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. Unlike GPA, GPT aligns closely with investors' geopolitical risk perceptions from ratings and surveys and predicts long-run consumption disasters. GPT is priced across individual US stocks, equity anomalies, international equity and bond indices, and it forecasts country-level equity premia and firm investment. 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.

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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)). Research at the ECB also finds that these tensions adversely impact consumers' expectations about future economic and financial conditions (Bańkowska et al. (2021)). 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 literature review).

As geopolitical tensions shape macroeconomic dynamics, firm behavior, and household expectations, it is key to understand how they affect investors' risk perceptions and, in turn, risk premia. Addressing this issue presents two fundamental challenges. First, geopolitical tensions reflect both the *realization* of adverse events and the *expectation or threat* of future developments, and their risk premia effects may differ.[1] Second, given that adverse geopolitical events are rare, there is substantial variation in their probability over time. During calm periods, limited variation in geopolitical risk may obscure its risk premia effect, necessitating a long sample to capture enough episodes of heightened geopolitical risk.

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.

[1]Geopolitical threats may play a particularly important role since asset prices are forward-looking (e.g., Jackson and Mitts (2023) provide evidence of trading in anticipation of adverse geopolitical events). More broadly, Clayton, Maggiori, and Schreger (2025a) and Clayton et al. (2025) demonstrate (theoretically and empirically) that current and threat-based geoeconomic pressures affect firm behavior in distinct ways.

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).

Our main finding is that GPT tracks investors' geopolitical risk perceptions and captures risk premia variation across assets and over time. Specifically, GPT strongly correlates with subjective geopolitical risk measures from risk ratings and fund manager surveys. Moreover, it is priced in the cross-section of individual US stocks, equity anomalies, and international equity and bond indices, and predicts time variation in country-level equity (but not bond) risk premia. In contrast, GPA has weaker, more unstable links to geopolitical risk perceptions and risk premia. We show that a potential channel for this difference is that GPR and GPT predict cumulative consumption disasters over different horizons: short-term and long-term, respectively. As we demonstrate theoretically, the long-run cumulative probability of disasters is more important for Epstein-Zin investors, and thus GPT is more relevant for risk perceptions and asset prices. These overall findings underscore the need to distinguish between geopolitical threats and acts when studying the pricing of geopolitical risks.

The impact of GPT on risk premia is incremental relative to the effects of many other risk indices. Over our long sample (1927 to 2024), 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)), and expected market volatility (EMV from Manela and Moreira (2017) and Baker et al. (2025)). Over our modern sample (starting in the early 1960s), we also consider news-based trade policy uncertainty (TPU from Caldara et al. (2020)) and other 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 all these indices, we provide a consistent and comprehensive analysis of the pricing of multiple risk indices over a long period, which is another important contribution of our paper relative to the prior literature.

Unpacking our Analysis

We begin by showing that GPT tends to rise in anticipation of major geopolitical conflicts, whereas GPA increases once those events materialize. Consequently, GPT appears more "forward-looking" than GPA, which may lead GPT to align more closely with investors' perceptions of geopolitical risk than GPA does. To explore this possibility, we examine two sources of geopolitical risk perceptions from institutional investors. The first source is the International Country Risk Guide (ICRG) ratings of the PRS Group, covering an unbalanced panel of annual data for 138 countries between 1984 and 2021. We find that the ICRG overall political risk rating is strongly positively related to GPT and (if anything) negatively related to GPA. Since the ICRG rating incorporates many categories that reflect political risk more broadly (rather than geopolitical risk specifically), we also explore an analogous measure that considers only the "internal conflict" and "external conflict" ICRG categories, finding similar results. The second source of geopolitical risk perceptions we consider (covering from 07-2007 to 12-2024) is the global fund manager survey conducted monthly by the Bank of America (BofA). Both the GPT and GPA indices relate positively to BofA geopolitical risk perceptions, but the GPT link is much stronger (with a correlation of 0.63) and subsumes the effect of GPA in a multivariate analysis.

GPT is also a better objective measure of disaster risk than GPA. Specifically, we find that GPA predicts cumulative consumption disasters over the short-term (one or three years) whereas GPT predicts cumulative consumption disasters over the long-term (five or ten years), which is natural given the more forward looking nature of GPT. This empirical result holds using either future realized consumption disasters (from the dataset in Nakamura et al. (2013)) or the ex-ante probability of consumption disasters (from the dataset in Marfè and Penasse (2025)). Theoretically, we derive the Stochastic Discount Factor (SDF) of an infinitely-lived investor with Epstein-Zin preferences and show that news to the long-run—rather than the short-run—prospects of disasters is a priced risk factor. Since GPT has a stronger link to long-run consumption disasters, this result implies GPT is more relevant for asset pricing than GPA.

Having established the connection of GPT with the subjective geopolitical risk perceptions of investors and with the objective long-run probability of disasters, 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 as is the case for GPT.

In terms of variation across assets, we start by studying individual US stocks through standard portfolio sorts. Specifically, we construct quintile portfolios sorted on rolling window univariate betas of stock returns onto the growth rate in GPT (and in other risk indices, including GPA). We find that only GPT beta 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 CAPM and the ICAPM (of Chabi-Yo, Gonçalves, and Loudis (2025)) as well as for many other widely used factor models (from Fama and French (1993, 2015, 2018), Hou, Xue, and Zhang (2015), Hou et al. (2021), and Daniel, Hirshleifer, and Sun (2020)). We also find that the GPT risk premium is concentrated in periods of high (lagged) levels of GPR (as well as GPT and GPA), which suggests that investors price GPT more strongly when attention to geopolitical risks (whether warranted or not) is elevated. 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 long sample, we focus on an analysis that starts in 1963 as there are many more anomalies over that period (so that our SPCA is based on a total of 2,408 anomaly portfolios). We find that the GPT growth rate mimicking factor provides an economically and statistically significant risk premium that remains present after controlling for the CAPM and ICAPM. However, in this case many other risk indices also lead to mimicking factors with strong risk premia (including GPA).

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 growth rate 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. These results also hold when using only US equity 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).

Given that GPT and GPA have different links to risk premia, it is natural to wonder whether firm investment responds differently to GPT and GPA. We find that it does. Specifically, we show that an increase in GPT (but not in GPA) predicts a decline in firm investment in the subsequent quarter (relative to its trend). This finding also holds using current investment, but it is stronger for future investment, which likely reflects short delays in the investment decision process (e.g., time-to-build frictions). Moreover, we find that higher GPT (but not higher GPA) is connected to an increase in perceived investment risk and government instability (from the ICRG), which suggests a cost of capital channel for the decline in future investment. These results are incremental to the effect of the risk indices we study.

Contribution to the Literature

We contribute to the broad literature on the economic effects of geopolitical tensions.[2] Our paper builds on Caldara and Iacoviello (2022), who propose an index for geopolitical risk (GPR) that is effectively a composite of their GPT and GPA indices, which we focus on in this paper. They also study the effects of GPR on some macro-finance outcomes, including firm investment, consumption disasters, and aggregate stock prices. Our contribution relative to Caldara and Iacoviello (2022) (and this literature more broadly) is not on the measurement front, but rather on providing two sets of novel empirical results. First, we show that geopolitical acts (through GPA) and threats (through GPT) have different fundamental links to perceptions of geopolitical risks by investors as well as to consumption disasters, firm investment, and perceived investment risk. Second, we study the pricing of geopolitical risks, showing that GPT (but not GPA) consistently captures risk premia variation across assets and over time.[3]

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 market volatility, consumption volatility, and even other forms of volatility and uncertainty in asset prices and macroeconomic variables.[4] Some other papers study the pricing of specific forms of uncertainty that have a

[2]See, for example, Caldara and Iacoviello (2022), Góes and Bekkers (2023), Caldara et al. (2024), Mignon and Saadaoui (2024), Wang, Wu, and Xu (2024), Franconi (2025), and Gopinath 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 (theoretical and empirical) analyses of threat-based geoeconomic pressures.

[3]Zaremba et al. (2022) show that changes in country-level GPR predict emerging market returns and Ma, Lu, and Tao (2022) find that GPT predicts S&P 500 returns over one month. Moreover, in work contemporaneous to ours, Sheng, Sun, and Wang (2025) construct an alternative GPR index using the methodology of Caldara and Iacoviello (2022), with three key differences: they rely exclusively on Wall Street Journal articles, add to keywords terms related to trade wars, and rely on data from a shorter sample (1984 to 2025). They show that their GPR index strongly predicts market returns over short horizons, while evidence for cross-sectional predictability in US stocks is mixed (no predictability from 1984 to 2025 and some predictability from 2000 to 2025).

[4]For some empirical papers covering the price of market volatility risk, see Eraker (2004), Ang et al. (2006), Adrian and Rosenberg (2008), Dew-Becker et al. (2017), Campbell et al. (2018), Kilic and Shaliastovich (2019), Berger, Dew-Becker, and Giglio (2020), and Chabi-Yo, Gonçalves, and Loudis (2025). For 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.[6] We add to Hirshleifer, Mai, and Pukthuanthong (2025a,b) by showing that geopolitical threats are connected to risk premia across assets and over time, with these results also

few empirical papers studying the price of consumption volatility risk, see Bansal and Shaliastovich (2013), Boguth and Kuehn (2013), Bansal et al. (2014), Segal, Shaliastovich, and Yaron (2015), and Tédongap (2015). For some empirical papers studying the price of other forms of macro-finance volatility or uncertainty, see Kelly and Jiang (2014), Bali and Zhou (2016), Bali, Brown, and Tang (2017), Huang et al. (2019), Segal (2019), Bali, Subrahmanyam, and Wen (2021), Dew-Becker, Giglio, and Kelly (2021), Eraker and Yang (2022), Gao et al. (2022), Dew-Becker and Giglio (2023), Bali et al. (2024), and Grigoris and Segal (2024).

[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 pricing 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 several papers studying the general pricing of political uncertainty as well as other economic effects such as political risk spillovers and factor structures (e.g., Berkman, Jacobsen, and Lee (2011), Kelly, Pástor, and Veronesi (2016), Liu, Shu, and Wei (2017), Brogaard et al. (2020), Gala, Pagliardi, and Zenios (2023), Gala et al. (2023), Liu and Shaliastovich (2023)). Uncertainty can also arise from wars, with Hirshleifer, Mai, and Pukthuanthong (2025a,b) studying the pricing of war discourse.

[6] Even though WAR can be viewed as a component of geopolitical tensions, Hirshleifer, Mai, and Pukthuanthong (2025a,b) focus on war discourse, referring to geopolitical risks only when discussing the GPR index from Caldara and Iacoviello (2022), which they argue is not priced. As we show, it is important to separate geopolitical threats (GPT) from acts (GPA) when studying the pricing of geopolitical risks (with GPR mostly reflecting GPA). In particular, GPT is forward-looking in nature, and thus more connected to investors' perception of geopolitical risks and to long-run consumption disasters. Moreover, GPT is significantly and consistently linked to risk premia whereas GPA has weaker and unstable links to risk premia.

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 perceptions of geopolitical risk by institutional investors, 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 in the SDF of Epstein-Zin investors. Moreover, GPT has strong links to geopolitical risk perceptions by market participants and to risk premia. 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 different links to historical geopolitical episodes, to investors' perception of geopolitical risks, and to consumption disasters. In turn, Section 2 describes the other risk indices we use. Then, Sections 3, 4, and 5 present results on how geopolitical risks relate to cross-sectional and time-series risk premia and firm investment. Section 6 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 highlights the differences between geopolitical threats and acts from the perspective of historical episodes. Sections 1.3 and 1.4 also studies the differences between geopolitical threats and acts, but in terms of their connection with risk perceptions from investors and consumption disasters, respectively.

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 words 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 the overall geopolitical risk (GPR) index of Caldara and Iacoviello (2022), which is based on both threats and acts. A more detailed discussion of the construction of these indices is provided in Caldara and Iacoviello (2022).

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). GPT and GPA have a moderately high correlation of 0.45, indicating that they reflect different 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.

Figures 1(a) and 1(b) provide a graphical representation of the correlation of GPT with GPA and GPR. It is visually clear that there are many periods of high GPT with low GPA and GPR (and vice versa). This aspect is critical for our analysis, which builds on the idea that GPT is a more appropriate index for asset pricing than GPA (and, consequently, than GPR as well). The next three subsections underscore the main reasons for that.

1.2 Geopolitical Threats vs Acts: Link to Historical Episodes

Figure 4 in Caldara and Iacoviello (2022) provides an analysis of particular historical episodes to highlight the differences between GPT and GPA. These differences are summarizes in their page 1204:

"Even if some spikes in the two indices coincide, there is also independent variation that is better highlighted when examining particular historical episodes. The beginning of World War I appears largely unexpected. Throughout the war, the GPA index remains elevated while the GPT index remains subdued, although a spike in threats when the US severs diplomatic relations with Germany in February 1917 is followed by the American entry into World War I two months later. The buildup to World War II sees the GPT index rise amid news coverage of the risk of war, for instance during the annexation of Czechoslovakia by Nazi Germany, whereas the GPA index spikes at the beginning of the war, after Pearl Harbor, and around D-Day. By contrast, the 1960s witnessed international crises captured by spikes in the GPT index that did not lead to wars such as the Berlin Crisis and the Cuban Missile Crisis. The GPT index surges in 1990 in the run-up Gulf war. The GPA index spikes after 9/11 and at the beginning of the Gulf War. Finally, the GPT index is high relative to its historical average during the recent tensions between the US and North Korea and Iran."

To complement their analysis, our Figure 2 plots (the z-scores of the) GPT and GPA indices from 2008 to 2024, highlighting some important events in the Russia-Ukrain Conflict. Most of the 2008-2021 events in the conflict are associated with spikes in GPT, but little movement in GPA. Beginning at the Russian invasion of Ukrain in February 24 of 2022, the two indices started to respond more similarly to new events and remained elevated until the end of our sample period. However, throughout this entire period the z-score of the GPA index has remained below 1, likely reflecting the fact that this conflict has remained local over the given sample period (with only indirect participation by the US and other countries). In contrast, the z-score of the GPT index has spiked to much higher values, reaching above 3 at the Russian invasion of Ukrain. This pattern is likely due to the perception that the threat of a global conflict has increase significantly with some of these events.

As the analysis in Caldara and Iacoviello (2022) and ours above indicate, GPT tends to better reflect the likelihood of a potential future global conflict whereas GPA tends to better reflect the realization of such conflicts. Our key argument in this paper is that this difference matters for asset pricing. In particular, since asset prices are forward looking, we would expect GPT to be priced in financial markets, whereas this statement is less clear for GPA (since asset prices may already reflect most relevant information once a geopolitical conflict materializes). Moreover, since GPR mostly reflects GPA, an isolated analysis of the pricing of GPR would not properly capture the pricing of geopolitical risks, which is the object of interest in this paper.

1.3 Geopolitical Threats vs Acts: Link to Risk Perceptions from Investors

We now show that beyond appearing more "forward looking" than GPA, GPT is also more connected to investors' perceptions of geopolitical risk than GPA is. We consider three measures of geopolitical risk perceptions from institutional investors, as detailed below.

Our first measure of subjective geopolitical risk is the country-year geopolitical risk score from the International Country Risk Guide (ICRG) ratings of the PRS Group.[7] 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 (low) values reflect low (high) risk, we use the negative of their values. Table 2 (Panel A) provides panel regressions (with country-fixed effects) 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 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

[7]Note that while the ICRG geopolitical risk rating reflects the geopolitical 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."

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". As before, Table 2 (Panel A) shows that GPT (but not GPA) has a significant positive association with this alternative ICRG-based 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).[8] 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. As Table 2 (Panel A) 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 effect weakens (and becomes statistically insignificant) when GPT and GPA are jointly included in the analysis.

Table 2 (Panel B) explores similar 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

[8]See Couts et al. (2024) for details about the data we use from the BofA surveys as we obtain these data directly from them. Also see Bastianello and Peng (2024) for a comprehensive analysis of BofA surveys.

risk, and counterparty risk (which are not related to subjective geopolitical risk), we see no significant connection with GPT or GPA.

Overall, the results indicate that GPT closely aligns with the geopolitical risk perceptions from institutional investors. In contrast, GPA has weaker, more unstable links to geopolitical risk perceptions. This finding is likely a consequence of the fact that GPT behaves in a more "forward looking" manner than GPA, thereby mimicking the beliefs of institutional investors.

1.4 Geopolitical Threats vs Acts: Link to Consumption Disasters

We now show that GPT is also a better objective measure of disaster risk than GPA. To do that, we start by establishing an important theoretical result. Specifically, Internet Appendix C shows that the log Stochastic Discount Factor (SDF) of an investor with Epstein-Zin preferences (Epstein and Zin (1989, 1991) and Weil (1989)), with time discount factor δ, intertemporal elasticity of substitution ψ, and relative risk aversion $\gamma > 1$, can be generally written as[9]

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

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 since

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

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

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

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.

As demonstrated in Internet Appendix C.6, the risk factors Δc, $N_{\mathbb{E}c}$, and $N_{\mathbb{V}}$ are standard factors present, for example, in the long-run risks model of Bansal and Yaron (2004). In that case, $N_{\mathbb{H}} = 0$ because log consumption growth follows a conditional normal distribution. In contrast, in a model in which rare consumption disasters exist and have time-varying probability, $N_{\mathbb{H}}$ captures news about the probability of disasters. 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 3 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 Penasse (2025). All specifications reflect panel regressions with country fixed effects. 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 $H = 5, 10$.[10]

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 1.2) that GPT anticipates future adverse geopolitical events whereas GPA is more reflective of the realization of such events. Moreover, it indicates GPT is more relevant for asset pricing than GPA given the log SDF in Equation 1.

2 Other Risk Indices

Throughout the paper, we also use risk indices beyond the geopolitical risk indices described in the prior section. These other indices serve two purposes in our paper. 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. Sections 2.1 and 2.2 briefly describe these other risk indices. In turn, Section 2.3 discusses

[10]The prior literature finds that some of the risk indices introduced in the next section also predict consumption disasters. Internet Appendix Section B.1 shows that the consumption disaster results from Table 3 continue to hold after controlling for these other risk indices.

their correlations, especially their correlations with geopolitical risks.

2.1 Risk Indices Available since the Early 1900s

Since our objective is to study geopolitical risks over a long sample, our initial set of risk indices is selected to capture important aspects of risk and uncertainty with coverage since at least the early 1900s. 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 New York Times news articles targeting the theme "war".[11] 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 the time-series of realized market returns. We instead opt for a news-based EMV index as it is closer in spirit to our general objective, which is to relate asset returns to external variables (like news coverage) rather than to second moments of asset returns.

[11]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 (which is 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 (which is the risk premia dimension studied in Hirshleifer, Mai, and Pukthuanthong (2025a)). Internet Appendix Section B.6 provides more details.

2.2 Risk Indices Available since the Early 1960s

Many papers that study the cross-section of risk premia start in the early 1960s due to COMPUSTAT data availability. While we do not face this restriction, for comparability with prior studies, our analyses of the cross-sectional link between geopolitical risks and risk premia also considers a sample that starts in the early 1960s (beyond our baseline sample). For these subsample analyses, we consider four extra risk indices, all of which 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.[12] 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 use asset pricing data on their construction, and thus deviate from the overall objective of focusing on risk indices constructed without the direct use of asset pricing data. However, we include them in our analyses since they are broad indices capturing the overall uncertainty present the macroeconomic and financial environments.

2.3 Sample Period and Correlations for the Risk Indices

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 (e.g., RUI and FUI), 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.

[12] Baker, Bloom, and Davis (2016) provide a trade policy uncertainty index that is a component of EPU and is highly correlated with TPU (see Caldara et al. (2020) for a comparison of these indices). However, this alternative trade policy uncertainty index starts in 01-1985 so we instead rely on TPU for our analysis.

Figure 1 plots the time-series of each risk and uncertainty index (in orange) against GPT (in blue). As it is clear from the figure, WAR is the only index (beyond GPA and GPR) that is highly correlated with GPT. This is perhaps not surprising since war is one of the categories of words included in the construction of the geopolitical risk indices. Nevertheless, 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 (in the next three sections) of the link between geopolitical risks, risk premia, and the macroeconomy is entirely based on the period starting in 01-1927 (the first month WAR is available), which allows us to provide risk premia results for GPT with and without controlling for WAR.

3 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 3.1 studies US individual stocks, Section 3.2 explores equity anomalies, and Section 3.3 covers an international panel of country-level equity and bond portfolios.

3.1 The Cross-Section of Individual Stock Risk Premia

We begin from the cross-section of individual stocks in the US using standard portfolio sorts.[13] 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]

[13] An important benefit of focusing on standard portfolio sorts (as we do) is that the resulting high-low factors are tradable in real time. This contrasts with more sophisticated methods designed to build econometrically efficient mimicking factors from non-tradable indices. That said, these econometric-oriented methods also have important (econometric) benefits, and thus we explore them in the next two subsections when studying equity anomaly portfolios and an international panel of country-level equity and bond portfolios.

[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, which ensures that a high-low portfolio has positive risk premium if its underlying risk index is priced.

We then sort the stocks into value-weighted quintile portfolios (with NYSE breakpoints) based on these beta estimates. Internet Appendix B.2 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 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). So, Table 4 provides results for the HML portfolio of each index over these two sample periods (with the TPU, RUI, MUI, and FUI indices only included in the modern sample).

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 GPA and WAR over the long sample and the TPU over the modern sample, all HML portfolios display a positive and significant mimicking beta. Consequently, HML portfolios should deliver positive risk premia if their respective indices are priced.

The second row of Table 4 considers HML risk premia. The GPT HML provides a strong annualized risk premium of 4.17% (t_{stat} = 2.85) over the long sample and 3.36% (t_{stat} = 1.99) over the modern sample. In contrast, all other HML portfolios provide statistically insignificant risk premia in both samples. One exception is GPR HML as it has a risk premium t_{stat} of 1.87 over the modern sample. However, GPR combines geopolitical threats and acts so that its risk premium reflects a weaker version of the GPT risk premium.

Since market prices can decline when geopolitical tensions increase, it is possible that the

[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 3.2. 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.

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 alphas of the GPT HML remain strong. Over the long sample, the GPT CAPM alpha is 4.84% ($t_{stat} = 3.23$), which is even stronger than its risk premium. Over the modern sample, the GPT CAPM alpha is lower than the respective risk premium, but remains strong at 3.00% ($t_{stat} = 1.80$). In contrast, the CAPM alphas for the other indices are weak (again, with the exception of GPR).

As we show in Internet Appendix C, the log SDF in Equation 1 can be alternatively written in an ICAPM format:

$$sdf_t \;= \kappa_{t-1} \;-\; \gamma \cdot r_{w,t} \;-\; \kappa_{\mathbb{E}} \cdot N_{\mathbb{E}r,t} \;+\; \kappa_{\mathbb{V}} \cdot N_{\mathbb{V},t} \;+\; \kappa_{\mathbb{H}} \cdot N_{\mathbb{H},t} \tag{3}$$

where $\kappa_{\mathbb{E}}$, $\kappa_{\mathbb{V}}$, and $\kappa_{\mathbb{H}}$ are positive, $r_{w,t}$ reflects returns on the investor's wealth portfolio, and $N_{\mathbb{E}r,t} = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{h=1}^{\infty} \delta^h \cdot r_{w,t+h}\right]$ captures expected return news.

Since geopolitical tensions can also affect $N_{\mathbb{E}r}$ and $N_{\mathbb{V}}$ (i.e., news about expected returns and volatility), the fourth row of Table 4 provides ICAPM alphas using the intertemporal factor model from Chabi-Yo, Gonçalves, and Loudis (2025) (which is based on tradable factors for r_w, $N_{\mathbb{E}r}$, and $N_{\mathbb{V}}$). We find that the GPT HML continues to deliver strong alphas over both the long sample (4.21% with $t_{stat} = 2.91$) and modern sample (3.24% with $t_{stat} = 1.90$).[17] Moreover, other indices continue to display weak and insignificant alphas (in this case, even GPR has a weak alpha over the long sample).

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

[17]Internet Appendix B.3 also reports alphas relative to the widely used factor models of Fama and French (1993, 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 effect).

to GPT tend to be weak and statistically insignificant (except for GPR). One exception to these results is that the GPT alpha relative to WAR is 2.22% and statistically insignificant over the modern sample. However, the WAR alpha relative to GPT is even weaker over the modern sample (-0.56% with $t_{stat} = -0.36$). Moreover, the GPT alpha relative to WAR is strong (3.39%) and statistically significant ($t_{stat} = 2.15$) over the long sample. So, overall, controlling for risk indices does not change the fact that GPT provides strong risk premia.

Figure 3 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).

Figure 4 shows 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. However, in rolling windows of 30 years the realized GPT risk premia are always positive over our sample period. As such, our finding of a positive GPT risk premium on average is not driven by any particular major event that induced a large realized return on the GPT HML.

While so far we have focused on the unconditional GPT risk premium or the realized GPT risk premia, another interesting variable is the conditional GPT risk premium. To study that, one needs to take a stand on what variable to condition on. In this context, we hypothesize that investors require a higher GPT risk premium when the relative attention to geopolitical tensions (in the form of news articles) is high. To test this hypothesis, Figure 5 plots the average GPT HML return (with 95% confidence intervals) conditioned on different levels of lagged GPR (based on quintiles of the historical GPR distribution).[18] The

[18]Note that conditioning on GPR (instead of GPA or GPT) is natural since we want to test whether the GPT risk premium is high in periods of high attention to geopolitical risk. GPR (and not GPT or GPA) is the best variable to capture the relative attention newspapers dedicate to geopolitical tensions (and we do not take a stand on whether that attention is warranted or not). We do find very similar (untabulated) results when conditioning on GPA or GPT. However, bivariate regressions of GPT HML returns on lagged values of GPT, GPA, and GPR indicate that GPT is subsumed by either of the other two variables. Due to

results indicate that the GPT risk premium concentrates in periods of high lagged GPR. 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 risk (whether warranted or not) is elevated.

3.2 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 is at the methodological frontier for the creation of 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.4, 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 2,408 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 2,132 decile portfolios from 115 anomaly signals (one set based on value-weights and one set based on equal-weights). The second source of

the high correlation between GPA and GPR, we lack sufficient statistical power to determine which is more relevant, but the coefficient signs suggest that GPR is more relevant (since the coefficient on GPR is positive while it is negative for GPA).

[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.

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 722 test portfolios (30% of the 2,408 test portfolios), with a sensitivity analysis provided in Internet Appendix B.5.

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 that the GPT mimicking factor risk premium is strong (2.83% per year) and statistically significant ($t_{stat} = 3.86$). However, in this case, the other risk indices also provide significantly positive risk premia (except for RUI, MUI, and FUI). The third and fourth rows provide CAPM and ICAPM alphas, highlighting that the GPT also provides significantly positive alphas. The fifth row shows the GPT alpha relative to each other index, which demonstrates that GPT risk premium is not due to exposure to any of the other indices we study. In particular, the GPT alpha relative to WAR (3.06%, $t_{stat} = 4.14$) is slightly stronger than the GPT risk premium (2.83%, $t_{stat} = 3.83$). The last row shows that the converse is also true: most indices provide an alpha relative to GPT (again, except for RUI, MUI, and FUI).

In summary, these results demonstrate that GPT is priced in the cross-section of anomaly portfolios. Moreover, this result is not driven by exposure to other risk indices. However, in this case GPT is not "special" in the sense that many other risk indices are also priced in the cross-section of anomaly portfolios (even after controlling for GPT).

3.3 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 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 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 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). Similar to the analysis of anomalies, 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. Panel A focuses on equities, showing that the GPT risk premia are strong economically and statistically (8.84% with $t_{stat} = 4.33$ over the long sample and 8.45% with $t_{stat} = 3.90$ over the modern sample). However, most of these risk premia are due to market exposure in the context of the World CAPM (WCAPM).[21] In particular, the WCAPM alphas for the GPT mimicking factor are much lower than its risk premia (2.73% with $t_{stat} = 1.92$ over the long sample and 3.30% with $t_{stat} = 1.78$ over the modern sample). We see a similar pattern for the other risk indices. One exception is WAR, which has negative risk premia and WCAPM alphas.

Table 6 (Panel B) focuses on government bonds. The GPT risk premia are also strong economically and statistically (6.90% with $t_{stat} = 3.61$ over the long sample and 7.06% with $t_{stat} = 3.00$ over the modern sample). In this case, the WCAPM alphas for the GPT mimicking factor are only a little lower than the risk premia (5.85% with $t_{stat} = 2.60$ over the long sample and 6.42% with $t_{stat} = 2.29$ over the modern sample). Results are more mixed for some of the other risk indices. While in this case the WAR index provide strong risk premia and WCAPM alphas, some other indices (like EPU, EMV, and TPU) have negative

[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).

[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 3.1 and 3.2 are not relevant here since they only account for exposure to the US market.

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 premia are strong economically and statistically (9.49% with $t_{stat} = 4.49$ over the long sample and 9.64% with $t_{stat} = 3.82$ over the modern sample). Moreover, while the WCAPM alphas of GPT are much lower than its risk premia, they remain strong economically and statistically (3.44% with $t_{stat} = 2.49$ over the long sample and 4.52% with $t_{stat} = 2.51$ over the modern sample). The results for other indices are more mixed, mirroring the findings from Panels A and B. In particular, the WAR index has negative risk premia and WCAPM alphas over the long and modern samples. Moreover, many other risk indices (e.g., EPU) have strong risk premia and relatively weak WCAPM alphas (particularly over the modern sample).

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 priced under some cross-sections and time periods, but not others.

4 Geopolitical Risks and the Time-Series of Risk Premia

We now turn to the link between geopolitical risks and the time-series of risk premia. Section 4.1 focuses on equity risk premia while Section 4.2 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 until 2020 used in Section 3.3 (from Jordà et al. (2019)).[22] Since time-series predictability results over short samples are known to be fragile, we focus on our long sample of almost 100 years, covering from 1927 to 2020. Accordingly, we only use the risk indices available throughout this entire period (GPT, GPA, GPR, WAR, EPU, and EMV).[23]

[22]Internet Appendix B.6 provides an analysis focused on the US returns using the (updated version of the) Goyal and Welch (2008) dataset. The key findings are similar to the ones we report in the main text.

[23]We continue to use the WAR index from Hirshleifer, Mai, and Pukthuanthong (2025b) (which is a cross-sectional paper) to be consistent with our analysis of the cross-section of risk premia. However, Internet

4.1 The Time-Series of Equity Risk Premia

Table 7 (Panel A) provides predictability results for 1-year returns (through panel regressions with country fixed effects). 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 4.00% (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 25.80% ($t_{stat} = 2.79$) higher equity excess return over the next 5 years.

While the findings above indicate GPT affects 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: geopolitical events are a component of rare disasters, but far from being the only source of rare disasters (or risks more broadly) in the world.

4.2 The Time-Series of Bond Risk Premia

Table 8 shows that (whether we focus on 1-year of 5-year returns), GPT has a very weak (effectively null) link to bond risk premia. This is true both economically and statistically.

Appendix B.6 replicates our analysis of the time-series of risk premia using 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.

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).

5 Geopolitical Risks and Firm Investment

Given that GPT and GPA have different links to risk premia, it is natural to wonder whether firm investment responds differently to GPT and GPA. This section shows that it does.

Table 9 (Panel A) reports regressions of investment onto our risk indices using quarterly US data from 1947-Q1 to 2024-Q4. Specifically, we provide regressions of log real investment per capita on a time trend and lagged risk indices.[24] We consider two investment measures: real private fixed investment (as in Caldara and Iacoviello (2022)) and real private nonresidential fixed investment (as in Gennaioli, Ma, and Shleifer (2015)), both obtained from the FRED. The $R^2_{partial} = (R^2 - R^2_{trend})/(1 - R^2_{trend})$ values capture the share of variance in detrended log investment explained by the lagged risk indices, comparing the R-squared values from regressions with (R^2) and without (R^2_{trend}) these indices.

The main finding from Table 9 (Panel A) is that an increase in GPT forecasts lower investment relative to its trend next quarter.[25] This finding is particularly strong in the specification that includes GPT and GPA, with a one standard deviation increase in GPT being associated with a (statistically significant) 4% lower investment relative to trend next period.

To explore the mechanism for the effect of GPT on investment, Table 9 (Panel B) reports panel regressions (with country fixed effects) of ICRG perceived risks related to investments (which are part of the ICRG ratings explored in Section 1.3) onto the risk indices we study.

[24]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). Nevertheless, Internet Appendix B.7 reports results (similar to the ones reported in the main text) that use two different stochastic trend specifications.

[25]We find similar (but somewhat weaker) results in untabulated specifications that regress investment on current levels of the risk indices. The difference we observe likely reflects short delays in the investment decision process (e.g., time-to-build frictions).

First, we have that a one standard deviation increase in GPT is associated with a 0.30 standard deviation increase in perceived investment risk ($t_{stat} = 1.65$), with this effect increasing to 0.50 ($t_{stat} = 3.15$) after controlling for GPA. We also have that a one standard deviation increase in GPT is associated with a 0.70 standard deviation increase in perceived government instability risk ($t_{stat} = 3.32$). Again, the effect gets stronger after controlling for GPA. These results are suggestive of a cost of capital channel for the effect of GPT on investment.

So, overall, an increase in GPT (but not in GPA) predicts a decline in firm investment in the subsequent quarter (relative to its trend) through an increase in perceived investment risk and government instability, which suggests a cost of capital channel for the decline in future investment. Moreover, these results are incremental to the effect of the other risk indices we study.

6 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 investors' perceptions of geopolitical risk and explains variation in risk premia across assets and over time. In contrast, GPA shows weaker and less stable links to investor beliefs and asset prices. These results suggest that distinguishing between anticipated and realized geopolitical tensions is essential for understanding how markets price geopolitical risks.

The GPT index closely tracks investors' geopolitical risk perceptions from risk ratings and surveys. It is also priced in the cross-section of individual stocks, equity anomalies, and international equity and bond portfolios, and predicts future country-level equity returns at long horizons. Moreover, the GPT premium strengthens when overall attention to geopolitical tensions is high, suggesting a role for salience or time-varying risk aversion. We further show that GPT, unlike GPA, is systematically associated with declines in firm investment and an increased likelihood of long-term consumption disasters, consistent with a rare disaster channel. These results remain robust when controlling for a broad set of alternative risk indices, confirming that GPT captures a distinct and economically meaningful dimension of risk.

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 effects 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.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work we used ChatGPT o4-mini in order to adjust small portions of the writing for improved readability. After using this tool, we reviewed and edited the content as needed and take full responsibility for the content of the publication.

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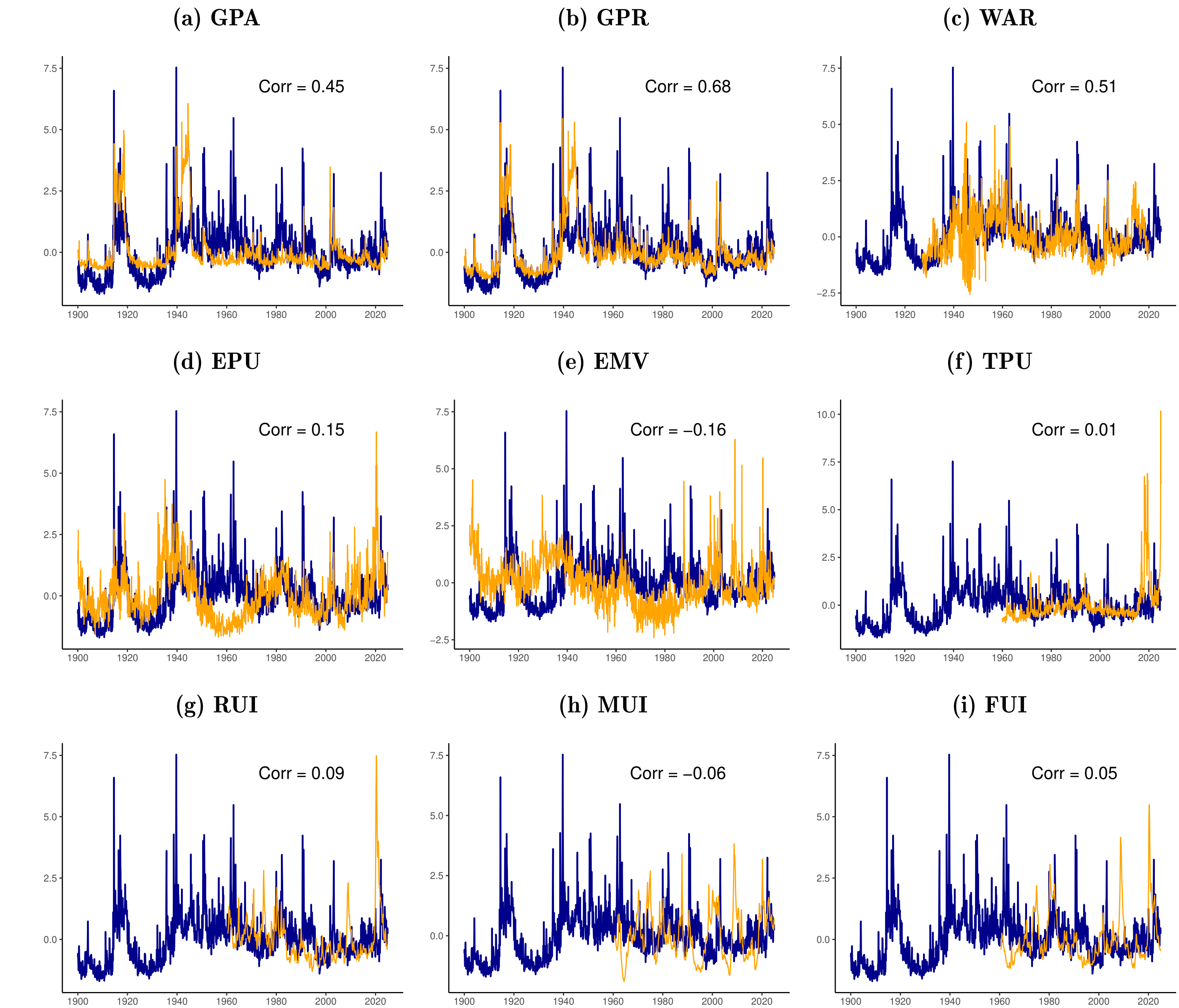

Figure 1
GPT (in blue) vs Other Risk Indices (in orange)

This figure plots the (z-scores of the) risk indices we use throughout the paper. 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. 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. Sections 1.1, 2.1, and 2.2 provide measurement details for these risk indices.

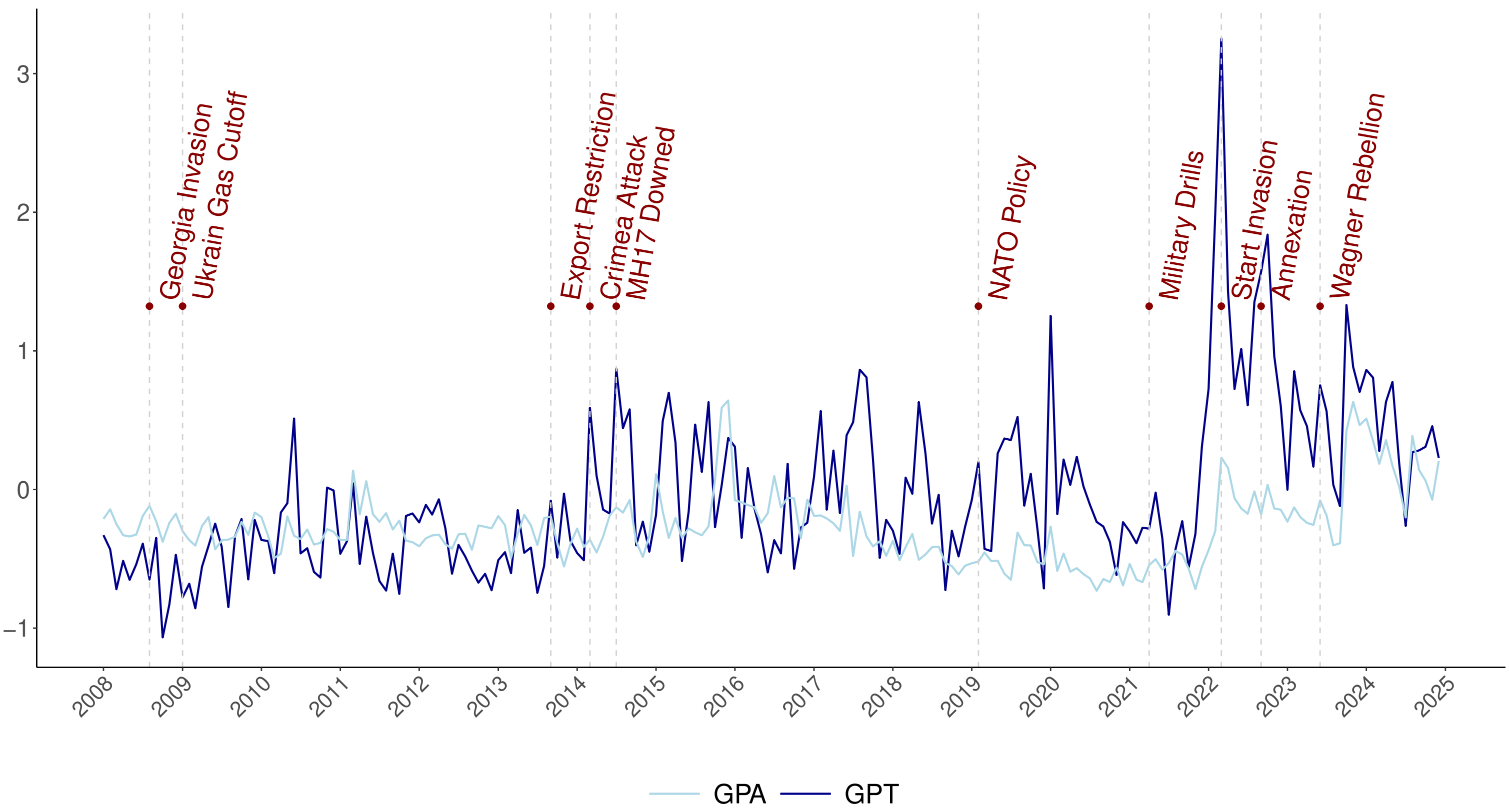

Figure 2
Case Study: Russia-Ukrain Conflict

This figure plots the (z-scores of the) news-based geopolitical threats (GPT) and acts (GPA) indices of Caldara and Iacoviello (2022) over the period starting in January of 2008. It also identifies important events related to the Russia-Ukrain conflict. Section 1.1 provides measurement details for the GPT and GPA indices while Section 1.2 covers the results from this figure.

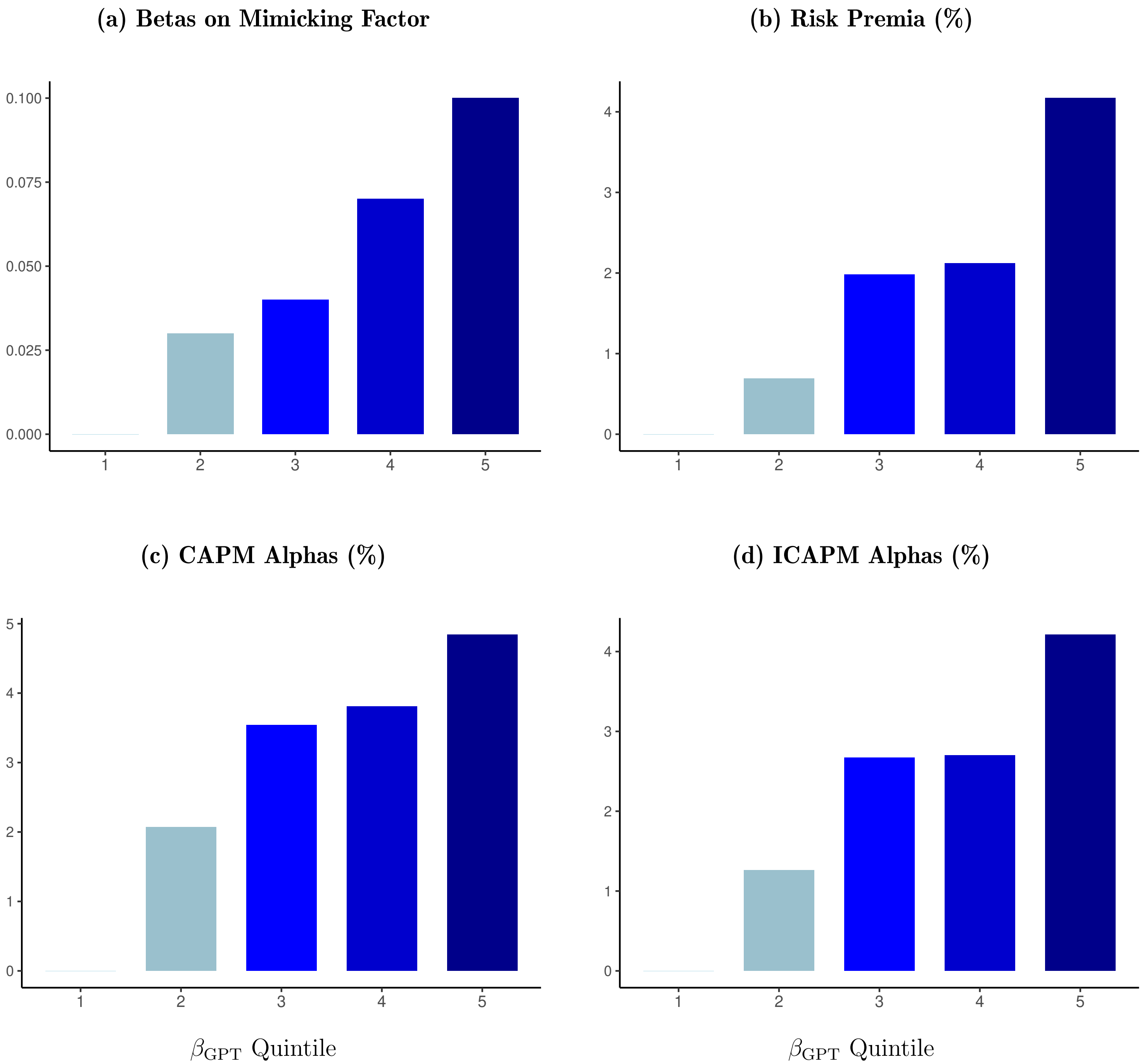

Figure 3
GPT Beta Quintile Portfolios: Betas, Risk Premia, and Alphas

This figure plots betas (i.e., univariate regression slopes onto the GPT mimicking factor), annualized risk premia (i.e., average returns multiplied by twelve), and annualized alphas (factor regression intercepts multiplied by twelve) of 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. Portfolios are value-weighted and use NYSE breakpoints, as suggested by Hou, Xue, and Zhang (2019). 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 3.2). Stock-level betas are estimated from the three-year rolling window univariate beta on the (negative of the) given index growth rate. 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). Section 1.1 provides measurement details for the GPT index while Section 3.1 covers the results from this figure.

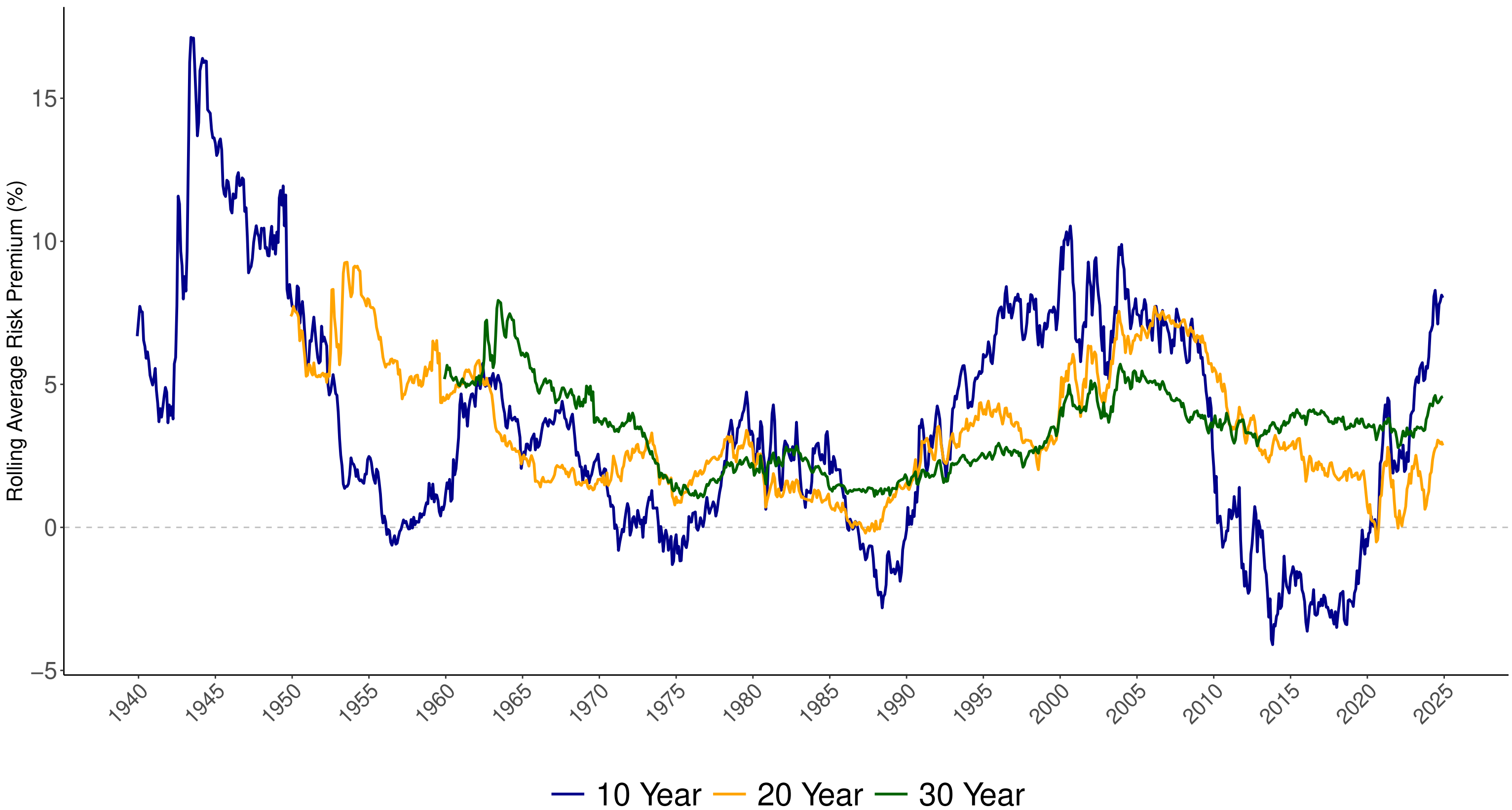

Figure 4
GPT High-Low Beta Quintile Portfolio Realized Risk Premia on a Rolling Window

This figure plots the annualized risk premia (i.e., average returns multiplied by twelve) of the high-low, H-L, returns on beta quintile portfolios that buy (sell) stocks with high (low) stock-level betas on the news-based geopolitical threats (GPT) index of Caldara and Iacoviello (2022). We consider 10-year, 20-year and 30-year rolling windows for the realized risk premia. Portfolios are value-weighted and use NYSE breakpoints, as suggested by Hou, Xue, and Zhang (2019). Stock-level betas are estimated from the three-year rolling window univariate beta on the (negative of the) given index growth rate. Section 1.1 provides measurement details for the GPT index while Section 3.1 covers the results from this figure.

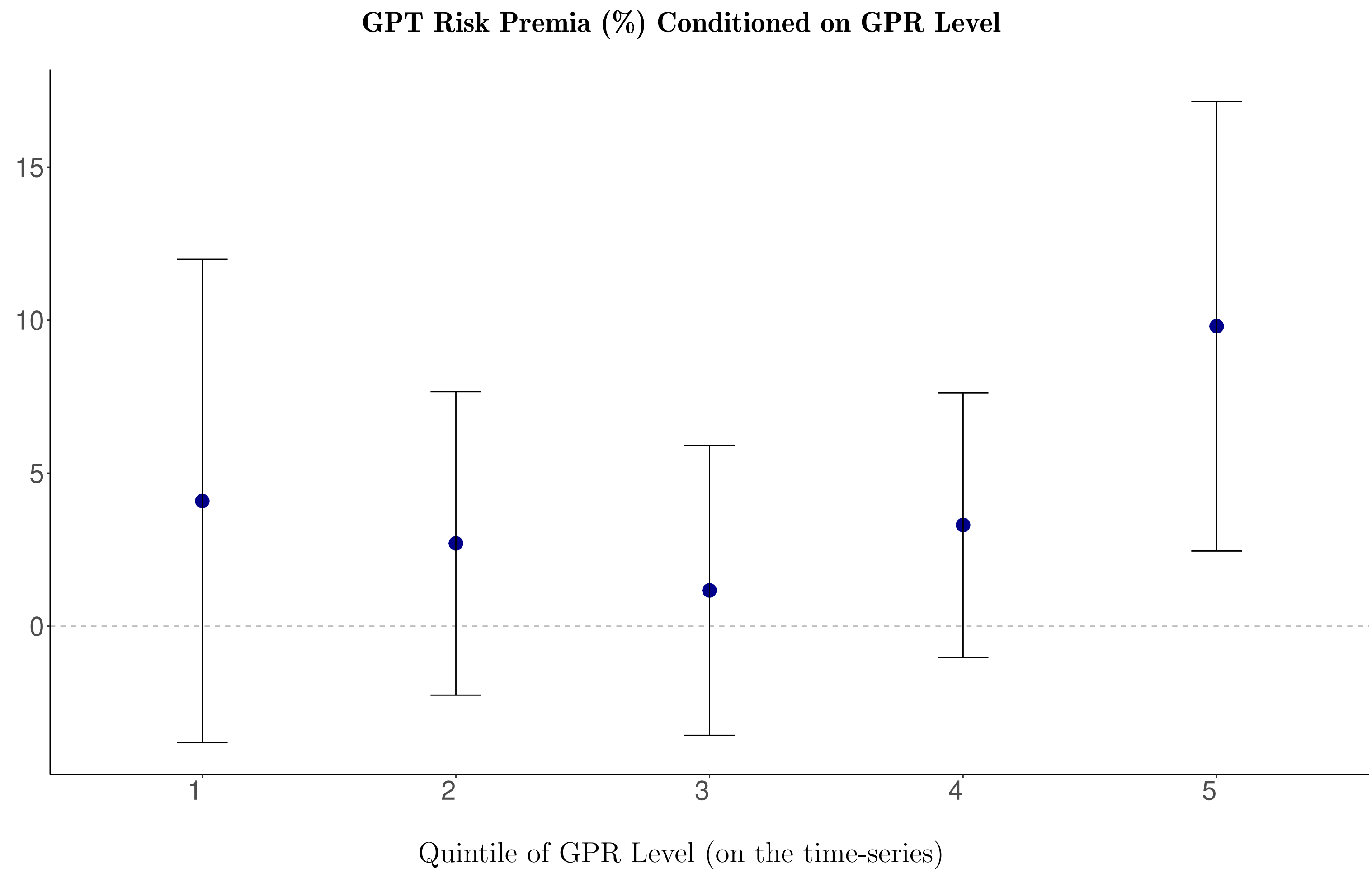

Figure 5
GPT High-Low Beta Quintile Portfolio Risk Premium as a Function of the GPR Level

This figure plots annualized risk premia (i.e., average returns multiplied by twelve) of the high-low, H-L, returns on beta quintile portfolios that buy (sell) stocks with high (low) stock-level betas on the news-based geopolitical threats (GPT) index of Caldara and Iacoviello (2022). Portfolios are value-weighted and use NYSE breakpoints, as suggested by Hou, Xue, and Zhang (2019). Stock-level betas are estimated from the three-year rolling window univariate beta on the (negative of the) GPT growth rate. The risk premia are conditioned on the level of GPR in the prior month. 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. 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 3.1 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. Sections 1.1, 2.1, and 2.2 provide measurement details for these 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

Geopolitical Risks and Perceptions of Risk from Investors

This table reports panel regressions of perceptions of risk from investors onto the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022). Panel A focuses on perceptions of geopolitical risk. The first and second measures are based 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 directly use the (negative of the) ICRG country-level rating (reflecting a time-series of geopolitical risk perception per country). It is based on sum of the ICRG rating from 12 components of geopolitical risk and designed to vary between 0 (the maximum geopolitical risk) and 1 (the minimum geopolitical risk). We take the negative sign so that high values reflect high geopolitical risk. For the second measure, use only 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 effects) of the geopolitical 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. Panel B focuses on perceptions of other types of risk, all obtained from the BofA surveys of global fund managers, and each resulting in a time-series from 07-2007 to 12-2024. We order them 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) for time-series regressions and on Driscoll and Kraay (1998) (with the number of autocorrelation lags selected following Newey and West (1994)) for panel regressions. Section 1.1 provides measurement details for the GPT and GPA indices while Section 1.3 covers the measurement of risk perception variables and results from this table.

PANEL A - Perceptions of Geopolitical Risk

	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]
R^2_{within}	10%	0%	14%	5%	0%	6%	40%	11%	40%
$\mathbb{C}or[Y_t, \widehat{Y}_t]$	0.16	0.03	0.19	0.17	0.00	0.18	0.63	0.33	0.63
# Obs	4,970	4,970	4,970	4,970	4,970	4,970	210	210	210

PANEL B - Perceptions of Other Risks

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	0.80		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]	[-1.20]
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]		[1.1]	[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 3

Geopolitical Risks and Consumption 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 effects 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 Penasse (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 the number of autocorrelation lags selected following Newey and West (1994). Sections 1.1 and 2.1 provide measurement details for the risk indices while Section 1.4 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	9.30		3.70	8.60		4.20	8.40		5.40	6.00		5.60
	[3.16]		[1.45]	[3.27]		[1.55]	[3.79]		[2.27]	[4.17]		[3.56]
GPA		13.20	11.60		10.90	9.00		8.50	6.10		3.20	0.70
		[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	1.40		0.40	1.50		1.00	1.30		1.10	0.60		0.80
	[3.00]		[1.61]	[3.12]		[2.46]	[2.72]		[2.41]	[2.12]		[2.89]
GPA		2.60	2.50		1.80	1.40		1.00	0.40		-0.10	-0.40
		[5.18]	[5.15]		[2.73]	[2.42]		[1.64]	[0.94]		[-0.18]	[-1.49]
R^2_{within}	24%	36%	36%	33%	35%	38%	39%	34%	39%	48%	46%	49%
# 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 4

Single Stocks: Betas, Risk Premia, and Alphas of High-Low Beta Quintile Portfolios

This table reports betas (i.e., univariate regression slopes onto the mimicking factors for the indices), annualized risk premia (i.e., average returns multiplied by twelve), and annualized alphas (factor regression intercepts multiplied by twelve) of high-low, H-L, returns on beta quintile portfolios that buy (sell) stocks with high (low) stock-level betas on the given risk or uncertainty index. Portfolios are value-weighted and use NYSE breakpoints, as suggested by Hou, Xue, and Zhang (2019). The mimicking factors used to estimate betas (with risk premia summarized in Table 5) are constructed applying the Supervised Principal Component Analysis (SPCA) method proposed by Giglio, Xiu, and Zhang (2025) to anomaly portfolios (as described in Section 3.2). 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 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 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. These last three indices are only available since 07-1960 (so that H-L returns are available as of 08-1963 given the three-year rolling window betas). Rows differ based on the statistic reported, with ICAPM alphas based on the model in Chabi-Yo, Gonçalves, and Loudis (2025). The t-statistics (in brackets) are based on Newey and West (1987, 1994). Sections 1.1, 2.1, and 2.2 provide measurement details for the risk indices used in this table while Section 3.1 covers the return data and results from this table.

	01-1930 to 12-2024						08-1963 to 12-2024									
INDEX =	**GPT**	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**GPT**	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**TPU**	**RUI**	**MUI**	**FUI**
Beta on Mimicking Factor	0.10	0.03	0.08	-0.07	0.20	0.07	0.10	0.05	0.09	0.17	0.20	0.07	0.05	0.73	1.23	1.14
	[3.15]	[1.06]	[2.46]	[-0.53]	[9.18]	[4.79]	[3.58]	[2.86]	[3.43]	[2.43]	[9.52]	[4.76]	[1.37]	[2.45]	[4.72]	[4.07]
Risk Premium (%)	4.17	1.69	2.71	1.22	2.99	0.68	3.36	2.33	3.51	-0.46	1.15	1.21	-0.49	2.56	2.39	2.40
	[2.85]	[0.98]	[1.65]	[0.87]	[1.42]	[0.40]	[1.99]	[1.14]	[1.87]	[-0.28]	[0.50]	[0.60]	[-0.30]	[1.36]	[1.22]	[1.05]
CAPM Alpha (%)	4.84	1.18	3.06	2.41	-1.08	0.15	3.00	1.75	3.02	-0.39	-2.44	-1.77	-1.12	0.26	-0.11	-0.42
	[3.23]	[0.72]	[1.90]	[1.61]	[-0.59]	[0.09]	[1.80]	[0.85]	[1.69]	[-0.24]	[-1.14]	[-0.95]	[-0.65]	[0.15]	[-0.06]	[-0.20]
ICAPM Alpha (%)	4.21	0.93	2.28	1.48	0.45	-1.27	3.24	2.01	3.44	-0.32	-1.57	-1.50	-1.23	1.18	0.99	0.62
	[2.91]	[0.53]	[1.38]	[0.97]	[0.25]	[-0.86]	[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		3.81	4.11	3.39	4.15	4.44		3.25	3.31	2.22	3.47	3.78	3.26	3.38	3.37	3.42
		[2.28]	[2.62]	[2.15]	[2.63]	[2.64]		[1.94]	[1.99]	[1.30]	[2.02]	[2.21]	[1.92]	[2.09]	[2.02]	[2.03]
INDEX Alpha w.r.t GPT		1.91	2.90	1.34	3.50	0.85		2.67	3.73	-0.56	1.51	1.57	-0.49	2.69	2.68	2.42
		[1.13]	[1.75]	[0.93]	[1.73]	[0.46]		[1.24]	[2.02]	[-0.36]	[0.67]	[0.76]	[-0.30]	[1.45]	[1.34]	[1.07]

Table 5

Equity Anomaly Portfolios: Risk Premia and Alphas of Mimicking Factors

This table reports annualized risk premia (i.e., average returns multiplied by twelve) and annualized alphas (i.e., factor regression intercepts multiplied by twelve) from mimicking factors for the (negative of the growth in the) given risk indices. Mimicking factors are normalized to have an annual volatility of 20%, which is similar to the market annual volatility. We consider ten risk indices in total. 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. Mimicking factors for the (negative of the growth in the) risk indices are constructed using the Supervised Principal Component Analysis (SPCA) method proposed by Giglio, Xiu, and Zhang (2025). The test assets are 2,408 anomaly portfolios. The first group of anomaly portfolios is from the Open Source Asset Pricing (OSAP) dataset of Chen and Zimmermann (2022), and comprises 2,132 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). For the SPCA tuning parameters, we use 5 factors and 722 test assets (30% of the 2,408 test assets), with a sensitivity analysis provided in Internet Appendix Table IA.5. 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). Sections 1.1, 2.1, and 2.2 provide measurement details for the risk indices used in this table while Section 3.2 covers the return data and results from this table.

	08-1963 to 12-2023									
INDEX =	**GPT**	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**TPU**	**RUI**	**MUI**	**FUI**
Mimicking Correlation	0.36	0.43	0.41	0.31	0.42	0.38	0.26	0.37	0.48	0.46
Risk Premium (%)	2.83	3.20	2.70	4.00	3.50	2.23	1.58	1.58	-0.20	1.33
	[3.86]	[4.61]	[3.88]	[4.89]	[5.51]	[3.20]	[1.91]	[1.55]	[-0.17]	[1.43]
CAPM Alpha (%)	2.48	2.63	2.16	3.98	2.13	1.14	1.94	0.79	-0.99	-0.10
	[3.22]	[3.77]	[3.04]	[4.80]	[3.43]	[1.60]	[2.41]	[0.93]	[-1.07]	[-0.13]
ICAPM Alpha (%)	2.30	2.18	1.82	3.70	2.39	1.58	1.71	1.04	-0.71	0.13
	[2.81]	[2.95]	[2.40]	[4.17]	[4.25]	[2.45]	[2.20]	[1.15]	[-0.66]	[0.17]
GPT Alpha w.r.t INDEX		3.49	3.51	3.06	3.11	2.87	2.67	2.84	2.84	2.85
		[4.43]	[4.66]	[4.14]	[4.08]	[3.85]	[3.58]	[3.85]	[3.85]	[3.89]
INDEX Alpha w.r.t GPT		3.67	3.26	4.32	3.65	2.23	1.44	1.65	-0.14	1.37
		[5.31]	[4.56]	[5.18]	[4.23]	[2.77]	[1.75]	[1.63]	[-0.12]	[1.47]

Table 6
Country-Level Equity and Bond Portfolios: Risk Premia and Alphas of Mimicking Factors

This table reports annual risk premia and world CAPM alphas from mimicking factors for the (negative of the growth in the) ten risk indices in our analysis. 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. Mimicking factors are constructed from the slope coefficients on 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 world market portfolio 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, 2.1, and 2.2 provide measurement details for the risk indices used in this table while Section 3.3 covers the return data and results from this table.

PANEL A - Only Equities

	1930 to 2020						1961 to 2020									
	GPT	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**GPT**	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**TPU**	**RUI**	**MUI**	**FUI**
Mimicking Correlation	0.23	0.19	0.20	0.24	0.43	0.40	0.17	0.17	0.17	0.23	0.47	0.49	0.39	0.17	0.32	0.47
Risk Premium (%)	8.84	9.81	10.05	-7.58	9.47	8.78	8.45	7.70	8.09	-6.96	7.57	7.55	6.69	8.18	7.94	7.86
	[4.33]	[4.17]	[4.66]	[-3.86]	[4.78]	[5.41]	[3.90]	[2.74]	[3.15]	[-4.20]	[3.20]	[4.02]	[2.72]	[3.86]	[5.38]	[4.78]
World CAPM Alpha (%)	2.73	3.82	3.78	-2.09	2.77	2.38	3.30	1.98	2.48	-0.97	1.17	1.55	2.65	2.16	2.56	1.96
	[1.92]	[2.14]	[2.44]	[-1.14]	[1.91]	[1.72]	[1.78]	[0.88]	[1.14]	[-0.68]	[0.73]	[1.18]	[1.13]	[1.40]	[2.04]	[1.65]

PANEL B - Only Bonds

	1930 to 2020						1961 to 2020									
	GPT	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**GPT**	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**TPU**	**RUI**	**MUI**	**FUI**
Mimicking Correlation	0.25	0.14	0.18	0.25	0.28	0.32	0.20	0.12	0.11	0.21	0.30	0.47	0.34	0.27	0.32	0.39
Risk Premium (%)	6.90	6.21	6.74	7.09	-5.75	-2.75	7.06	6.31	7.15	7.44	-3.36	-0.33	-5.44	-1.04	6.38	0.11
	[3.61]	[3.05]	[3.36]	[3.60]	[-3.16]	[-1.55]	[3.00]	[2.68]	[2.83]	[3.02]	[-1.74]	[-0.23]	[-2.93]	[-0.33]	[3.33]	[0.04]
World CAPM Alpha (%)	5.85	5.78	5.96	7.04	-6.14	-4.22	6.42	6.57	6.61	7.68	-5.48	-2.66	-5.16	0.08	5.72	-0.88
	[2.60]	[2.77]	[2.78]	[3.34]	[-2.77]	[-2.19]	[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

	1930 to 2020						1961 to 2020									
	GPT	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**GPT**	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**	**TPU**	**RUI**	**MUI**	**FUI**
Mimicking Correlation	0.26	0.21	0.22	0.27	0.44	0.41	0.20	0.17	0.18	0.25	0.47	0.50	0.42	0.19	0.34	0.48
Risk Premium (%)	9.49	10.33	10.77	-6.89	9.14	8.60	9.64	7.93	8.78	-6.33	7.44	7.42	7.80	8.15	8.34	7.80
	[4.49]	[4.31]	[4.77]	[-3.56]	[4.65]	[5.30]	[3.82]	[2.78]	[3.21]	[-4.19]	[3.15]	[3.99]	[2.45]	[4.02]	[5.26]	[4.75]
World CAPM Alpha (%)	3.44	4.34	4.52	-1.39	2.45	2.21	4.52	2.22	3.14	-0.33	1.05	1.43	1.67	2.18	3.09	1.92
	[2.49]	[2.46]	[3.04]	[-0.82]	[1.68]	[1.61]	[2.51]	[0.98]	[1.47]	[-0.23]	[0.69]	[1.19]	[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) as well as on three other indices that are also based on news articles. They are 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. We estimate panel regressions with country fixed effects and observations at the country-year level (from 1927 to 2020). 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 always normalized to z-scores and t-statistics (in brackets) are based on Driscoll and Kraay (1998) (with the number of autocorrelation lags selected following Newey and West (1994)). Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section 4.1 covers the results from this table. Internet Appendix Tables IA.6 and IA.8 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	3.20						3.00	2.90	4.60	3.10	3.20	4.00
	[1.52]						[1.37]	[1.25]	[2.37]	[1.57]	[1.62]	[2.11]
GPA		1.50					0.50					-0.30
		[1.35]					[0.53]					[-0.33]
GPR			2.20					0.50				
			[1.44]					[0.50]				
WAR				0.70					-1.90			-1.20
				[0.39]					[-1.06]			[-0.56]
EPU					1.90					1.80		1.80
					[1.51]					[1.42]		[0.99]
EMV						-0.40					0.20	-0.50
						[-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	25.80						29.00	32.40	33.30	25.10	26.20	31.90
	[2.79]						[2.71]	[2.71]	[2.80]	[3.08]	[2.78]	[2.57]
GPA		0.30					-9.20					-17.20
		[0.06]					[-1.60]					[-3.61]
GPR			7.50					-11.30				
			[0.81]					[-1.76]				
WAR				9.90					-9.80			-2.20
				[1.23]					[-1.00]			[-0.21]
EPU					14.50					13.70		18.80
					[2.16]					[2.13]		[2.29]
EMV						-3.20					1.80	-2.60
						[-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
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) as well as on three other indices that are also based on news articles. They are 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. We estimate panel regressions with country fixed effects and observations at the country-year level (from 1927 to 2020). 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 always normalized to z-scores and t-statistics (in brackets) are based on Driscoll and Kraay (1998) (with the number of autocorrelation lags selected following Newey and West (1994)). Sections 1.1 and 2.1 provide measurement details for the risk indices used in this table while Section 4.2 covers the results from this table. Internet Appendix Tables IA.7 and IA.9 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						-0.40	-0.50	-0.30	-0.30	0.00	-0.20
	[-0.51]						[-0.72]	[-0.79]	[-0.24]	[-0.57]	[-0.05]	[-0.17]
GPA		0.20					0.40					0.10
		[0.84]					[1.37]					[0.39]
GPR			0.10					0.40				
			[0.15]					[1.11]				
WAR				-0.20					0.00			0.10
				[-0.33]					[-0.04]			[0.11]
EPU					0.40					0.40		0.10
					[1.01]					[1.04]		[0.20]
EMV						1.00					1.00	1.00
						[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	-2.40						-1.70	-0.80	-0.50	-2.50	-1.00	1.80
	[-0.96]						[-0.64]	[-0.28]	[-0.14]	[-1.02]	[-0.42]	[0.42]
GPA		-2.50					-2.00					-3.20
		[-1.96]					[-1.41]					[-1.69]
GPR			-3.20					-2.70				
			[-2.01]					[-1.65]				
WAR				-2.80					-2.50			-2.10
				[-1.58]					[-0.84]			[-0.62]
EPU					1.30					1.40		0.10
					[0.78]					[0.83]		[0.04]
EMV						5.60					5.40	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 9
Geopolitical Risks and Firm Investment

This table reports regressions of variables related to firm investment onto the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022) as well as on three other indices that are also based on news articles. They are 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. Panel A uses quarterly US data from 1947-Q1 to 2024-Q4, regressing log real investment per capita on a time trend and lagged risk indices (see Internet Appendix Table IA.10 for stochastic trend specifications). We consider two investment measures: real private fixed investment (as in Caldara and Iacoviello (2022)) and real private nonresidential fixed investment (as in Gennaioli, Ma, and Shleifer (2015)), both obtained from the FRED. The $R^2_{partial} = (R^2 - R^2_{trend})/(1 - R^2_{trend})$ captures the share of variance in detrended log investment explained by the lagged risk indices, comparing the R-squared values from regressions with (R^2) and without (R^2_{trend}) these indices. Panel B analyzes an unbalanced panel of annual data for 138 countries (1984-2021), regressing risk perception measures on contemporaneous risk indices with country fixed effects. The risk perception measures are based on the (negative of the) International Country Risk Guide (ICRG) rating of the PRS Group. The risk indices as well as risk perception indices are normalized to z-scores. The t-statistics (in brackets) are based on Newey and West (1987, 1994) for time-series regressions (Panel A) and on Driscoll and Kraay (1998) (with the number of autocorrelation lags selected following Newey and West (1994)) for panel regressions (Panel B). Sections 1.1 and 2.1 provide measurement details for the risk indices while Section 5 covers the results from this table.

PANEL A - Aggregate Firm Investment

	Y = Real Private Fixed Investment								**Y = Real Private Nonresidential Fixed Investment**							
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**
GPT	-0.03					-0.04	-0.01	-0.02	-0.03					-0.04	-0.01	-0.02
	[-1.57]					[-3.07]	[-0.69]	[-1.93]	[-1.61]					[-3.04]	[-0.97]	[-2.06]
GPA		0.04				0.07		0.09		0.03				0.06		0.05
		[0.99]				[3.69]		[3.73]		[0.58]				[1.91]		[1.86]
WAR			-0.04				-0.03	-0.04			-0.03				-0.02	-0.02
			[-2.84]				[-3.28]	[-3.98]			[-1.86]				[-1.56]	[-1.94]
EPU				-0.01				-0.02				0.00				0.01
				[-0.49]				[-1.14]				[0.10]				[0.57]
EMV					-0.01			-0.00					-0.00			0.00
					[-0.45]			[-0.19]					[-0.24]			[0.05]
$R^2_{partial}$	6%	2%	12%	1%	1%	13%	12%	22%	5%	2%	8%	0%	0%	10%	9%	15%
# Obs	312	312	292	312	312	312	292	292	312	312	292	312	312	312	292	292

PANEL B - Perception of Investment-Related Risks (from ICRG)

	Y = Perceived Investment Risk								**Y = Perceived Government Instability Risk**							
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**
GPT	0.30					0.50	0.60	0.60	0.70					0.90	0.60	0.60
	[1.65]					[3.15]	[2.58]	[4.31]	[3.32]					[6.84]	[2.61]	[6.57]
GPA		-0.50				-0.80		-0.90		-0.60				-1.10		-1.00
		[-2.46]				[-2.97]		[-2.72]		[-1.38]				[-4.27]		[-4.34]
WAR			0.00				-0.20	-0.20			0.30				0.10	0.10
			[-0.56]				[-2.18]	[-2.40]			[2.38]				[0.97]	[0.77]
EPU				-0.20				-0.20				0.10				0.10
				[-1.93]				[-1.10]				[0.76]				[0.77]
EMV					-0.30			-0.20					-0.50			-0.30
					[-3.12]			[-1.72]					[-3.36]			[-2.99]
R^2_{within}	6%	5%	0%	5%	9%	16%	11%	28%	16%	3%	9%	0%	16%	28%	17%	35%
# Obs	4,970	4,970	4,696	4,970	4,970	4,970	4,696	4,696	4,970	4,970	4,696	4,970	4,970	4,970	4,696	4,696

Internet Appendix

"The Pricing of Geopolitical Tensions over a Century"

Contents

A Data Sources

This section provides the data sources for the risk indices (Section A.1) as well as the macro-finance variables (Section A.2), asset returns (Section A.3), and factor models (Section A.4) 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 Macro-Finance Variables

- **Real Private Fixed Investment per Capita:** this variable is used in Caldara and Iacoviello (2022) to proxy for firm investment. We construct it using three variables from the Federal Reserve Economic Data (FRED). Fixed Private Investment (code FPI), its implicit price deflator (code A007RD3Q086SBEA), and the US population (code B230RC0Q173SBEA).

- **Real Private Nonresidential Fixed Investment per Capita:** this variable is used in Gennaioli, Ma, and Shleifer (2015) to proxy for firm investment. We construct it using three variables from the Federal Reserve Economic Data (FRED). Private Nonresidential Fixed Investment (code PNFI), its implicit price deflator (code A008RD3Q086SBEA), and the US population (code B230RC0Q173SBEA).

- **Real GDP per Capita:** we construct it using two variables from the Federal Reserve Economic Data (FRED). Real Gross Domestic Product (code GDPC1) and the US population (code B230RC0Q173SBEA).

- **Real S&P500 Price:** we obtain it from the equity predictor dataset of Goyal, Welch, and Zafirov (2024) (updated to 2023), available under https://sites.google.com/view/agoyal145.

- **Realized Consumption Disasters:** we obtain the country-level indicator of realized consumption disasters of Nakamura et al. (2013) (updated to 2019) from the Caldara and Iacoviello (2022) replication package, available under https://www.openicpsr.org/openicpsr/project/154781/version/V1/view.

- **Probability of Consumption Disasters:** we obtain the country-level probability of consumption disasters of Marfè and Penasse (2025) from https://robertomarfe.altervista.org/.

A.3 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 12-2023), 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.4 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 Risks and Disasters (Controlling for other Risk Indices)

The results in Section 1.4 show that GPA and GPT are associated with the probability of consumption disasters over the short- and long-term, respectively (see Table 3). 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.1 provides the relevant results (with specifications analogous to Table 3). Panel A shows that both GPT and GPA are linked to consumption disasters in the subsequent year. However, GPA has a stronger effect, 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 effects 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).

B.2 High-Low Beta Quintile Portfolios (Alternative Specifications)

The results in Section 3.1 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.2 (which replicates 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.2 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 different sample periods to estimate the autoregressive processes, and thus we do not take this approach. However, the results for WAR 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 consider an alternative specification that uses a 10-year 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.3 High-Low Beta Quintile Portfolios (Controlling for Factor Models)

The alphas studied in Section 3.1 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 GPT results (for comparability) and also presents GPT 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).

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

The results are provided in Table IA.3. Since the data for different factor models (detailed in Section A.4) are available over different 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 effect).

B.4 Equity Anomaly Portfolios (1930-2023)

The results in Section 3.2 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 12-2023 (see Table 5). In this section, we consider an analysis over the long sample used for individual stocks (01-1930 to 12-2023), at the cost of a lower number of anomaly portfolios. We keep the tuning parameters the same as in Section 3.2 and use the same data sources for anomaly portfolios. However, the overall number of anomalies is lower. In particular, we have a total of 728 anomaly portfolios from two sources. The first source is the Open Source Asset Pricing (OSAP) dataset of Chen and Zimmermann (2022), which yields 648 decile portfolios from 37 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.4. 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 a 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 the other risk indices analyzed as they also produce economically and statistically significant risk premia and alphas.

B.5 Equity Anomaly Portfolios (Alternative SPCA Tuning Parameters)

The results in Section 3.2 are based on the Supervised Principal Component Analysis (SPCA) of Giglio, Xiu, and Zhang (2025) using 5 factors and 722 test portfolios (30% of the 2,408 test portfolios) as SPCA tuning parameters (see Table 5). In this section, we provide a sensitivity analysis on these tuning parameters. Specifically, Table IA.5 considers 3, 4, 6, and 7 factors (as an alternative to 5 factors) as well as 20%, 25%, 35%, 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. One exception is that if we use only 3 factors then the GPT mimicking factor has a much weaker correlation with GPT growth and the risk premium on the GPT mimicking factor is no longer statistically significant (albeit it remains positive). However, given the prior literature on factor models (e.g., Kozak, Nagel, and Santosh (2018)), it is hard to imagine that 3 factors spam the space of anomaly portfolio returns. So, it is perhaps not surprising that a specification with 3 factors yields relatively weak GPT mimicking factor correlation and GPT risk premium.

B.6 The Time-Series of Risk Premia (Alternative Specifications)

The results in Section 4 are based on panel regressions of country-level returns onto the risk indices we study with country fixed effects (see Tables 7 and 8). This section considers two alternative specifications relative to what we report in the main text.

First, Tables IA.6 and IA.7 replicate Tables 7 and 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.8 and IA.9 replicate Tables 7 and 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.7 Geopolitical Risks and Investment (Alternative Trend Specifications)

Some of the results in Section 5 are based on time-series regressions of log real investment per capita on a time trend and lagged risk indices (see Table 9, Panel A). In this section, we consider alternative specifications for the investment trend. In particular, we estimate two stochastic trend specifications whereas the main text uses a deterministic time trend specification. Table IA.10 (Panel A) adds log real GDP per capita to the trend specification since log real GDP is a common variable in macroeconomics to capture the stochastic trend in investment. Table IA.10 (Panel B) further adds the log of the S&P 500 real price, which is used in Caldara and Iacoviello (2022) to capture the stochastic trend in investment. In both panels, the overall results are similar to the ones we report in the main text. In particular, specifications that include GPT and GPA show that an increase in GPT is associated with a decline in future investment.

C Deriving the General Epstein-Zin SDF

This section derives the general Stochastic Discount Factor (SDF) under Epstein-Zin preferences (i.e., Equations 1 and 3 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 $crw_t = -log(e^{-cw_t} - 1)$ 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,

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

$$\Downarrow$$

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

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 $\psi = 1$, which implies that this log-linear approximation is exact with $\overline{\delta} = \delta$ 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

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

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

or in log terms,

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

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 $crw_t = -log(e^{-cw_t} - 1)$, 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

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

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

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

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

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

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

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

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

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

The consumption FOC then yields

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

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

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

so that combining the two optimality conditions gives

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

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:

$$(V_t/W_t)^{1-1/\psi} \;=\; (1-\delta)\cdot(C_t/W_t)^{-1/\psi} \tag{IA.32}$$

$$\Downarrow$$

$$cw_t \;=\; \psi\cdot log(1-\delta) \;+\; (1-\psi)\cdot vw_t, \tag{IA.33}$$

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

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

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

$$\Downarrow$$

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

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

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

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

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

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

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

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

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

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

C.4 Deriving the Recursive Equation for vw

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

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

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 log SDF in Equation 3 with $\kappa_{\mathbb{E}} = (\gamma - 1)$, $\kappa_{\mathbb{V}} = 0.5 \cdot (\gamma - 1)^2$, and $\kappa_{\mathbb{H}} = (\gamma - 1)$.

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

Equation IA.55 is the 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 Effect 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 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.

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

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

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]

More a more general model, the dynamics of disasters (e.g., time-varying disaster severity) can also affect $N_{\mathbb{H}}$ 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 effect 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 effect of π_t shocks on $N_{\mathbb{E}}$ and $N_{\mathbb{V}}$ would be minor relative to the effect 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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Table IA.1

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) as well as on three other indices that are also based on news articles. They are 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. Observations are at the country-year level and all specifications consider an unbalanced panel from 1927 to 2019, with country fixed effects 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 Penasse (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 the number of autocorrelation lags selected following Newey and West (1994). Sections 1.1 and 2.1 provide measurement details for the risk indices while Section B.1 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	9.30					3.70	9.50	3.30	1.40					0.40	1.50	0.40
	[3.16]					[1.45]	[3.15]	[1.14]	[3.00]					[1.61]	[3.26]	[1.64]
GPA		13.20				11.60		11.60		2.60				2.50		2.50
		[6.63]				[6.56]		[6.67]		[5.18]				[5.15]		[5.55]
WAR			3.90				-1.00	-1.00			0.60				-0.20	-0.30
			[1.49]				[-0.51]	[-0.65]			[1.42]				[-0.62]	[-1.02]
EPU				6.80				2.70				1.00				0.60
				[2.01]				[1.04]				[1.89]				[1.97]
EMV					-1.10			1.90					-0.60			0.10
					[-0.45]			[0.98]					[-1.40]			[0.52]
R^2_{within}	21%	26%	18%	19%	17%	26%	21%	27%	24%	36%	19%	21%	19%	36%	24%	37%
# 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	8.60					4.20	9.00	4.10	1.50					1.00	1.80	1.10
	[3.27]					[1.55]	[3.38]	[1.50]	[3.12]					[2.46]	[4.18]	[3.01]
GPA		10.90				9.00		9.00		1.80				1.40		1.40
		[5.49]				[4.58]		[4.49]		[2.73]				[2.42]		[2.67]
WAR			3.20				-1.60	-1.60			0.60				-0.40	-0.40
			[1.33]				[-0.88]	[-1.20]			[1.30]				[-1.50]	[-1.70]
EPU				6.20				2.20				1.10				0.60
				[1.90]				[0.80]				[2.16]				[1.74]
EMV					-0.90			1.40					-0.50			0.10
					[-0.44]			[0.90]					[-1.82]			[0.29]
R^2_{within}	25%	28%	23%	23%	21%	28%	25%	29%	33%	35%	26%	29%	26%	38%	34%	40%
# 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.1
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	8.40					5.40	9.50	5.70	1.30					1.10	1.60	1.20
	[3.79]					[2.27]	[4.19]	[2.38]	[2.72]					[2.41]	[3.52]	[2.67]
GPA		8.50				6.10		6.10		1.00				0.40		0.50
		[4.21]				[3.32]		[3.34]		[1.64]				[0.94]		[1.09]
WAR			2.80				-2.40	-2.20			0.50				-0.50	-0.40
			[1.30]				[-1.56]	[-1.80]			[1.11]				[-2.45]	[-2.22]
EPU				6.10				2.40				1.10				0.70
				[2.20]				[0.96]				[2.61]				[2.09]
EMV					-0.90			1.10					-0.30			0.10
					[-0.57]			[0.80]					[-1.52]			[0.36]
R^2_{within}	29%	29%	26%	27%	25%	31%	29%	32%	39%	34%	32%	36%	31%	39%	39%	41%
# 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	6.00					5.60	7.80	4.20	0.60					0.80	0.90	0.50
	[4.17]					[3.56]	[4.81]	[2.95]	[2.12]					[2.89]	[3.03]	[2.12]
GPA		3.20				0.70		0.50		-0.10				-0.40		-0.40
		[1.82]				[0.56]		[0.57]		[-0.18]				[-1.49]		[-2.78]
WAR			2.10				-3.30	-1.60			0.20				-0.40	-0.20
			[1.17]				[-2.22]	[-1.42]			[0.74]				[-2.22]	[-1.03]
EPU				7.30				5.40				1.20				1.10
				[5.65]				[4.58]				[5.95]				[5.43]
EMV					-0.30			0.70					-0.20			0.00
					[-0.23]			[0.77]					[-0.90]			[0.15]
R^2_{within}	36%	34%	34%	37%	33%	36%	37%	38%	48%	46%	46%	54%	46%	49%	49%	55%
# 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

Table IA.2
Single Stocks: Risk Premia & Alphas of High-Low Beta Portfolios (Alternative Specifications)

This table reports annualized risk premia (i.e., average returns multiplied by twelve) and CAPM alphas (i.e., intercepts form market regression multiplied by twelve) of high-low, H-L, returns on beta sorted portfolios that buy (sell) stocks with high (low) stock-level betas on F_t. Unless otherwise noted, F_t reflects the growth rate of the given risk or uncertainty 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 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. Rows differ 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, 2.1, and 2.2 provide measurement details for the risk indices used in this table while Section B.2 covers the results from this table.

PANEL A - Risk Premia (%)

	01-1930 to 12-2024						08-1963 to 12-2024									
$IND =$	GPT	GPA	GPR	WAR	EPU	EMV	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Baseline	4.17	1.69	2.71	1.22	2.99	0.68	3.36	2.33	3.51	-0.46	1.15	1.21	-0.49	2.56	2.39	2.40
	[2.85]	[0.98]	[1.65]	[0.87]	[1.42]	[0.40]	[1.99]	[1.14]	[1.87]	[-0.28]	[0.50]	[0.60]	[-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	3.16	2.04	2.81	-0.54	1.07	0.22	-0.82	2.52	2.28	2.34
	[1.92]	[1.07]	[1.70]	[0.81]	[1.48]	[-0.07]	[2.02]	[1.02]	[1.44]	[-0.33]	[0.49]	[0.12]	[-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	2.64	1.37	2.43	-0.81	1.76	-1.29	-0.45	2.64	2.32	2.34
	[2.16]	[0.95]	[1.63]	[0.82]	[1.66]	[-0.58]	[1.65]	[0.69]	[1.31]	[-0.50]	[0.80]	[-0.64]	[-0.28]	[1.37]	[1.17]	[0.99]
$F_t = IND_t$	4.21	1.84	3.37	-0.35	2.57	1.53	4.50	0.86	3.36	-0.39	2.16	1.81	1.50	1.22	0.47	4.69
	[2.50]	[1.04]	[1.79]	[-0.23]	[1.55]	[0.82]	[2.22]	[0.49]	[1.61]	[-0.24]	[1.26]	[0.81]	[0.85]	[0.63]	[0.24]	[2.20]
Decile Portfolios	4.41	2.53	3.47	0.27	2.85	2.07	4.26	3.64	3.34	-2.58	0.66	3.22	-1.17	3.63	3.09	2.72
	[2.38]	[1.13]	[1.63]	[0.13]	[1.18]	[1.04]	[1.95]	[1.30]	[1.37]	[-1.15]	[0.24]	[1.30]	[-0.56]	[1.58]	[1.21]	[0.93]
Tercile Portfolios	2.95	1.06	2.29	0.74	2.06	1.03	2.26	1.13	2.62	-0.43	1.05	1.44	-0.18	1.14	2.26	2.30
	[2.55]	[0.78]	[1.67]	[0.55]	[1.26]	[0.75]	[1.62]	[0.70]	[1.73]	[-0.31]	[0.58]	[0.87]	[-0.14]	[0.78]	[1.43]	[1.24]
Equal Weighted Portfolios	2.37	1.80	2.46	1.48	1.15	0.71	1.40	1.17	1.59	-0.14	-0.60	1.24	-0.63	1.86	2.02	2.32
	[2.08]	[1.41]	[1.96]	[1.39]	[0.77]	[0.54]	[1.23]	[0.92]	[1.23]	[-0.13]	[-0.39]	[0.78]	[-0.59]	[1.36]	[1.30]	[1.40]
$\beta = -\mathbb{C}orr_{3y}[r, F] \cdot \mathbb{V}ol_{1y}[r]$	4.47	2.28	3.47	1.14	3.90	1.34	4.01	2.99	3.79	-0.09	1.69	1.45	-0.62	2.14	1.77	1.80
	[2.70]	[1.28]	[1.99]	[0.64]	[1.83]	[0.73]	[2.38]	[1.38]	[2.01]	[-0.05]	[0.79]	[0.70]	[-0.36]	[1.11]	[0.88]	[0.75]
$\beta = -\mathbb{C}orr_{10y}[r, F] \cdot \mathbb{V}ol_{1y}[r]$	3.28	1.13	2.06	0.30	2.53	0.44	3.85	1.13	3.22	-0.70	0.42	1.33	-2.51	1.76	0.89	2.07
	[1.82]	[0.69]	[1.22]	[0.19]	[1.17]	[0.30]	[2.15]	[0.58]	[1.62]	[-0.46]	[0.17]	[0.62]	[-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	3.36	2.33	3.51	-0.46	1.15	1.21	-0.49	2.56	2.39	2.40
	[3.20]	[1.07]	[2.38]	[1.13]	[1.10]	[1.12]	[1.99]	[1.14]	[1.87]	[-0.28]	[0.50]	[0.60]	[-0.30]	[1.36]	[1.22]	[1.05]

Table IA.2
Single Stocks: Risk Premia of High-Low Beta Portfolios (Alternative Specifications)
(Continued)

PANEL B - CAPM Alphas (%)

	01-1930 to 12-2024						08-1963 to 12-2024									
$IND =$	GPT	GPA	GPR	WAR	EPU	EMV	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Baseline	4.84	1.18	3.06	2.41	-1.08	0.15	3.00	1.75	3.02	-0.39	-2.44	-1.77	-1.12	0.26	-0.11	-0.42
	[3.23]	[0.72]	[1.90]	[1.61]	[-0.59]	[0.09]	[1.80]	[0.85]	[1.69]	[-0.24]	[-1.14]	[-0.95]	[-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	2.99	1.64	2.48	-0.48	-2.42	-2.57	-1.61	0.21	-0.21	-0.40
	[3.01]	[0.77]	[1.97]	[1.65]	[-0.54]	[-0.25]	[1.93]	[0.82]	[1.32]	[-0.28]	[-1.23]	[-1.59]	[-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	2.53	0.98	2.21	-0.71	-1.78	-4.01	-1.39	0.29	-0.26	-0.51
	[2.91]	[0.75]	[2.13]	[1.67]	[-0.39]	[-0.95]	[1.57]	[0.50]	[1.23]	[-0.43]	[-0.92]	[-2.30]	[-0.83]	[0.17]	[-0.14]	[-0.24]
$F_t = IND_t$	4.72	1.51	3.44	1.00	1.16	0.49	5.31	1.71	4.40	0.98	0.50	-1.42	1.70	0.48	-0.29	2.81
	[2.91]	[0.93]	[1.92]	[0.71]	[0.63]	[0.30]	[2.65]	[0.97]	[2.12]	[0.57]	[0.25]	[-0.73]	[0.95]	[0.23]	[-0.14]	[1.45]
Decile Portfolios	5.06	2.43	4.02	1.76	-1.72	1.72	3.70	3.06	2.81	-2.12	-3.27	-0.23	-2.09	1.06	-0.01	-0.78
	[2.69]	[1.07]	[1.95]	[0.91]	[-0.78]	[0.90]	[1.71]	[1.13]	[1.14]	[-0.95]	[-1.38]	[-0.10]	[-0.95]	[0.49]	[-0.01]	[-0.30]
Tercile Portfolios	3.52	0.63	2.56	1.99	-1.20	0.62	2.03	0.59	2.31	-0.42	-1.78	-0.96	-0.69	-0.68	0.27	0.18
	[2.83]	[0.48]	[1.98]	[1.63]	[-0.74]	[0.48]	[1.47]	[0.36]	[1.62]	[-0.30]	[-1.05]	[-0.64]	[-0.48]	[-0.49]	[0.19]	[0.11]
Equal Weighted Portfolios	2.94	1.51	2.63	2.58	-1.93	0.52	0.99	0.66	1.05	0.00	-3.00	-1.09	-0.76	0.19	0.28	0.38
	[2.58]	[1.23]	[2.13]	[2.31]	[-1.43]	[0.42]	[0.85]	[0.53]	[0.82]	[-0.00]	[-2.15]	[-0.75]	[-0.68]	[0.16]	[0.19]	[0.22]
$\beta = -\mathbb{C}orr_{3y}[r,F] \cdot \mathbb{V}ol_{1y}[r]$	5.70	2.21	4.30	2.76	-0.71	1.25	3.81	2.52	3.36	0.17	-2.16	-1.83	-1.52	-0.41	-1.05	-1.14
	[3.80]	[1.18]	[2.56]	[1.82]	[-0.37]	[0.69]	[2.27]	[1.15]	[1.82]	[0.10]	[-1.16]	[-0.94]	[-0.82]	[-0.23]	[-0.58]	[-0.53]
$\beta = -\mathbb{C}orr_{10y}[r,F] \cdot \mathbb{V}ol_{1y}[r]$	4.29	0.95	2.88	2.02	-2.39	-0.12	2.96	0.65	2.61	0.39	-4.58	-2.63	-2.57	-1.13	-2.76	-1.90
	[2.51]	[0.58]	[1.70]	[1.45]	[-1.07]	[-0.07]	[1.67]	[0.36]	[1.42]	[0.27]	[-2.24]	[-1.39]	[-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	3.00	1.75	3.02	-0.39	-2.44	-1.77	-1.12	0.26	-0.11	-0.42
	[2.83]	[1.01]	[2.18]	[0.73]	[-1.14]	[-0.22]	[1.80]	[0.85]	[1.69]	[-0.24]	[-1.14]	[-0.95]	[-0.65]	[0.15]	[-0.06]	[-0.20]

PANEL C - ICAPM Alphas (%)

	01-1930 to 12-2024						08-1963 to 12-2024									
$IND =$	GPT	GPA	GPR	WAR	EPU	EMV	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
Baseline	4.21	0.93	2.28	1.48	0.45	-1.27	3.24	2.01	3.44	-0.32	-1.57	-1.50	-1.23	1.18	0.99	0.62
	[2.91]	[0.53]	[1.38]	[0.97]	[0.25]	[-0.86]	[1.90]	[0.96]	[1.87]	[-0.19]	[-0.81]	[-1.05]	[-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	3.18	2.27	2.85	-0.46	-1.43	-2.29	-2.09	1.14	0.91	0.66
	[2.25]	[0.74]	[1.58]	[0.99]	[0.32]	[-1.30]	[1.98]	[1.14]	[1.46]	[-0.29]	[-0.74]	[-1.68]	[-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	2.64	1.42	2.36	-0.57	-0.62	-3.83	-1.92	1.20	0.87	0.51
	[2.19]	[0.62]	[1.53]	[1.04]	[0.54]	[-1.95]	[1.62]	[0.72]	[1.31]	[-0.36]	[-0.36]	[-2.62]	[-1.18]	[0.87]	[0.58]	[0.22]
$F_t = IND_t$	4.38	1.29	2.97	0.57	0.86	-0.97	5.41	2.04	4.53	0.91	-0.05	-1.37	1.16	-0.80	-1.08	2.36
	[2.59]	[0.76]	[1.60]	[0.39]	[0.49]	[-0.58]	[2.46]	[1.07]	[1.97]	[0.51]	[-0.03]	[-0.75]	[0.63]	[-0.38]	[-0.53]	[1.21]
Decile Portfolios	4.02	1.99	3.02	0.78	-0.57	0.23	3.58	3.46	2.66	-2.15	-2.80	-0.12	-2.37	1.87	1.67	0.55
	[2.15]	[0.83]	[1.44]	[0.38]	[-0.29]	[0.13]	[1.65]	[1.18]	[1.08]	[-0.93]	[-1.22]	[-0.06]	[-1.05]	[1.04]	[0.81]	[0.20]
Tercile Portfolios	3.02	0.41	2.05	1.08	-0.05	-0.42	2.32	0.69	2.51	-0.46	-0.98	-0.74	-0.92	-0.07	1.16	0.99
	[2.59]	[0.30]	[1.54]	[0.84]	[-0.04]	[-0.36]	[1.71]	[0.43]	[1.71]	[-0.33]	[-0.64]	[-0.61]	[-0.64]	[-0.06]	[0.96]	[0.50]
Equal Weighted Portfolios	2.32	0.89	1.95	1.72	-0.77	-0.53	1.10	0.36	1.02	-0.22	-2.52	-1.10	-0.93	0.66	1.08	0.93
	[2.14]	[0.72]	[1.63]	[1.49]	[-0.68]	[-0.48]	[0.92]	[0.28]	[0.79]	[-0.20]	[-2.14]	[-0.99]	[-0.85]	[0.60]	[0.85]	[0.53]
$\beta = -\mathbb{C}orr_{3y}[r,F] \cdot \mathbb{V}ol_{1y}[r]$	4.93	1.80	3.65	1.66	0.94	-0.05	4.03	2.65	3.74	0.28	-1.56	-2.07	-1.66	0.54	0.04	0.01
	[3.33]	[0.96]	[2.11]	[1.01]	[0.55]	[-0.03]	[2.46]	[1.21]	[2.08]	[0.16]	[-0.92]	[-1.34]	[-0.90]	[0.40]	[0.02]	[0.00]
$\beta = -\mathbb{C}orr_{10y}[r,F] \cdot \mathbb{V}ol_{1y}[r]$	3.37	-0.20	1.49	0.86	0.03	-0.99	3.29	0.23	2.56	-0.06	-2.86	-2.14	-1.91	-0.97	-2.44	-0.83
	[1.93]	[-0.11]	[0.86]	[0.61]	[0.01]	[-0.61]	[1.83]	[0.11]	[1.32]	[-0.04]	[-1.53]	[-1.46]	[-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	3.24	2.01	3.44	-0.32	-1.57	-1.50	-1.23	1.18	0.99	0.62
	[3.11]	[0.94]	[2.21]	[0.84]	[-0.54]	[-0.33]	[1.90]	[0.96]	[1.87]	[-0.19]	[-0.81]	[-1.05]	[-0.72]	[0.88]	[0.66]	[0.27]

Table IA.3
High-Low Beta Quintile Portfolios: Risk Premia and Alphas Controlling for Factor Models

This table reports annualized risk premia (average returns multiplied by twelve) and annualized alphas (factor regression intercepts multiplied by twelve) 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) in the case of risk premia and alphas. In the case of b, they are based on GMM standard errors with Newey and West (1987, 1994) applied to the spectral density matrix. Sections 1.1, 2.1, and 2.2 provide measurement details for the risk indices used in this table while Section B.3 covers the results from this table.

Factor Model =	**None**	**CAPM**	**ICAPM**	**FF3**	**FF5**	**FF3+MOM**	**FF5+MOM**	**q4**	**q5**	**DHS**
Risk Premia (%)	4.17	4.17	4.17	4.17	3.34	4.17	3.34	3.61	3.61	3.57
	[2.85]	[2.85]	[2.85]	[2.85]	[1.98]	[2.85]	[1.98]	[2.05]	[2.05]	[1.86]
Alphas (%)	4.17	4.84	4.21	5.16	3.22	5.17	3.75	4.87	4.86	3.79
	[2.85]	[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	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	12-2024	12-2023

Table IA.4
Equity Anomaly Portfolios: Risk Premia and Alphas of Mimicking Factors (1930-2023)

This table reports annualized risk premia (i.e., average returns multiplied by twelve) and annualized alphas (i.e., factor regression intercepts multiplied by twelve) from mimicking factors for the (negative of the growth in the) given risk indices. Mimicking factors are normalized to have an annual volatility of 20%, which is similar to the market annual volatility. We consider ten risk indices in total. 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. Mimicking factors for the (negative of the growth in the) risk indices are constructed using the Supervised Principal Component Analysis (SPCA) method proposed by Giglio, Xiu, and Zhang (2025). The test assets are 728 anomaly portfolios. The first group of anomaly portfolios is from the Open Source Asset Pricing (OSAP) dataset of Chen and Zimmermann (2022), and comprises 648 decile portfolios from 37 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 722 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). 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.4 covers the results from this table.

	01-1930 to 12-2023					
INDEX =	**GPT**	**GPA**	**GPR**	**WAR**	**EPU**	**EMV**
Mimicking Correlation	0.29	0.42	0.36	0.15	0.34	0.34
Risk Premium (%)	2.62	2.77	2.53	2.66	3.17	1.80
	[4.31]	[4.82]	[4.31]	[3.97]	[5.69]	[3.17]
CAPM Alpha (%)	2.21	2.60	2.19	2.87	1.96	1.09
	[3.70]	[4.78]	[3.98]	[4.22]	[4.21]	[1.88]
ICAPM Alpha (%)	1.86	1.66	1.57	2.38	1.74	1.18
	[3.00]	[3.07]	[2.79]	[3.36]	[3.58]	[2.10]
GPT Alpha w.r.t INDEX		3.21	3.28	2.76	2.86	2.65
		[5.06]	[5.34]	[4.28]	[4.63]	[4.35]
INDEX Alpha w.r.t GPT		3.18	3.04	2.85	3.32	1.81
		[5.60]	[5.33]	[4.12]	[4.78]	[3.07]

Table IA.5
Equity Anomaly Portfolios: Risk Premia (Alternative SPCA Tuning Parameters)

This table reports annualized risk premia (i.e., average returns multiplied by twelve) from mimicking factors for the (negative of the growth in the) given risk indices. Mimicking factors are normalized to have an annual volatility of 20%, which is similar to the market annual volatility. Mimicking factors for the (negative of the growth in the) risk indices are constructed using the Supervised Principal Component Analysis (SPCA) method proposed by Giglio, Xiu, and Zhang (2025) (with details provided in Section 3.2). We consider ten risk indices in total and test assets based on anomaly portfolios over the period from 08-1963 to 12-2023 (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 3, 4, 6, and 7 factors instead of 5 as well as 20%, 25%, 35%, 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). Sections 1.1, 2.1, and 2.2 provide measurement details for the risk indices used in this table while Section B.5 covers the results from this table.

# of Factors	% of Test Assets	Statistic	GPT	GPA	GPR	WAR	EPU	EMV	TPU	RUI	MUI	FUI
		Mimicking Correlation	0.36	0.43	0.41	0.31	0.42	0.38	0.26	0.37	0.48	0.46
5	30%	Risk Premium (%)	2.83	3.20	2.70	4.00	3.50	2.23	1.58	1.58	-0.20	1.33
		[t-stat]	[3.85]	[4.62]	[3.87]	[4.94]	[4.78]	[3.00]	[2.02]	[1.64]	[-0.18]	[1.50]
		Mimicking Correlation	0.26	0.25	0.22	0.08	0.38	0.35	0.25	0.36	0.43	0.47
3	30%	Risk Premium (%)	0.97	0.36	-0.02	2.68	3.38	1.83	3.12	3.63	1.29	1.56
		[t-stat]	[1.26]	[0.50]	[-0.02]	[3.40]	[4.63]	[2.49]	[4.37]	[4.07]	[1.40]	[1.82]
		Mimicking Correlation	0.36	0.40	0.38	0.01	0.33	0.25	0.17	0.26	0.33	0.40
4	30%	Risk Premium (%)	2.06	1.90	1.85	1.47	1.54	0.97	0.47	2.22	1.11	1.37
		[t-stat]	[2.83]	[2.96]	[2.76]	[1.91]	[1.93]	[1.28]	[0.59]	[2.50]	[1.22]	[1.61]
		Mimicking Correlation	0.44	0.54	0.51	0.12	0.51	0.43	0.35	0.48	0.57	0.48
6	30%	Risk Premium (%)	2.40	2.48	3.37	3.63	2.43	1.80	3.17	2.73	2.31	1.78
		[t-stat]	[3.41]	[3.82]	[5.18]	[4.72]	[3.36]	[2.39]	[4.52]	[2.98]	[2.28]	[2.11]
		Mimicking Correlation	0.45	0.56	0.57	0.15	0.53	0.48	0.38	0.49	0.58	0.53
7	30%	Risk Premium (%)	1.75	1.51	2.13	2.29	2.10	0.58	2.01	2.77	1.79	2.37
		[t-stat]	[2.55]	[2.25]	[3.17]	[2.98]	[2.87]	[0.79]	[2.74]	[3.03]	[1.72]	[2.61]
		Mimicking Correlation	0.41	0.51	0.55	0.10	0.44	0.42	0.29	0.46	0.55	0.47
5	20%	Risk Premium (%)	2.73	3.09	2.63	2.93	2.79	2.07	1.61	1.73	0.85	1.34
		[t-stat]	[3.79]	[4.89]	[4.03]	[3.80]	[4.23]	[2.82]	[2.14]	[1.87]	[0.85]	[1.57]
		Mimicking Correlation	0.38	0.45	0.52	0.11	0.46	0.49	0.33	0.49	0.56	0.49
5	25%	Risk Premium (%)	2.75	2.75	3.20	2.23	3.14	1.44	1.39	2.09	2.14	0.65
		[t-stat]	[3.74]	[4.30]	[4.89]	[2.90]	[4.84]	[1.90]	[1.88]	[2.20]	[2.12]	[0.76]
		Mimicking Correlation	0.32	0.41	0.38	0.08	0.40	0.33	0.26	0.43	0.45	0.44
5	35%	Risk Premium (%)	2.56	2.80	2.76	4.00	2.28	2.45	1.51	0.63	1.01	2.24
		[t-stat]	[3.52]	[4.44]	[4.04]	[5.20]	[3.39]	[3.31]	[2.01]	[0.70]	[1.04]	[2.46]
		Mimicking Correlation	0.30	0.39	0.35	0.07	0.36	0.31	0.24	0.33	0.42	0.43
5	40%	Risk Premium (%)	2.58	2.47	2.31	3.76	2.48	2.34	1.57	2.39	1.42	1.84
		[t-stat]	[3.55]	[3.84]	[3.38]	[4.88]	[3.51]	[3.19]	[2.07]	[2.67]	[1.47]	[2.01]

Table IA.6
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) as well as on three other indices that are also based on news articles. They are the war discourse (WAR) index from Hirshleifer, Mai, and Pukthuanthong (2025a), 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. We estimate panel regressions with country fixed effects and observations at the country-year level (from 1927 to 2020). 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 always normalized to z-scores and t-statistics (in brackets) are based on Driscoll and Kraay (1998) (with the number of autocorrelation lags selected following Newey and West (1994)). 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.

PANEL A - Next 1 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	3.20						3.00	2.90	4.00	3.10	3.20	3.30
	[1.52]						[1.37]	[1.25]	[1.75]	[1.57]	[1.62]	[1.48]
GPA		1.50					0.50					-0.30
		[1.35]					[0.53]					[-0.25]
GPR			2.20					0.50				
			[1.44]					[0.50]				
WAR				2.30					-1.50			-0.40
				[0.81]					[-0.47]			[-0.11]
EPU					1.90					1.80		2.00
					[1.51]					[1.42]		[1.10]
EMV						-0.40					0.20	-0.50
						[-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	25.80						29.00	32.40	36.90	25.10	26.20	32.50
	[2.79]						[2.71]	[2.71]	[2.69]	[3.08]	[2.78]	[2.42]
GPA		0.30					-9.20					-16.70
		[0.06]					[-1.60]					[-3.34]
GPR			7.50					-11.30				
			[0.81]					[-1.76]				
WAR				16.50					-19.40			-4.20
				[1.40]					[-1.14]			[-0.24]
EPU					14.50					13.70		18.70
					[2.16]					[2.13]		[2.27]
EMV						-3.20					1.80	-2.50
						[-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.7
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) as well as on three other indices that are also based on news articles. They are the war discourse (WAR) index from Hirshleifer, Mai, and Pukthuanthong (2025a), 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. We estimate panel regressions with country fixed effects and observations at the country-year level (from 1927 to 2020). 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 always normalized to z-scores and t-statistics (in brackets) are based on Driscoll and Kraay (1998) (with the number of autocorrelation lags selected following Newey and West (1994)). 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.

PANEL A - Next 1 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	-0.30						-0.40	-0.50	-0.60	-0.30	0.00	-0.40
	[-0.51]						[-0.72]	[-0.79]	[-0.51]	[-0.57]	[-0.05]	[-0.34]
GPA		0.20					0.40					0.10
		[0.84]					[1.37]					[0.18]
GPR			0.10					0.40				
			[0.15]					[1.11]				
WAR				0.00					0.50			0.60
				[-0.05]					[0.32]			[0.32]
EPU					0.40					0.40		0.20
					[1.01]					[1.04]		[0.28]
EMV						1.00					1.00	0.90
						[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	-2.40						-1.70	-0.80	0.10	-2.50	-1.00	2.20
	[-0.96]						[-0.64]	[-0.28]	[0.02]	[-1.02]	[-0.42]	[0.49]
GPA		-2.50					-2.00					-2.80
		[-1.96]					[-1.41]					[-1.52]
GPR			-3.20					-2.70				
			[-2.01]					[-1.65]				
WAR				-4.30					-4.30			-3.60
				[-1.63]					[-0.89]			[-0.73]
EPU					1.30					1.40		0.10
					[0.78]					[0.83]		[0.04]
EMV						5.60					5.40	5.80
						[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.8
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 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) as well as on three other indices that are also based on news articles. They are 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. 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.6 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	0.34						0.32	0.28	0.38	0.31	0.36	0.30
	[1.72]						[1.52]	[1.25]	[1.81]	[1.62]	[2.00]	[1.43]
GPA		0.19					0.08					-0.05
		[1.30]					[0.53]					[-0.27]
GPR			0.29					0.11				
			[1.75]					[0.61]				
WAR				0.19					0.01			0.09
				[1.45]					[0.08]			[0.56]
EPU					0.41					0.39		0.41
					[2.32]					[2.18]		[1.80]
EMV						0.07					0.10	-0.10
						[0.28]					[0.45]	[-0.46]
R^2_{within}	0.3%	0.0%	0.1%	0.0%	0.6%	-0.1%	0.2%	0.2%	0.3%	0.8%	0.2%	0.4%
# Obs	1,163	1,163	1,163	1,114	1,163	1,163	1,163	1,163	1,114	1,163	1,163	1,114

PANEL B - Next 5 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	20.57						21.75	22.54	17.69	19.98	19.54	16.09
	[3.23]						[3.30]	[3.15]	[2.65]	[3.05]	[3.21]	[2.45]
GPA		4.47					-3.35					-6.42
		[0.73]					[-0.77]					[-1.47]
GPR			11.38					-3.25				
			[1.62]					[-0.61]				
WAR				13.62					5.21			7.45
				[2.52]					[1.11]			[1.68]
EPU					8.28					6.70		13.23
					[1.38]					[1.16]		[2.24]
EMV						-10.27					-8.23	-11.40
						[-1.67]					[-1.60]	[-2.38]
R^2_{within}	10%	0%	3%	5%	2%	3%	10%	10%	10%	11%	11%	15%
# Obs	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104

Table IA.9
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) as well as on three other indices that are also based on news articles. They are 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. 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.6 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	-0.12	-0.05	-0.08	-0.04	-0.05
	[-1.01]						[-1.25]	[-1.52]	[-0.66]	[-1.19]	[-0.66]	[-0.75]
GPA		0.05					0.08					0.00
		[1.14]					[1.71]					[0.03]
GPR			0.01					0.09				
			[0.18]					[1.68]				
WAR				-0.05					-0.02			0.01
				[-0.78]					[-0.37]			[0.14]
EPU					0.11					0.11		0.11
					[1.61]					[1.70]		[1.45]
EMV						0.24					0.24	0.22
						[2.77]					[2.73]	[2.27]
R^2_{within}	0.0%	-0.1%	-0.1%	-0.1%	0.1%	0.9%	0.0%	0.0%	-0.1%	0.1%	0.9%	0.9%
# Obs	1,163	1,163	1,163	1,114	1,163	1,163	1,163	1,163	1,114	1,163	1,163	1,114

PANEL B - Next 5 Year Returns

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
GPT	-1.10						0.57	2.73	2.74	-1.38	-1.63	2.89
	[-0.19]						[0.08]	[0.30]	[0.54]	[-0.28]	[-0.39]	[0.63]
GPA		-4.55					-4.75					-5.48
		[-1.69]					[-0.89]					[-1.69]
GPR			-4.55					-6.32				
			[-3.63]					[-1.02]				
WAR				-5.64					-6.94			-5.91
				[-3.59]					[-2.27]			[-2.20]
EPU					3.06					3.17		5.58
					[0.84]					[0.93]		[1.40]
EMV						-4.07					-4.24	-5.63
						[-0.87]					[-0.98]	[-1.44]
R^2_{within}	0%	2%	2%	3%	1%	2%	2%	2%	4%	1%	2%	10%
# Obs	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104

Table IA.10
Geopolitical Risks and Firm Investment (Alternative Trend Specifications)

This table reports regressions of variables related to firm investment onto the news-based geopolitical threats (GPT) and acts (GPA) indices from Caldara and Iacoviello (2022) as well as on three other indices that are also based on news articles. They are 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. Both panels use quarterly US data from 1947-Q1 to 2024-Q4. Table 9 regresses log real investment per capita on a time trend (leading to a deterministic investment trend) and lagged risk indices. In this table, Panel A adds log real GDP per capital (which is a common variable to capture a potential stochastic investment trend) and Panel B also adds the log of the S&P500 real price (used in Caldara and Iacoviello (2022) to capture a potential stochastic investment trend). We consider two investment measures: real private fixed investment (as in Caldara and Iacoviello (2022)) and real private nonresidential fixed investment (as in Gennaioli, Ma, and Shleifer (2015)), both obtained from the FRED. The $R^2_{partial} = (R^2 - R^2_{trend})/(1 - R^2_{trend})$ captures the share of variance in detrended log investment explained by the lagged risk indices, comparing the R-squared values from regressions with (R^2) and without (R^2_{trend}) these indices. The risk indices are normalized to z-scores. 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 while Section B.7 covers the results from this table.

PANEL A - Adding $log(GDP)$ to Investment Trend

	Y = Real Private Fixed Investment								Y = Real Private Nonresidential Fixed Investment							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
GPT	-0.01					-0.02	-0.02	-0.02	-0.02					-0.03	-0.02	-0.03
	[-0.95]					[-2.16]	[-1.62]	[-2.83]	[-1.45]					[-2.19]	[-1.21]	[-2.17]
GPA		0.03				0.05		0.06		0.02				0.04		0.04
		[0.84]				[1.78]		[2.44]		[0.46]				[1.00]		[1.12]
WAR			-0.01				-0.00	-0.01			-0.01				-0.01	-0.01
			[-0.40]				[-0.07]	[-0.74]			[-1.24]				[-0.58]	[-0.93]
EPU				0.00				-0.01				0.01				0.01
				[0.01]				[-0.62]				[0.66]				[0.95]
EMV					0.01			0.01					0.01			0.01
					[0.91]			[0.80]					[0.32]			[0.48]
$R^2_{partial}$	2%	2%	1%	0%	1%	6%	2%	10%	2%	1%	2%	1%	0%	6%	3%	9%
# Obs	312	312	292	312	312	312	292	292	312	312	292	312	312	312	292	292

PANEL B - Adding $log(GDP)$ and $log(P_{S\&P500})$ to Investment Trend

	Y = Real Private Fixed Investment								Y = Real Private Nonresidential Fixed Investment							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
GPT	-0.01					-0.02	-0.01	-0.02	-0.02					-0.03	-0.02	-0.03
	[-1.01]					[-1.92]	[-1.38]	[-2.35]	[-1.47]					[-2.11]	[-1.19]	[-2.03]
GPA		0.03				0.05		0.05		0.02				0.04		0.04
		[0.94]				[1.74]		[2.16]		[0.42]				[0.90]		[1.00]
WAR			-0.01				-0.00	-0.01			-0.01				-0.01	-0.01
			[-0.70]				[-0.27]	[-0.97]			[-1.15]				[-0.47]	[-0.93]
EPU				0.01				-0.00				0.01				0.02
				[0.41]				[-0.22]				[0.94]				[1.14]
EMV					0.01			0.01					0.01			0.01
					[0.68]			[0.59]					[0.36]			[0.48]
$R^2_{partial}$	1%	2%	1%	1%	1%	6%	2%	9%	2%	1%	2%	1%	0%	6%	3%	9%
# Obs	308	308	292	308	308	308	292	292	308	308	292	308	308	308	292	292