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Investment-at-Risk of Geopolitical Tensions★

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Abstract

This paper shows that geopolitical risk is an important predictor of tail risks in the investment growth distribution. Using the growth-at-risk framework, we document that higher geopolitical risk predicts lower left tails, while having no impact on the other parts of the distribution. We document higher uncertainty during periods of heightened geopolitical risks, when also the distribution becomes more left-skewed, leading extremely negative outcomes to become more likely. Additional structural analysis based on local projections shows that GPR shocks have larger dynamic effects on the left tail of the distribution, affecting particularly and significantly downside risk.

Keywords: Geopolitical Risk, Investment, Quantile Regressions, Local Projections.
JEL: E31, E32, D24

1. Introduction

Global relationships are deteriorating in many parts of the world and bilateral conflicts arise in a worrying manner. This path is reshaping the geopolitical landscape, and, of course, this is also going to have economic consequences in the short term. The rise in geopolitical risks may be quite harmful to the economy, as has already been documented from the seminal work by Caldara and Iacoviello (2022). Geopolitical shocks are found to lower economic activity, investment, and stock market returns.

Increasing geopolitical risks can be quite harmful for the economic outlook as they can induce an increase in uncertainty about the future. Geopolitical shocks can raise a fear of physical disruptions and a widely perceived weaker environment among economic agents, leading to potential revisions in the implementation of investment projects. Quoted in the seminal paper by Bloom (2009) mentioning a statement of the Federal Open Market Committee (FOMC), *'the events of September 11 produced a marked increase in uncertainty [...] depressing investment by fostering*

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an increasingly widespread wait-and-see attitude[1]*.'* The same paper by Bloom (2009) mentions other major geopolitical episodes, such as the Cuban missile crisis and the assassination of President John Fitzgerald Kennedy. This suggests that geopolitical risk can be an important predictor of future investment growth. This is the issue that this paper deals with. We study the distribution of future investment growth conditional on current geopolitical conditions in the US, through quantile regressions, following the Growth-at-risk (GaR) framework proposed by the seminal paper by Adrian et al. (2019).

We show that raising geopolitical tensions leads to an increase in the downside risk to investment growth, whereas the central and right parts of the distribution do not react to increasing geopolitical risks. The left tail of the one-quarter ahead investment growth distribution is characterized by a higher volatility, which gets worse around major historical episodes of geopolitical risk and uncertainty. During such periods, we document large increases in downside risks and uncertainty in the distribution of future investment growth, which becomes more left-skewed, thus leading very bad outcomes to become more likely. Typically, a higher geopolitical risk is associated with increasing financial stress (De Luca et al., 2025). However, we find that, after controlling for financial stress, a higher GPR is still associated with increasing effects across the quantiles of the future investment growth distribution.

This result remains robust to the use of alternative empirical strategies, such as distribution regressions (Foresi and Peracchi, 1995). Following Loria et al. (2025), we estimate the impulse response functions using local projections for the quantiles of the distribution and the interquantile range after a geopolitical risk shock.

The remainder of the paper is structured as follows. Section 2 discusses related literature. We first recall the "at-risk" framework, which is becoming very widespread in the empirical macroeconomic literature, and then we discuss the evidence on the relationship between uncertainty and geopolitical risk with investment. Section 3 presents the empirical analysis with a discussion on the results, and Section 4 provides some additional robustness checks. Section 5 shows the results of the local projections. Section 6 concludes, while an Appendix contains additional results and robustness checks.

2. Related literature

2.1. The "at-risk" framework

The Growth-at-Risk (GaR) framework has evolved as a central paradigm in macrofinancial risk analysis, capturing not only expected outcomes, but also the asymmetry and fat tails that characterize the distribution of macroeconomic outcomes under stress. Its conceptual basis stems from the Value-at-Risk (VaR) models in finance, but its adaptation to the macroeconomic domain has opened up new possibilities for understanding economic vulnerabilities. Instead of asking how much value a portfolio might lose, GaR asks how bad macroeconomic outcomes, such as GDP growth, inflation, or public debt, can become, given current financial and economic conditions.

[1]Ginn and Saadaoui (2025) shown that, after a geopolitical risk shock, the policy reaction is accommodating in the short run (1 to 2 months) to limit the negative effects on consumer sentiment. In the medium term (12 to 15 months), the central bank is more committed to combating inflation pressures.

This is achieved by estimating full conditional distributions, typically through quantile regressions (Koenker and Bassett, 1978), allowing slope coefficients to vary between quantiles and capturing asymmetric relationships among predictors and macroeconomic outcomes. This framework has been introduced by the seminal paper by Adrian et al. (2019), which documents how tighter financial conditions, proxied by the Chicago Fed's National Financial Conditions Index (NFCI), affect the lower quantiles of GDP growth much more than the upper ones. They revealed a strong asymmetry in the relationship between current financial conditions and future GDP growth, where latent downside risks intensify even during periods of low realized volatility, echoing the dynamics predicted by financial accelerator models (Bernanke et al. (1999)).

This foundational work triggered a wave of empirical applications examining how different predictors, policy tools, and macroeconomic fundamentals influence the entire distribution of different macroeconomic outcomes. We can list some relevant examples below.

Boyarchenko et al. (2020) apply this framework in the context of capital requirements in the banking sector and show that higher Tier-1 capital ratios substantially mitigate the lower tail of growth while leaving the median relatively unchanged. This confirms that capital requirements can function as a form of macroprudential insurance against adverse outcomes, especially through credit stress channels. Gelos et al. (2022) developed a Capital-Flows-at-Risk (CaR) framework to quantify the vulnerability of portfolio inflows to global shocks. Their results highlight that macroprudential policies, especially FX interventions and capital flow management tools, can significantly compress the left tail of capital inflows, reducing the risk of sudden stops. However, discretionary capital controls can inadvertently worsen downside risk by amplifying uncertainty. Lopez-Salido and Loria (2024) study the conditional distribution of inflation for a panel of OECD countries, finding a low and stable evolution of the mean but a high volatility in the tails, with financial conditions affecting asymmetrically the inflation distribution. Furceri et al. (2025) focus on the public debt-to-GDP distribution and analyze how economic, financial, and political factors affect the debt-to-GDP distribution. They construct a Debt-at-Risk measure across 90 countries and find highly non-linear effects of global financial conditions and fiscal fundamentals on the 95th percentile of future debt ratios. Kladakis and Skouralis (2025) further document that sovereign credit rating downgrades exert large and persistent downward shifts in the 5th percentile of GDP growth, particularly for countries with speculative grade bonds[2].

This shows that this framework has been widely applied and used to study the relationship between different predictors and for other macroeconomic outcomes beyond GDP growth. We contribute to this literature by providing the first analysis on how current geopolitical conditions affect the distribution of future investment growth.

2.2. *Investment-at-risk*

Another related field of studies is the one that analyzes the relationship between uncertainty / geopolitical risk and investment. The modern debate on how uncertainty shapes capital formation begins with theory establishing two opposing forces. Under convex profits and flexible adjustment,

[2]There are several other examples which we do not detail here for the sake of brevity, which however witnesses that the approach adopted in this paper has been widely used to study the asymmetric relationship between diferent predictors and macroeconomic outcomes.

uncertainty can increase the marginal value of capital, as described by the Oi-Hartman-Abel mechanism (Abel, 1983, Hartman, 1972). In contrast, when investment is irreversible, uncertainty increases the option value of waiting and depresses investment, an insight formalized in real-options models (McDonald and Siegel, 1986) and synthesized by Dixit and Pindyck (1994). Early empirical work quickly tilted the balance towards this latter view in real economies: policy and political uncertainty were shown to act like a tax on private investment, especially in developing countries (Rodrik, 1991), and aggregate and firm-level evidence linked higher uncertainty to weaker capital spending (Ferderer, 1993, Guiso and Parigi, 1999, Leahy and Whited, 1996).

In the 2000s and early 2010s, the literature moved from "uncertainty in general" to political / geopolitical channels and to the near-term propagation of shocks. Bloom (2009) showed that uncertainty shocks generate sharp but temporary freezes in hiring and capex canonical real-option dynamics in macro data. War and conflict depress trade, offering a concrete path from geopolitics to investment through external demand and supply chains (Glick and Taylor, 2010). At the microfinance interface, the corporate capex was shown to fall around national elections (Julio and Yook, 2012), while asset pricing work demonstrated that political uncertainty increases risk premia and tightens financial conditions (Pástor and Veronesi, 2013). The arrival of scalable text-based measures, most notably economic policy uncertainty (EPU), enabled systematic documentation that increased policy uncertainty is associated with lower investment and hiring across countries (Baker et al., 2016). Related work on trade-policy uncertainty showed depressed export entry and technology upgrade investment (Handley and Limão, 2017), again mapping political risk into real corporate decisions.

A decisive step in the last decade was to measure geopolitical risk (GPR) directly. Caldara and Iacoviello (2022) constructed a news-based GPR index that increases near wars and major geopolitical crises and critically foreshadows a decrease in investment and employment in macro-data. This measure catalyzed a wave of studies quantifying the investment response through three mutually strengthening channels. First, there is an uncertainty channel / real options, where GPR increases the value of waiting and reduces capex; second, there is a risk premium channel / cost of capital, through which geopolitical tensions lift required returns and tighten financial conditions, lowering q and investment (extending Pástor and Veronesi (2013)); and third, there is a trade channel / energy / supply chain, through which GPR disrupts input markets and export prospects, depressing the profitability of long-lived projects (Glick and Taylor, 2010, Handley and Limão, 2017). At the same time, cross-border flow surveillance documents that an increasingly fraught geopolitical environment is associated with weak or rerouted FDI, consistent with firms' preference for predictable policies and secure supply lines.

At the firm level, the evidence from the past decade is especially clear. Using the GPR index, Wang et al. (2024) show a strong negative relation between GPR and corporate investment in U.S. data: a doubling of GPR predicts roughly a 14% decline in next-quarter investment relative to its sample mean. The effect is stronger for firms with more irreversible capital and greater market power, precisely as real-options logic predicts, while operational flexibility, e.g., substituting labor for capital, attenuates the decline. In other words, the empirical evidence shows that the real option force dominates the theoretical countervailing Oi–Hartman–Abel effect in practice. Complementing these capex results, recent corporate finance studies find that higher geopolitical risk is associated with more conservative financial policies (e.g., lower leverage) and altered liquidity management, further tightening the link from GPR to investment through the financing margin.

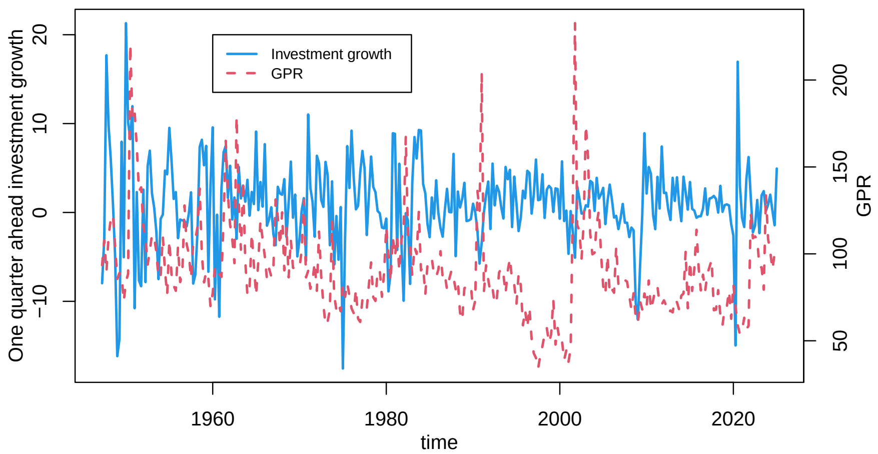
With credible GPR measurement in hand, the post-2015 literature converges largely: geopolitical risk depresses investment. In macro data, GPR shocks lead to weaker capex and employment through uncertainty, higher risk premia, and trade/energy disruptions (Caldara and Iacoviello, 2022). In micro data, exposure and irreversibility magnify cuts, while flexibility and diversified supply chains cushion them (Wang et al., 2024). Therefore, the literature so far has shown that the real-options channel dominates and therefore there is a negative relationship between geopolitical risk and investment. However, there are no studies that specifically analyze how geopolitical risk affects the distribution of future investment growth. This is the gap that this study tries to fill.

3. Data and empirical analysis

3.1. Data description

We use the Geopolitical Risk Index (GPR), developed by Caldara and Iacoviello (2022), to capture the evolutions of geopolitical tensions and the quarter-on-quarter growth rate of Gross Private Domestic Investment (GPDI) to gauge investment growth conditions in the US economy.

Figure 1: Historical GPR and quarter-on-quarter investment growth.



Note The left-hand side vertical axis is for investmente growth, whose series is shown by the blue solid line. The right-hand side vertical axis is for the GPR index, which is shown by the red dashed line.

Our sample is on a quarterly frequency and spans the period 1947q1-2025q1. We use the Historical GPR index, which is available for a longer time span and allows us to exploit the full sample period in which data on investment are available. The data were downloaded from Matteo Iacoviello's website. The index is at monthly frequency, and to match the quarterly frequency of the series on investment, we take the average of the three months of each quarter. The investment data are taken from the FRED database. We collect the variable at constant prices and then compute the quarter-on-quarter growth rate as the first difference of the log of investment. The resulting series are shown in Figure 1.

3.2. Empirical analysis

As already mentioned in the Introduction, geopolitical shocks can be detrimental to investment (Bloom, 2009), therefore a rise in geopolitical risk can be an important predictor of future investment growth. However, as recently highlighted in the literature on growth-at-risk, traditional OLS forecasts only predict average outcomes, and as a consequence they fail to capture the asymmetric risks and the periods of high volatility that, in our case, may be of paramount importance (Furno et al., 2025). In fact, investment growth is particularly volatile, as can be seen in Figure 1, and is much more volatile than other macroeconomic variables such as GDP growth. Moreover, the time evolution of the variables also suggests that there are periods of heightened geopolitical shocks, which are large in magnitude.

Let us then start from a simple OLS forecast in which an AR(1) model for the investment growth is augmented with current realizations of the GPR index:

$$y_{t+h} = \alpha + \beta x_t + \gamma y_t + \varepsilon_{t+h} \tag{1}$$

where y_t is investment growth and x_t is the GPR index. The results are in Table 1, where the first column shows the results of a simple AR(1) model, while the second column provides the estimates when we include the GPR as additional predictor.

Table 1: OLS estimation of equation (1) with and without the GPR.

	y_{t+1}	
α	0.825	1.238
	(0.291)	(0.881)
y_t	0.172	0.171
	(0.081)	(0.082)
x_t		-0.005
		(0.009)

Note: The first column shows the results of the OLS estimation of an AR(1) model for investment growth, while the second column adds the GPR index. In brackets are the HAC standard errors.

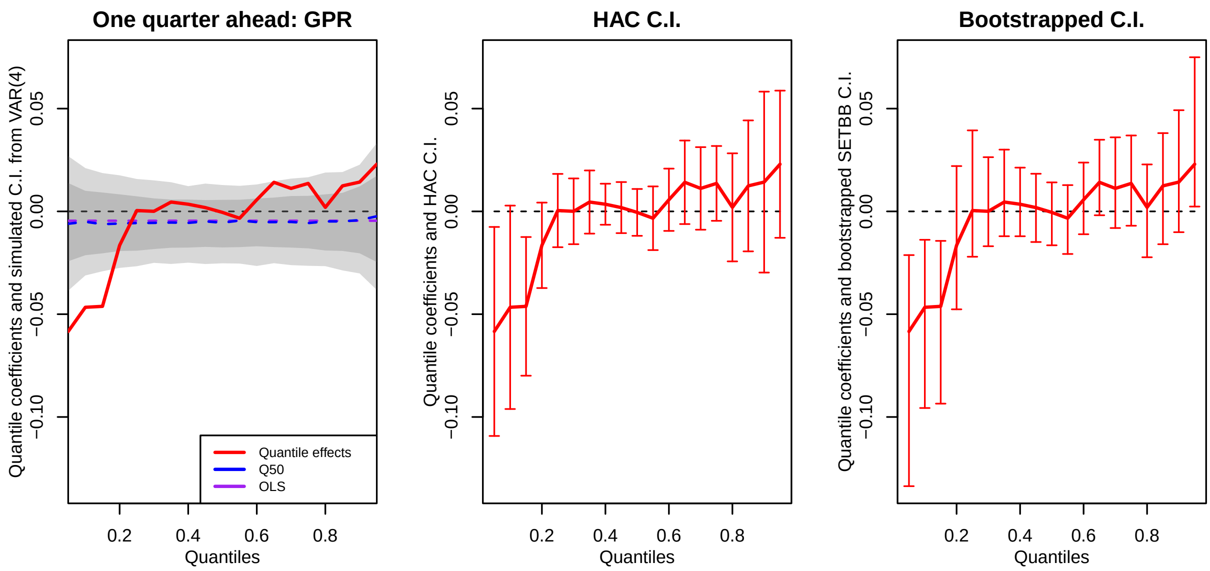
The first thing we may notice is that investment growth is characterized by some degree of persistence, as the AR(1) coefficient approaches 0.20 and is statistically significant. However, turning to our interest in the role of the GPR, the second column shows that the coefficient is negative, but it is not statistically significant. Thus, we may be tempted to conclude that geopolitical risks do not play a role in explaining a quarter ahead of investment growth. In what follows, we show that this conclusion is not correct and that the relationship between heightened geopolitical tensions is highly asymmetric. We borrow the growth-at-risk methodology from (Adrian et al., 2019), relying on quantile regressions, to assess how geopolitical shocks affect the distribution of future investment growth asymmetrically. This approach is gaining prominence in the field of empirical macroeconomics, and its application is growing faster and faster, with extensions that go beyond the original relationship between financial conditions and GDP growth (Boyarchenko et al., 2020, Kladakis and Skouralis, 2025), and beyond growth-at-risk to explore tail risks in other macroeconomic variables (Furceri et al., 2025, Gelos et al., 2022, Lopez-Salido and Loria, 2024).

Thus, we estimate equation (1) for different quantiles, and the conditional quantile function will be given by the following:

$$Q_{\tau}\left(y_{t+h}|x_t, y_t\right) = \alpha_{\tau} + \beta_{\tau}x_t + \gamma_{\tau}y_t \tag{2}$$

The main coefficient of interest is β_{τ}, which tells us whether a higher geopolitical risk in the current quarter heterogeneously affects the distribution of investment growth in the next quarter. We estimate this coefficient for τ that varies from the 5-th quantile to the 95-th quantile, with steps equal to 5.

Figure 2: Estimated quantile coefficients of one quarter ahead investment growth on GPR.



Note The red solid lines indicate the estimated quantile coefficients β_{τ} associated with the GPR index in equation (2), for τ ranging between the 5-th up to the 95-th quantile. The left panel plot the 68% and 90% confidence intervals obtained from a simulated VAR(4) process (see Adrian et al. (2019)) with gray shaded areas. The whiskers in the middle and right panel show the 90% confidence intervals around the point estimates, based on, respectively, the HAC estimator for quantile regressions (Galvao and Yoon (2024)) and the smooth extended tapered block bootstrap (SETBB) for quantile regressions (Gregory et al. (2018)).

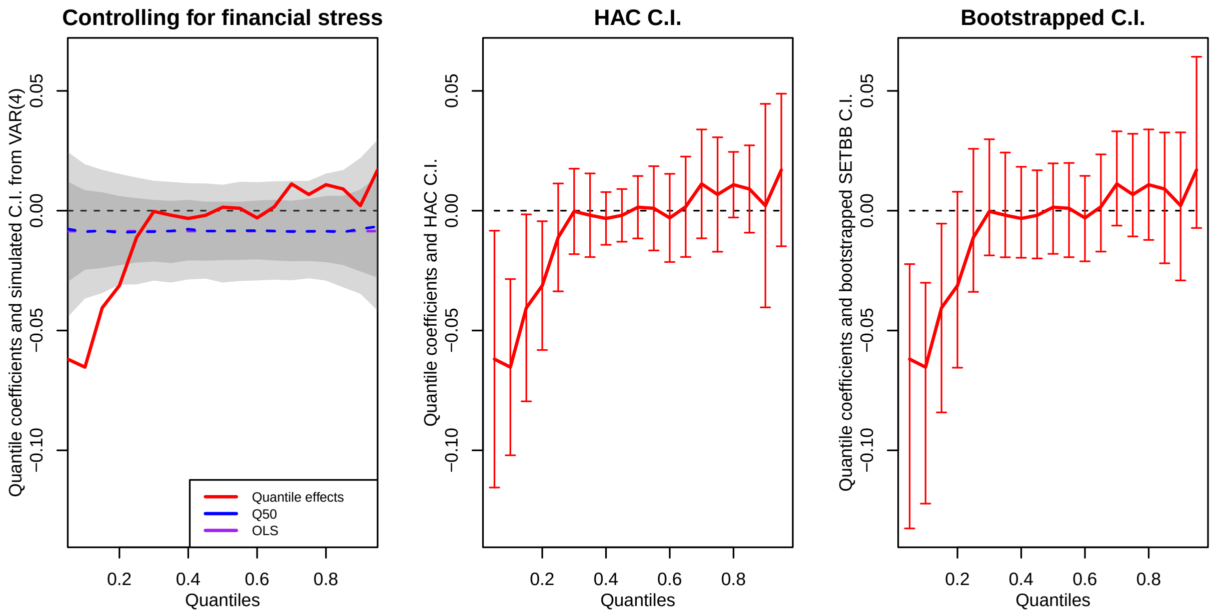
We carry out inference on this quantile regression following Furno et al. (2025). First, we test whether the quantile effects are statistically significantly different from a linear model as in Adrian et al. (2019). We estimate a VAR(4) with the GPR and investment growth, and simulate 1000 samples from the VAR DGP. For each sample, we estimate the quantile regression in equation (2) and compute the confidence limits for the null hypothesis that the true data generation process (DGP) is linear (see Figure 2 left panel).

Second, as in Furno et al. (2025), we additionally conduct direct inference on the quantile coefficients using HAC standard errors for quantile regressions, recently introduced by Galvao and Yoon (2024) (see Figure 2 middle panel), and we also rely on the smooth extended tapered block bootstrap (SETBB) for quantile regressions with time series proposed by Gregory et al. (2018) (see

Figure 2 right panel), which has been used in the growth-at-risk framework by previous papers such as Boyarchenko et al. (2020).

Figure 2 clearly shows that the relationship between geopolitical risk and investment growth is asymmetric and that relying on linear models would mistakenly lead us to conclude that geopolitical shocks and future investment growth are completely unrelated. The results tell us that a higher GPR significantly predicts a much lower left tail in the future investment growth distribution, while not impacting the rest of the distribution. The coefficients on the left tail go outside the confidence bounds for the null hypothesis that the relationship is linear, and the confidence intervals around the point estimates do not contain zero. The effect is particularly the strongest on the fifth quantile, which, borrowing the jargon from the growth-at-risk literature, we can define as investment-at-risk.

Figure 3: Estimated quantile effects of GDP on future investment growth controlling for financial stress.

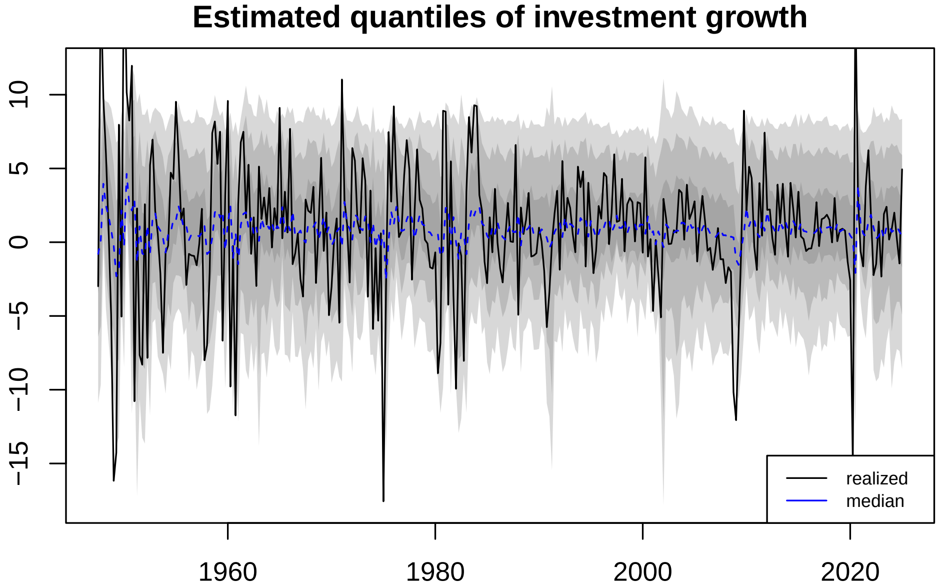


Note The red solid lines indicate the estimated quantile coefficients, β_τ, associated with the GPR index in equation (2) when the financial stress index, constructed in Appendix Appendix B, is added as additional control, for τ ranging between the 5-th up to the 95-th quantile. The left panel plot the 68% and 90% confidence intervals obtained from a simulated VAR(4) process with investment growth, the GPR and the financial stress index (see Adrian et al. (2019)) with gray shaded areas. The whiskers in the middle and right panel show the 90% confidence intervals around the point estimates, based on, respectively, the HAC estimator for quantile regressions (Galvao and Yoon (2024)) and the smooth extended tapered block bootstrap (SETBB) for quantile regressions (Gregory et al. (2018)).

Therefore, higher geopolitical risk increases the downside risk to investment, predicting lower left tails in the investment growth distribution while not having any effects on the rest of the distribution. Thus, it leads to an outward shift of the left tail of the investment growth distribution, raising investment vulnerabilities.

Moreover, geopolitical shocks affect the financial markets inducing financial stress (De Luca et al., 2025), which in turn may depress investment. However, as shown by Figure 3 the asymmetric relationship between current GPR and future investment growth is still present even if we add a financial stress index[3] into our baseline quantile regression model in equation (2)[4].

Figure 4: Conditional quantiles of one quarter ahead investment growth



Note The plot shows the realized series of investment growth along with the conditional median, whereas the shaded areas are delimited by the interquartile range (25-th and 75-th quantiles), the range between the 10-th and 90-th quantiles and between the 5-th and the 95-th quantile, obtained by computing fitted values for the selected quantiles in equation (2).

Finally, we show here that, as a result of the analysis conducted above, the left tail will be more volatile, while the right tail is fairly stable, as it is clearly shown by Figure 4, and this is what we could not have captured relying on standard OLS, as we would have seen both the right and the left tail moving in parallel with the central part of the distribution (Furno et al., 2025).

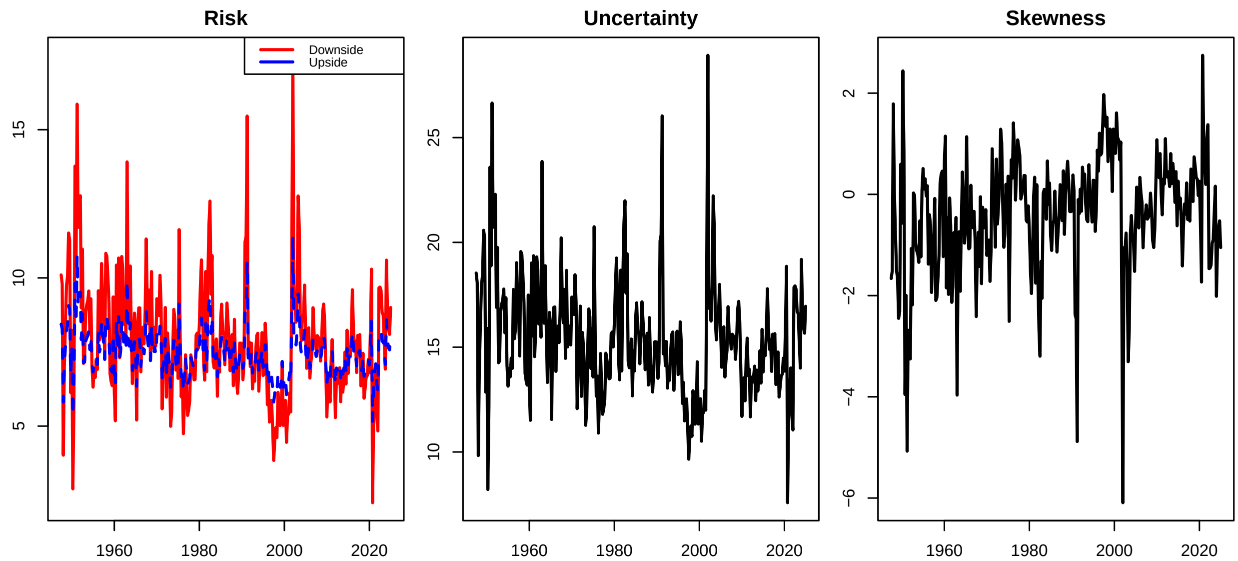
[3]Unfortunately, there are no financial stress indexes that cover our entire sample. In order to construct a proxy, we merge the Financial Stress Index constructed by Püttmann (2018), through newspapers text search methods, which run from 1889:I up to 2016:IV and the Financial Stress Index developed by the FED of St. Louis, which runs from 1994:I up to 2025:I. Details on the construction of the index are in Appendix B.

[4]In Appendix A, we show that the GPR is not a predictor of the growt-at-risk. Indeed, Figure Appendix A.1 shows that there are no asymmetric effects of current GPR on the one quarter ahead GDP growth distribution. Therefore, this highlights that our baseline result is not driven by higher macroeconomic risks, but rather still confirms that there is an expectation channel that induces wait and see behaviors, as extensively discussed in sections 1 and 2.2. This last channel is also corroborated by the results in Figures Appendix A.3 and Appendix A.4 which show that are the threats of raising geopolitical risks to determine the heterogeneity in the quantile coefficients, rather than the acts. Finally, excluding the sample after 2019, to rule out the Covid-19 observations, characterized by relevant movements in the investment series, does not affect our baseline results (see Figure Appendix A.2).

To shed further light on the evolution over time of the risks surrounding the future investment growth distribution after an increase in geopolitical risk, and gauge their asymmetric relationship over time, in particular around historical episodes of heightened tensions, we also compute three further measures, as in Forni et al. (2024), which are given by the following:

- Downside risk: $\hat{Q}_{0.50}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right) - \hat{Q}_{0.05}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right)$;
- Upside risk: $\hat{Q}_{0.95}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right) - \hat{Q}_{0.50}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right)$;
- Uncertainty: $\hat{Q}_{0.95}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right) - \hat{Q}_{0.05}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right)$;
- Skewness: $\hat{Q}_{0.95}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right) + \hat{Q}_{0.05}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right) - 2\hat{Q}_{0.50}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right)$;

Figure 5: Evolution over time of risk, uncertainty and asymmetry in the conditional distribution of investment growth.

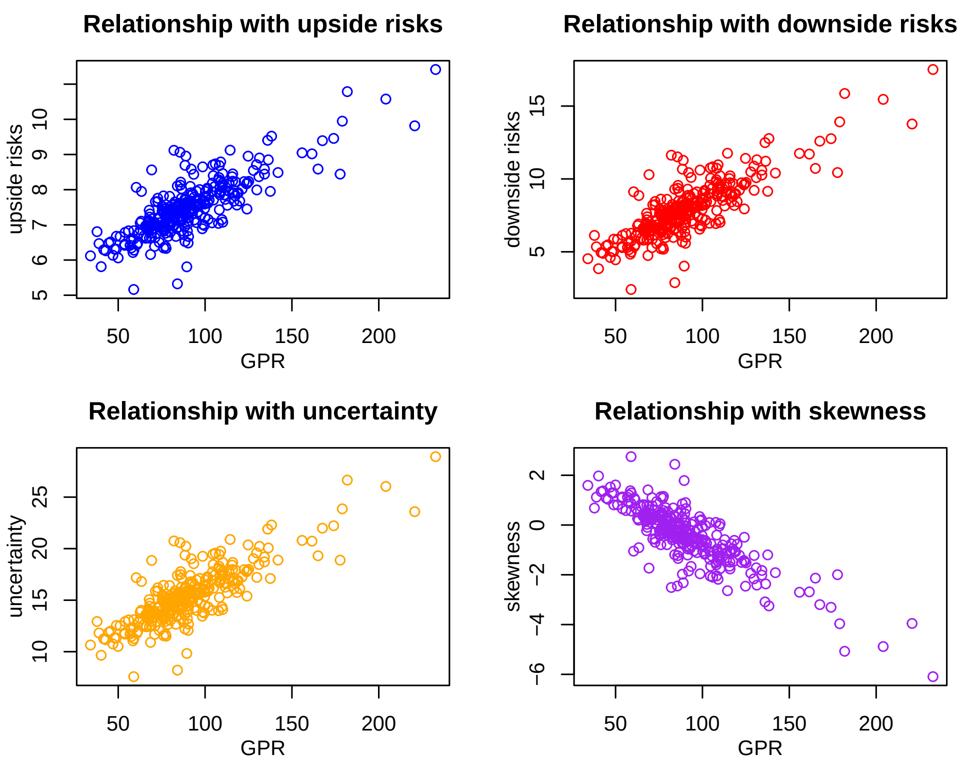


Note The left panel shows the evolution over time of the downside (red solid line) and upside (blue dashed line) risks to the conditional investment growth distribution, computed as, respectively, $\hat{Q}_{0.50}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right) - \hat{Q}_{0.05}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right)$ and $\hat{Q}_{0.95}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right) - \hat{Q}_{0.50}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right)$. The middle and right panels show the evolution overt time of uncertainty and skewness in the conditional distribution, computed as, respectively, $\hat{Q}_{0.95}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right) - \hat{Q}_{0.05}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right)$ and $\hat{Q}_{0.95}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right) + \hat{Q}_{0.05}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right) - 2\hat{Q}_{0.50}\left(\Delta I_{t+1}|GPR_t, \Delta I_t\right)$.

Figure 5 shows the evolution of these measures. It can be seen that downside risk is more volatile and reaches higher peaks than upside risk, especially during major geopolitical disruptions. Moreover, both uncertainty and asymmetry show a high time variation. These series record peaks at major geopolitical events such as the Korean War in the early 1950s, during the OPEC crises and the wars in the Middle East in the 1970/80s, around the 'cold war' period, and markedly so at the time of the 9/11 terrorist attacks. Other minor peaks occur with the beginning of the Russian-Ukrainian conflict. During and around these episodes, we document greater increases in downside risk than upside risk, accompanied by a marked growth in investment uncertainty. Finally, the distribution of future investment growth becomes more skewed to the left as geopolitical tensions arise, as shown by the right panel of Figure 5. The skewness measure becomes more negative during the historical episodes of heightened geopolitical tensions highlighted above. Therefore, higher GPR leads very bad outcomes to become more likely.

Figure 6 confirms this narrative discussion, by showing scatterplots of the measures computed above against the realizations of the GPR. A positive relationship between GPR and risks and uncertainty, and a negative relationship between GPR and skewness are found. Higher geopolitical risks tend to be followed by higher risks to investment growth, by a higher uncertainty in the distribution and by a more negative skewness.

Figure 6: Relationships between GPR and predicted quantiles of future investment growth.



Note The figure plots the 95-th predicted quantile, the 5-th predicted quantile, the predicted median, and the predicted variance (given by the difference bewteen the 95-th and 5-th predicted quantiles), computed using fitted values of the selected quantiles from equation (2), against the realizations of the GPR.

4. Evidence based on distribution regressions

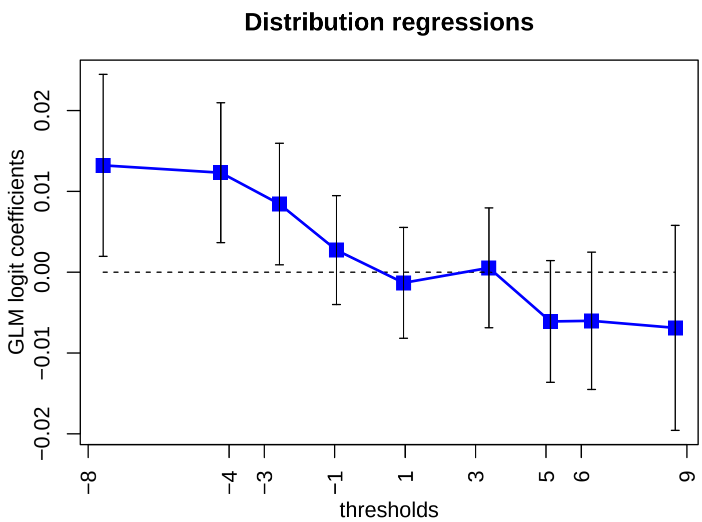
So far, we have relied on quantile regressions in order to capture the asymmetric relationship between current geopolitical risks and future investment growth. In this section, we show that we reach the same conclusions even when adopting alternative estimation strategies to gauge the effects of higher GPR on the distribution of future investment growth. Quantile regressions provide a tool to capture the effects of current geopolitical conditions on the distribution of future investment growth. However, there are other interesting tools that have been proposed to estimate the effects of a predictor on the distribution of an outcome variable, such as distribution regressions see (Foresi and Peracchi, 1995).

In this section, we follow (Boyarchenko et al., 2020) and use alternatively this strategy, in order to see whether the results are robust to the modeling approach. The idea is to estimate the effects of a predictor on the probability that the outcome variable will fall below a specific threshold, say k. This approach is considered as an alternative to estimating linear conditional quantile models (Koenker and Hallock, 2001). Thus, following this approach, we, first, define a dummy variable which equals 1 if the one quarter ahead investment growth is less than or equal to a threshold k. Then, we estimate a series of logistic regressions of this binary variable, one for each threshold k, on the predictors in the baseline model:

$$\log\left(\frac{\pi_{t+h,k}}{1-\pi_{h,t+h,k}}\right) = \alpha_k + \beta_k x_t + \gamma_k y_t + \omega_{t+h,k} \tag{3}$$

with $\pi_{h,t+h,k} = Pr(y_{t+h} \leq k)$. Therefore, we estimate equation (3) for different values of k and, in particular, we consider the 5-th, 10-th, 15-th, 25-th, 50-th, 75-th, 85-th, 90-th, and 95-th quantiles of the investment growth distribution as thresholds. This allows us to trace out the relationship between the predictor and the cumulative density function of the outcome variable (see Boyarchenko et al. (2020)).

Figure 7: Results from the distribution regressions in equation (3).



Note The plot shows the estimated logit coefficients (blue line with squares), $\hat{\beta}_k$ in equation (3), for the effects of the GPR index on the probability that investment growth next quarter ahead will fall below different thresholds k indicated in the x-axis. The whiskers represent the 90% HAC confidence intervals around the point estimates.

Figure 7 shows the results from the estimation of equation (3). The blue line with squares indicates the estimated values of the coefficient $\hat{\beta}_k$, for the thresholds k indicated in the x-axis, which correspond to the 5-th, 10-th, 15-th, 25-th, 50-th, 75-th, 85-th, 90-th, and 95-th quantiles of the unconditional distribution of investment growth, as already mentioned above. For example, the first square on the left part of the blue line represents the logit coefficient for the effects of the GPR on the probability that investment growth one quarter ahead will fall below -8%. Then, the second square starting from the left of the plot indicates the logit coefficient for the effects of the GPR on the probability that investment growth one quarter ahead will fall below -4%, and so on. This allows us to gauge the effects of GPR on the distribution of future investment growth, as already explained above. If the logit coefficients were constant across thresholds, a change in the GPR today would only be a location shifter of the future investment growth distribution (Foresi and Peracchi, 1995). However, we can see that such coefficients are heterogeneous across thresholds and confirm what we find through quantile regressions. Indeed, the coefficients change from positive values to non-significant negative ones, with a decreasing path as the threshold increases.

This confirms the results from quantile regressions and suggests that higher geopolitical risk predicts much lower left tail, whereas it does not affect the right tail of future investment growth. This shows that our baseline results are genuine features of the data and are not affected by the choice of the particular estimation method, thus ensuring the robustness of the findings from the quantile regressions.

5. Local Projections

This section studies the dynamic effect of a geopolitical risk (GPR) shock on the entire conditional distribution of U.S. investment growth. We adopt the two–step quantile–local-projection (QR-LP) approach of Loria et al. (2025) to obtain impulse responses for distributional quantiles and inter-quantile ranges. In the first step, we use the fitted quantiles from the QR in Section 3 as our time-t measures of "investment-at-risk". In the second step, we trace how these quantiles react over horizon s to an innovation in GPR. This procedure separates the forecast horizon of the quantile (fixed at one period ahead) from the impulse-response horizon s (quarters or months after the shock), and it places minimal structure on the data-generating process.

5.1. Setup and identification

We study how a geopolitical risk (GPR) shock reshapes the *entire* conditional distribution of U.S. investment growth by combining the one–step–ahead quantile forecasts from Eq. (2) with local projections (LP) for those quantiles.[5] Let $q_{\tau,t}$ denote the fitted τ–quantile of next–period investment growth from Eq. (2), with $\tau \in \{0.05, 0.50, 0.95\}$.

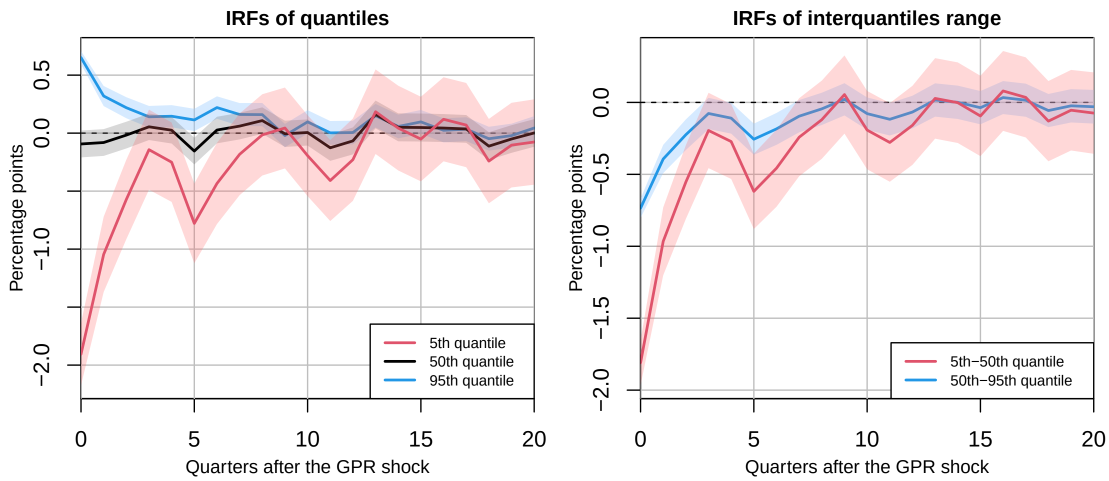
For horizons $s = 0, \dots, S$, we estimate

$$q_{\tau,t+s} \;=\; \delta^s_\tau \;+\; \theta^s_\tau\, \varepsilon^{\mathrm{GPR}}_t \;+\; \sum_{j=1}^{p} \phi^s_{\tau,j}\, Z_{t-j} \;+\; u^s_{\tau,t+s}, \tag{4}$$

[5]Our QR–LP implementation mirrors the two–step approach in Loria, Matthes and Zhang, *The Economic Journal*, "Assessing Macroeconomic Tail Risk," which cleanly separates the *forecast horizon* of the quantile from the *impulse–response horizon* and propagates uncertainty from both steps via bootstrap.

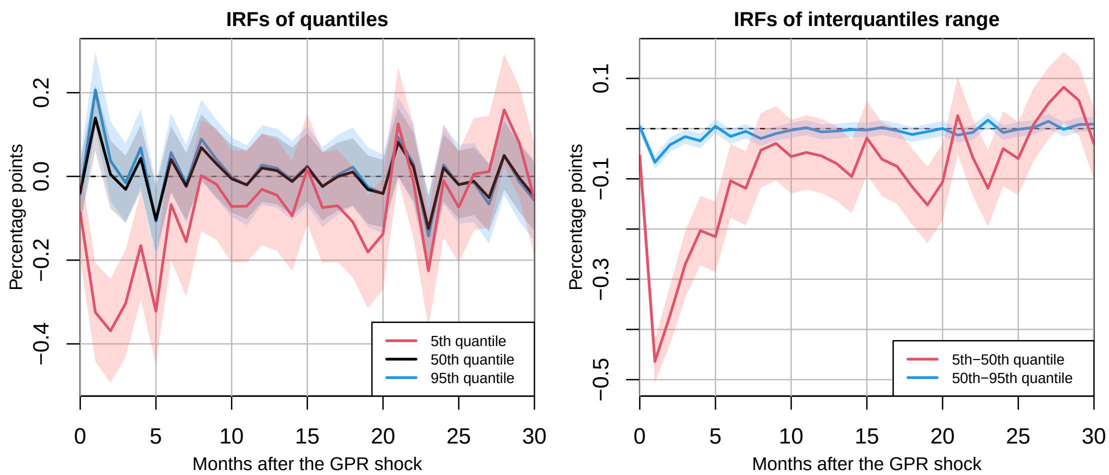
where $\varepsilon_t^{\text{GPR}}$ is a one–standard–deviation innovation to the GPR index (standardized change), and Z_t collects controls (frequency–specific below). To assess tail asymmetry directly, we also run inter-quantile LPs. Confidence bands are at 95%. Horizons are in quarters (monthly) when the data are quarterly (monthly). Point estimates are reported together with shaded bands in the figures below.

Figure 8: Local Projections estimates (quarterly data).



Note The chart shows the IRFs of the quantiles and interquantiles ranges to a GPR shock, with the associated 95% confidence intervals represented by shaded areas. The analysis is based on local projections estimated using quarterly data.

Figure 9: Local Projections estimates (monthly data).



Note The chart shows the IRFs of the quantiles and interquantiles ranges to a GPR shock, with the associated 95% confidence intervals represented by shaded areas. The analysis is based on local projections estimated using monthly US national account constructed by Barrett (2025).

5.2. *Quarterly specification: no controls, full sample*

For the quarterly LP, we include *no additional controls*, i.e., $Z_t = \varnothing$, and use the full quarterly sample available for investment and GPR (1947:Q1–2025:Q1). The fitted quantiles $q_{\tau,t}$ entering in Eq. (4) are obtained from the *full-sample* estimates of Eq. (2). We set $S = 20$ quarters.

Figure 8 summarizes the impulse responses of the 5th, 50th, and 95th quantiles (left panel) and of the inter-quantile ranges (right panel). A GPR shock depresses the left tail (5th percentile) markedly and persistently, while the median moves much less and the 95th percentile is near zero; correspondingly, the (5th – 50th) range becomes significantly negative over several quarters, whereas the (50th – 95th) range is statistically indistinguishable from zero. These results indicate a *left-tail amplification* rather than a uniform location shift.[6]

5.3. *Monthly specification: controls for VIX and Consumer Sentiment, VIX-start sample*

For the monthly LP, we rely on the US national account data constructed by Barrett (2025). We augment the specification with financial-market and consumer expectations controls,

$$Z_t \;=\; \big[\,\mathrm{VIX}_{t-j},\ \mathrm{UMCSENT}_{t-j}\,\big]_{j=1}^{4},$$

where VIX is the CBOE volatility index and ICS is the University of Michigan Index of Consumer Sentiment; twelve monthly lags absorb persistence and mitigate confounding. The sample starts when VIX is first available (early 1990s; we use 1990:M1 as the baseline start) and runs to the end of our monthly sample; we set $S = 30$ months.

Figure 9 reports the monthly IRFs. The wedge between the 5th and 50th percentiles opens quickly and remains negative for an extended period, while the (50th – 95th) response is small and not statistically different from zero. Hence, even after conditioning on market volatility and household sentiment, GPR shocks disproportionately load the left tail of the one-month-ahead investment-growth distribution.[7]

5.4. *Presentation and inference*

In all plots, the solid lines depict point estimates and shaded areas the 95% bands. Horizons on the x-axis are measured in quarters (Figure 8) or months (Figure 9). Because our object of interest is distributional, we report both quantile-specific IRFs and inter-quantile IRFs; the latter provide a formal test that the lower tail reacts more than the center or the upper tail. Methodologically, this mirrors the QR-LP design in Loria et al. (2025), which shows that focusing on inter-quantile responses is essential to document tail-specific dynamics robustly.

5.5. *Findings and interpretation*

Across frequencies, the 5th percentile of the one-period-ahead investment-growth distribution responds much more than the median to a GPR shock, while the 95th percentile barely reacts. The inter-quantile IRFs confirm that the (5th–50th) range becomes significantly more negative, indicating an increase in downside risk conditional on higher geopolitical tensions; by contrast,

[6] See Figure 8 ("Local Projections estimates (quarterly data)") for the full set of IRFs and 95% bands.

[7] See Figure 9 ("Local Projections estimates (monthly data)") for quantile and inter-quantile IRFs with 95% bands.

the (50th–95th) range is close to zero. These results—shown in Figure 8 (quarterly) and Figure 9 (monthly with VIX and US consumer sentiment controls)—are consistent with the macro-risk pattern documented by Loria et al. (2025): adverse shocks redistribute probability mass toward the left tail far beyond their effect on average outcomes, a hallmark of non-linear propagation.

6. Conclusions

This paper is a first attempt to understand how geopolitical shocks heterogeneously predict the one-quarter ahead investment growth distribution in the US, by using quantile regressions. We show that higher geopolitical risk today is more likely to increase downside risks to investment rather than fueling the upside risk. Higher GPR today predicts lower left tails in the future investment growth distribution, thus very negative outcomes become more likely relative to very good outcomes.

We document that periods of heightened geopolitical risk are associated with higher downside risks, uncertainty, and negative skewness in the future investment growth distribution. Therefore, geopolitical shocks happening today may be detrimental for the evolution of the economy in the next few months after, by making it more likely that investment will be depressed. Additional structural evidence based on local projections shows that GPR shocks affect the left tail of investment growth more, while the central part of the distribution and the right tail are hardly impacted. Therefore, GPR shocks are important contributors to the downside risk to investment growth. This has relevant practical and policy implications. Being investment an important contributor to GDP and the engine of growth and future development, this can create severe issues for the entire economy.

Therefore, this suggests that policymakers should care about periods of heightened geopolitical risk and uncertainty, by designing policy interventions that help to caution against the potential increases in the downside risk to investment and to reestablish the investors' confidence, in order to avoid that the economy slips into a recession.

This opens up new spaces for future research that tries to analyze whether monetary, fiscal, or other macroeconomic policies can be more effective during periods of heightened geopolitical risks.

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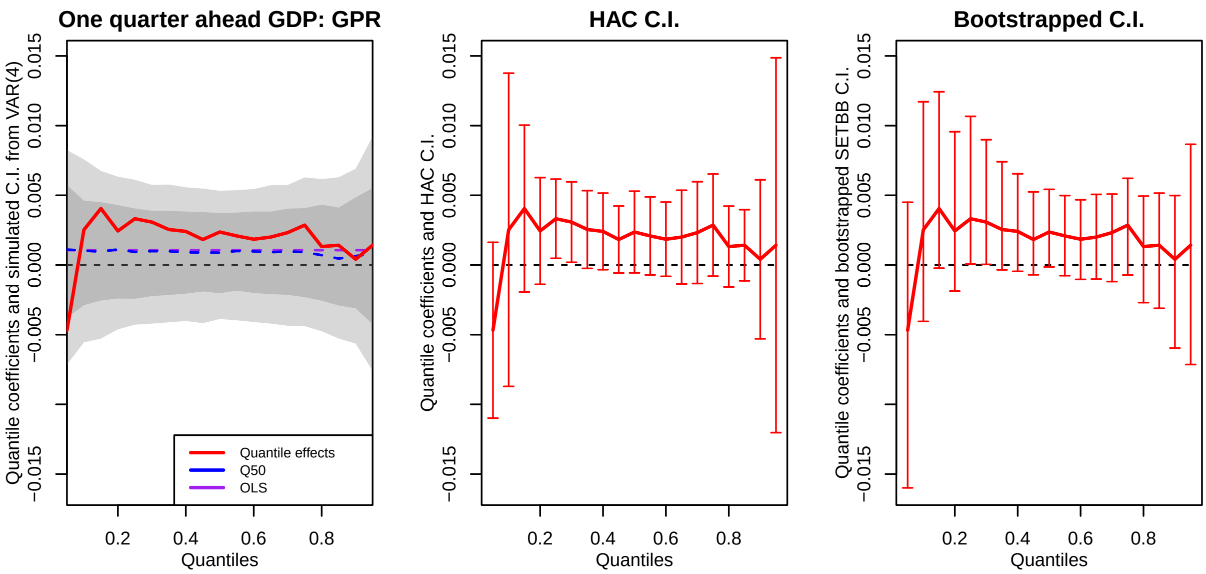
Appendix A. Additional results and robustness checks

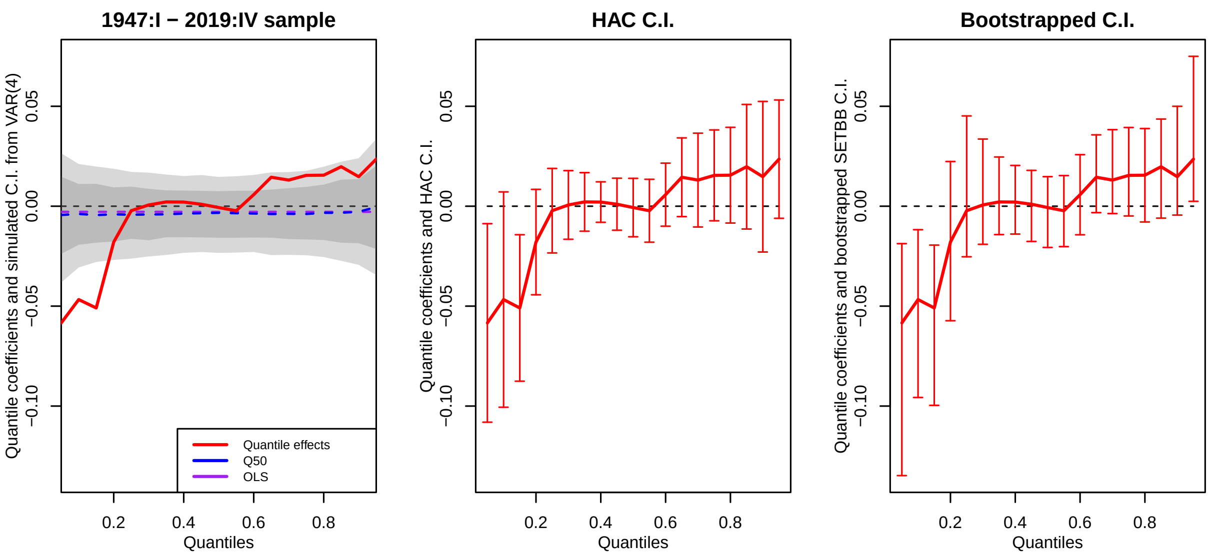
Appendix A.1. Growth-at-risk

Figure Appendix A.1: Estimated quantile coefficients of GPR on one quarter ahead GDP growth.



Appendix A.2. Exclusion of the Covid-19 sample and subsequent samples.

Figure Appendix A.2: Baseline model estimated over the restricted sample 1947:I - 2019:IV.



Appendix A.3. Geopolitical acts and threats

Figure Appendix A.3: Estimated quantile coefficients for geopolitical acts.

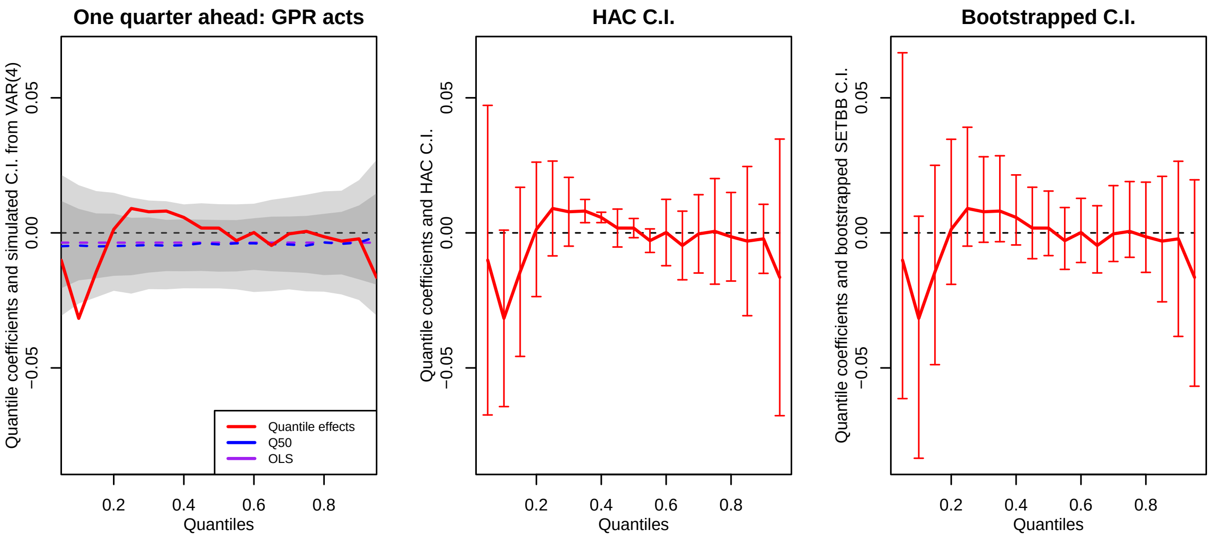
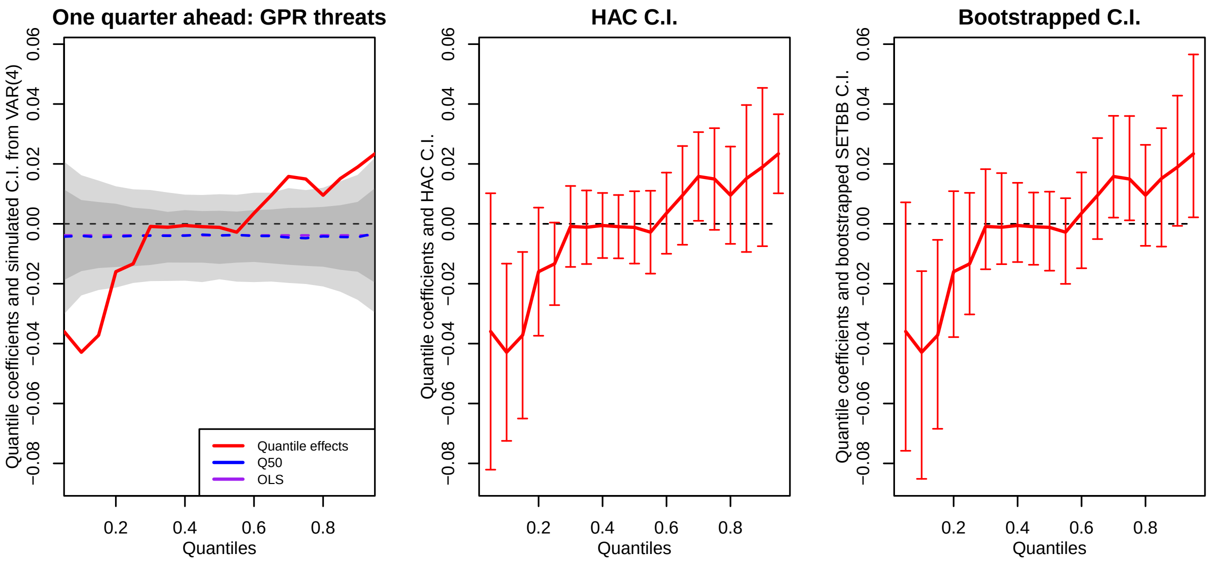


Figure Appendix A.4: Estimated quantile coefficients for geopolitical threats.

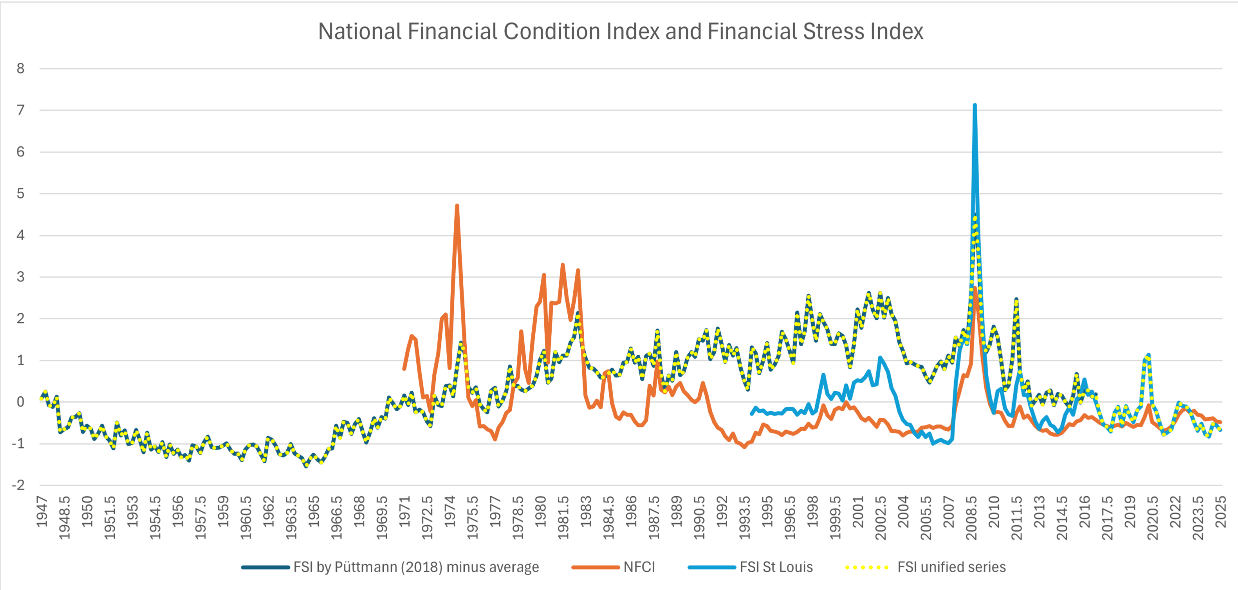


Appendix B. Construction of a time series for financial stress

There are no data on financial condition indexes or stress for the entire sample that we have (1947:II - 2025:I). Thus, we need to construct a proxy. To do so, we can use a Financial Stress Index (FSI) developed by Püttmann (2018), which is based on newspapers text search. This index is standardized as to have mean equal to 100 and unitary standard deviation. It runs from 1889 but unfortunately stop at 2016. Therefore, we combine it with the Financial Stress Index from the FRED of Saint Louis. Since this latter has a mean close to zero and a standard deviation close to 1, we remove the mean of 100 from the FSI developed by Püttmann (2018).

The following figure shows these two time series with the unified one, and also compare them with the popular National Financial Condition Index (NFCI) for the US, developed by the Chicago FED.

Figure Appendix B.1: Construction financial stress proxy.



Note: The FSI developed by Püttmann (2018), normalized to have mean zero (subtracting 100) is represented by the blue solid line. The St. Louis FED FSI is represented by the light blue line, and the two series have been merged at the first quarter of 2017, namely, the FSI from Püttmann (2018) up to 2016:IV and the FSI from the St. Louis FED from 2017:I up to the end of the sample. This unified series is represented by the dotted yellow line.

Source of the data:

- FSI from Püttmann (2018) has beed retrieved from https://www.policyuncertainty.com/financial_stress.html.
- The St. Lous Financial Stress Index have been downloaded from FRED https://fred.stlouisfed.org/series/STLFSI4#, at quarterly frequency (using the average).
- The NFCI has been downloaded from FRED https://fred.stlouisfed.org/series/NFCI, at quarterly frequency (using the average).