.98			7.37
				[2.49]					[1.07]			[1.67]
EPU					8.49					6.98		13.46
					[1.42]					[1.24]		[2.33]
EMV						-10.10					-8.07	-11.41
						[-1.66]					[-1.59]	[-2.40]
R^2_{within}	9%	0%	3%	5%	2%	3%	10%	9%	10%	11%	11%	15%
# Obs	1,116	1,116	1,116	1,114	1,116	1,116	1,116	1,116	1,114	1,116	1,116	1,114

Table IA.12
Predicting the Bond Risk Premia over Time (Only US)

This table reports regressions of government bond excess returns (relative to the risk-free asset) over the next 1 month or 5 years onto current values of the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). Some columns control for the other three risk indices that are available since the beginning of our full sample, which are detailed in Table 1 and cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV). We estimate time-series regressions with monthly observations (from 01-1927 to 12-2024). The predicted returns are based on the US bond index from the Goyal and Welch (2008) dataset. Predictive variables are always normalized to z-scores and t-statistics (in brackets) are based on Newey and West (1987, 1994). Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section B.8 covers the results from this table.

PANEL A - Next 1 Month Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	-0.07						-0.10	-0.13	-0.05	-0.08	-0.04	-0.05
	[-1.04]						[-1.28]	[-1.56]	[-0.66]	[-1.22]	[-0.71]	[-0.75]
GPA		0.05					0.08					0.00
		[1.09]					[1.68]					[0.03]
GPR			0.01					0.09				
			[0.15]					[1.69]				
WAR				-0.05					-0.02			0.01
				[-0.78]					[-0.37]			[0.14]
EPU					0.11					0.11		0.11
					[1.59]					[1.68]		[1.45]
EMV						0.24					0.24	0.22
						[2.75]					[2.70]	[2.27]
R^2_{within}	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	1%	1%
# Obs	1,175	1,175	1,175	1,114	1,175	1,175	1,175	1,175	1,114	1,175	1,175	1,114

PANEL B - Next 5 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	-1.04						0.56	2.64	2.62	-1.28	-1.58	2.73
	[-0.18]						[0.08]	[0.28]	[0.51]	[-0.25]	[-0.38]	[0.58]
GPA		-4.36					-4.56					-5.10
		[-1.57]					[-0.83]					[-1.51]
GPR			-4.36					-6.07				
			[-3.40]					[-0.96]				
WAR				-5.46					-6.70			-5.74
				[-3.48]					[-2.17]			[-2.13]
EPU					2.60					2.69		5.03
					[0.72]					[0.80]		[1.24]
EMV						-4.13					-4.29	-5.59
						[-0.88]					[-0.99]	[-1.38]
R^2_{within}	0%	2%	2%	3%	1%	2%	2%	2%	4%	1%	2%	9%
# Obs	1,116	1,116	1,116	1,114	1,116	1,116	1,116	1,116	1,114	1,116	1,116	1,114

Table IA.13
Geopolitical Risks and Consumption Disasters (Controlling for other Risk Indices)

This table reports panel regressions of disaster-related outcomes onto the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022) and their overall geopolitical risk (GPR) index (which uses both threats and acts). Some columns control for the other three risk indices that are available since the beginning of our full sample, which are detailed in Table 1 and cover war discourse (WAR), economic policy uncertainty (EPU), expected market volatility (EMV). Observations are at the country-year level and all specifications consider an unbalanced panel from 1927 to 2019, with country fixed e ects and 26 (42) countries when predicting disasters (disaster probabilities). Panel A predicts the number of disasters over the next year as well as the disaster probability level at the end of the current year. Panels B, C, and D provide analogous results considering a period of $H = 3, 5, 10$ years. For instance, Panel D predicts the average number of disasters over the next ten years as well as the average disaster probability level at the end of the current and next ten years. The realized disasters and disaster probability levels are from Nakamura et al. (2013) and Marfè and Pénasse (2025), respectively. Following the prior literature exploring disasters empirically (e.g., Nakamura et al. (2013) and Caldara and Iacoviello (2022)), all specifications control for structural changes in the expectation and variability of consumption growth using dummy variables for Pre-1946, 1946-1972, and Post-1972. Predictive variables are always normalized to z-scores and t-statistics (in brackets) are based on Driscoll and Kraay (1998) (with lag selection from Newey and West (1994)), which is robust to residual correlation over time and across countries. Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section B.9 covers the results from this table.

PANEL A - Disasters over the Next 1 Year

	$\mathbf{Y_t = Disaster_{t+1}}$								$\mathbf{Y_t = Prob_t[Disaster_{t+1}]}$							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
GPT	9.34					3.72	9.54	3.26	1.41					0.42	1.54	0.43
	[3.16]					[1.45]	[3.15]	[1.14]	[2.98]					[1.58]	[3.23]	[1.63]
GPA		13.18				11.56		11.63		2.63				2.44		2.47
		[6.63]				[6.56]		[6.67]		[5.14]				[5.12]		[5.52]
WAR			3.93				-1.01	-0.98			0.62				-0.21	-0.29
			[1.49]				[-0.51]	[-0.65]			[1.39]				[-0.68]	[-1.06]
EPU				6.81				2.73				1.02				0.58
				[2.01]				[1.04]				[1.88]				[1.96]
EMV					-1.08			1.87					-0.56			0.11
					[-0.45]			[0.98]					[-1.40]			[0.49]
R^2_{within}	21%	26%	18%	19%	17%	26%	21%	27%	24%	36%	20%	21%	19%	37%	24%	38%
# Obs	2,418	2,418	2,392	2,418	2,418	2,418	2,392	2,392	3,666	3,666	3,666	3,666	3,666	3,666	3,666	3,666

PANEL B - Disasters over the Next 3 Years

	$\mathbf{Y_t = 1/3 \cdot \sum_{h=0}^{2} Disaster_{t+h+1}}$								$\mathbf{Y_t = 1/3 \cdot \sum_{h=0}^{2} Prob_{t+h}[Disaster_{t+h+1}]}$							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
GPT	8.63					4.24	9.01	4.13	1.53					0.99	1.76	1.06
	[3.27]					[1.55]	[3.38]	[1.50]	[3.09]					[2.44]	[4.15]	[3.00]
GPA		10.86				9.02		8.97		1.78				1.33		1.34
		[5.49]				[4.58]		[4.49]		[2.68]				[2.37]		[2.61]
WAR			3.17				-1.58	-1.57			0.61				-0.36	-0.38
			[1.33]				[-0.88]	[-1.20]			[1.29]				[-1.54]	[-1.71]
EPU				6.24				2.18				1.07				0.57
				[1.90]				[0.80]				[2.14]				[1.72]
EMV					-0.89			1.41					-0.47			0.05
					[-0.44]			[0.90]					[-1.85]			[0.22]
R^2_{within}	24%	36%	20%	21%	19%	37%	24%	38%	34%	36%	27%	29%	26%	39%	34%	41%
# Obs	2,366	2,366	2,340	2,366	2,366	2,366	2,340	2,340	3,576	3,576	3,576	3,576	3,576	3,576	3,576	3,576

Table IA.13
Geopolitical Risks and Consumption Disasters (Controlling for other Risk Indices)
(Continued)

PANEL C - Disasters over the Next 5 Years

	$\mathbf{Y_t = 1/5 \cdot \sum_{h=0}^{4} Disaster_{t+h+1}}$								$\mathbf{Y_t = 1/5 \cdot \sum_{h=0}^{4} Prob_{t+h}[Disaster_{t+h+1}]}$							
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**
GPT	8.36					5.37	9.53	5.68	1.32					1.15	1.61	1.20
	[3.79]					[2.27]	[4.19]	[2.38]	[2.69]					[2.41]	[3.47]	[2.66]
GPA		8.47				6.14		6.15		0.92				0.40		0.41
		[4.21]				[3.32]		[3.34]		[1.57]				[0.85]		[0.98]
WAR			2.84				-2.44	-2.19			0.45				-0.45	-0.39
			[1.30]				[-1.56]	[-1.80]			[1.11]				[-2.40]	[-2.14]
EPU				6.06				2.42				1.09				0.67
				[2.20]				[0.96]				[2.59]				[2.06]
EMV					-0.91			1.08					-0.31			0.05
					[-0.57]			[0.80]					[-1.58]			[0.22]
R^2_{within}	29%	29%	26%	27%	25%	31%	29%	32%	40%	35%	33%	37%	32%	40%	40%	43%
# Obs	2,314	2,314	2,288	2,314	2,314	2,314	2,288	2,288	3,486	3,486	3,486	3,486	3,486	3,486	3,486	3,486

PANEL D - Disasters over the Next 10 Years

	$\mathbf{Y_t = 1/10 \cdot \sum_{h=0}^{9} Disaster_{t+h+1}}$								$\mathbf{Y_t = 1/10 \cdot \sum_{h=0}^{9} Prob_{t+h}[Disaster_{t+h+1}]}$							
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**
GPT	5.98					5.63	7.76	4.24	0.57					0.74	0.85	0.48
	[4.17]					[3.56]	[4.81]	[2.95]	[2.03]					[2.85]	[2.86]	[2.01]
GPA		3.17				0.73		0.49		-0.09				-0.42		-0.45
		[1.82]				[0.56]		[0.57]		[-0.26]				[-1.56]		[-2.97]
WAR			2.12				-3.31	-1.59			0.20				-0.42	-0.14
			[1.17]				[-2.22]	[-1.42]			[0.74]				[-2.05]	[-0.81]
EPU				7.27				5.42				1.17				1.09
				[5.65]				[4.58]				[5.87]				[5.39]
EMV					-0.27			0.73					-0.16			-0.01
					[-0.23]			[0.77]					[-0.99]			[-0.05]
R^2_{within}	36%	34%	34%	37%	33%	36%	37%	38%	50%	48%	48%	56%	48%	51%	50%	57%
# Obs	2,184	2,184	2,158	2,184	2,184	2,184	2,158	2,158	3,261	3,261	3,261	3,261	3,261	3,261	3,261	3,261