Disaster Risk through Investors' Eyes: a Yield Curve Analysis*

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Abstract

This paper develops a model to estimate investors' perceived probability of disaster from yield curve data. By integrating an asset pricing model with Datastream yield curve data, I provide daily estimates of the one-year-ahead disaster probability as perceived by investors for around 60 countries from 2000 to 2023. These probabilities provide insights into investors' beliefs, with applications in identifying market-stabilizing policies and assessing investors' forecast accuracy. I demonstrate these applications with case studies, including Mario Draghi's "whatever it takes" speech and the Russian-Ukrainian war. The theoretical framework also explains the upward-sloping yield curve puzzle and yield curve inversion before recessions in the US.

Keywords: Disaster Risk, Yield Curve, Asset Pricing

JEL Classification: E20, G01, G12, G15, G17

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1 Introduction

Investors' beliefs are not innocuous. They can have real economic effects and serious welfare implications. If investors assign a higher probability of government default, they will demand higher returns, increasing the debt burden and, in turn, making default more likely.[1] Even if the default does not occur, the increased debt burden raises financial stress, amplifying uncertainty and reducing public goods provision.[2] For these reasons, authorities seek to manage investors' beliefs through effective communication and policy interventions.[3] This is particularly relevant for economic disasters, such as defaults, wars, or depressions, where even minor fears can have large consequences. Therefore, measuring and monitoring investors' perceived probability of disaster is essential for evaluating financial stability and informing policy actions to ensure social welfare. The challenge is that investors' beliefs are not directly observable. However, since asset prices are directly influenced by these beliefs,[4] they can be used to reveal investors' perceived probability of disaster.[5]

This paper provides a model to extract investors' perceived probability of disaster from yield curve data. The yield curve is a graph that plots government bonds' yield against their maturity dates. By consolidating investors' expectations over different time horizons, it provides additional useful variation. Furthermore, the yield curve is widely regarded as a crucial financial indicator with proven forecasting power.[6] By integrating an asset pricing model with Datastream yield curve data, I provide daily estimates of the one-year-ahead disaster probability as perceived by investors for around 60 countries from 2000 to 2023. These probabilities offer valuable insights for several applications, two of which I exemplify here through case studies. First, they can be used to identify how government policies or significant events shape investors' beliefs. While clear communication and policy interventions by central banks can strongly influence market expectations, market reactions are not always predictable or fully aligned with the intended outcomes.[7] By analyzing investors' perceived probability of disaster through this model,

1. Lorenzoni and Werning (2019) show that high interest rates, driven by fears of default, can create self-fulfilling debt crises. De Grauwe and Ji (2013) find that Eurozone government bond markets are susceptible to self-fulfilling liquidity crises.

2. Reinhart and Rogoff (2010) find that countries with debt exceeding 90 percent of GDP experience notably lower median and mean growth rates. In emerging economies, they identify a more sensitive threshold, where total gross external debt exceeding 60 percent of GDP leads to an approximate two percent decline in annual growth.

3. Blinder et al. (2008) highlights that communication has become a crucial tool in monetary policy, with significant influence on financial markets, the predictability of policy decisions, and achieving macroeconomic objectives.

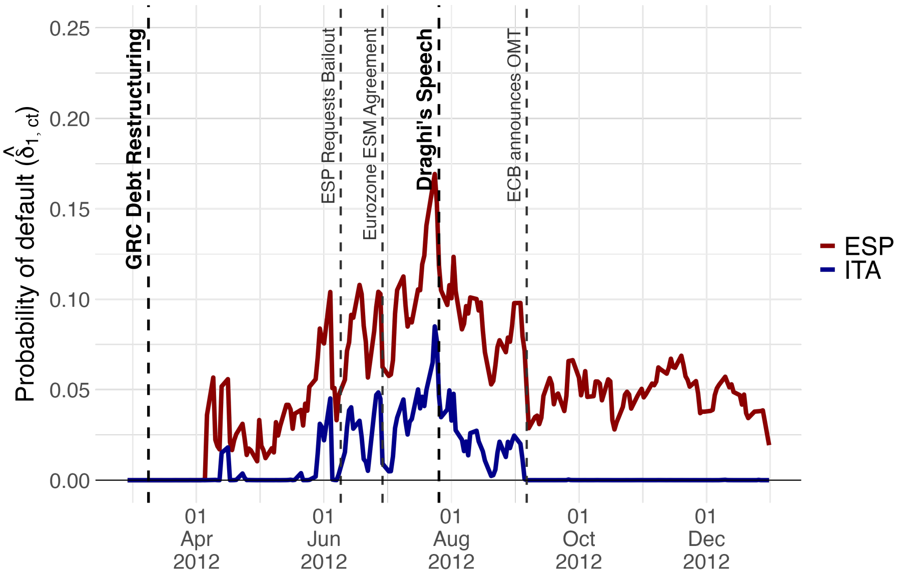
4. Ross (2015) refers to disaster risk as *dark matter*: "It is unseen and not directly observable but exerts a force that can change over time and profoundly influence markets."

5. Media coverage and professional forecasts reflect independent evaluations that may not necessarily align with investors' beliefs. They can also carry biases that differ from those of investors and often suffer from time lags. In contrast, asset prices offer a more immediate and accurate reflection of investors' expectations.

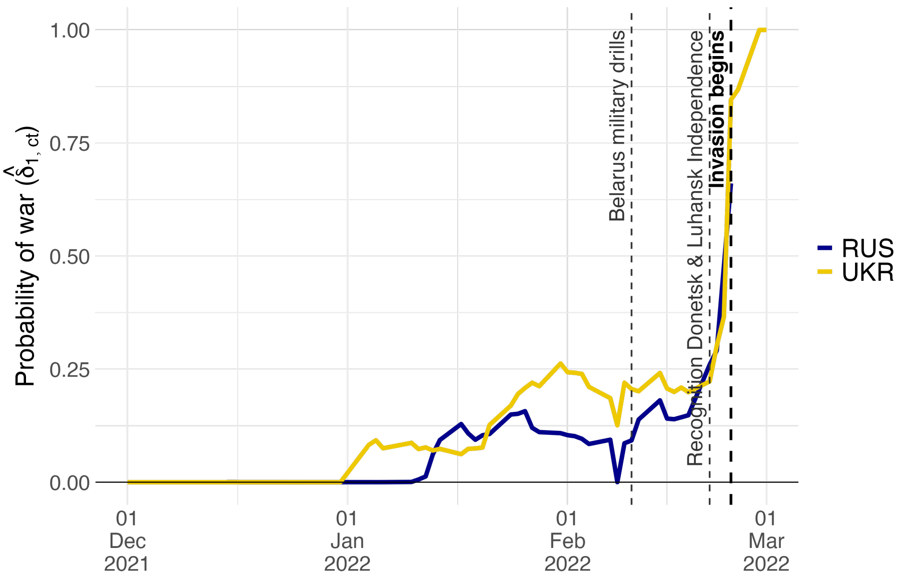
6. Substantial empirical evidence suggests that the yield curve is one of the most informative indicators, particularly for forecasting economic downturns (Estrella and Hardouvelis 1991; Estrella and Mishkin 1998; Ang, Piazzesi, and Wei 2006). Even the Federal Reserve Bank of New York has a webpage dedicated to the yield curve and its predictive power for recessions. See https://www.newyorkfed.org/research/capital_markets/ycfaq.html and https://www.newyorkfed.org/medialibrary/media/research/capital_markets/Prob_Rec.pdf. Furthermore, other studies show that the yield curve responds to economic policy uncertainty (Leippold and Matthys 2022), political uncertainty (Pástor and Veronesi 2013; Smales 2016) and international political risk (Huang et al. 2015).

7. Blinder et al. (2008) note that, despite its effectiveness, central banks differ widely in their communication strategies, indicating no clear consensus on an optimal approach.

we can better understand the effectiveness of such interventions. Second, they can be used to assess investors' forecasting abilities. Since investors have skin in the game, they might be more accurate than other forecasting methods. This evaluation can provide a useful benchmark for predictive models.



(a) Probability of default in Spain and Italy



(b) Probability of inter-state war in Russia and Ukraine

Figure 1: Preliminary of results: estimated disaster probabilities

Notes: Panel (a) displays the significant decline in default risk after Mario Draghi's "whatever it takes" speech in 2012, illustrating the impact of central bank communication on investor sentiment. Panel (b) shows the estimated probability of inter-state war before the Ukrainian-Russian conflict, indicating investors' short anticipation.

Source: Author's calculations.

I use a classic asset pricing model, based on Rietz (1988) and Barro (2006), that incorporates time-varying disaster probabilities. A representative consumer maximizes expected consumption in a closed economy where she can invest in government bonds. The equilibrium conditions imply that prices depend on the expectation of consumption growth, inflation, and sovereign default. The occurrence of a disaster induces significant shifts in these variables, which I refer to as "jumps". Thus, the probability of such disasters shapes investors' expectations regarding these variables, and then prices. The nature of these "jumps" varies depending on the type of disaster being analyzed: sovereign default or interstate war. The model implies that observed bond prices can be decomposed into a theoretical non-disaster price and a disaster wedge. The non-disaster price reflects the price determined by current business cycle conditions. The theoretical model is general and simple enough to be calibrated to many countries and compute the non-disaster theoretical prices for each of them over time. I bring the model to the data by regressing observed bond prices on computed theoretical non-disaster prices using a fixed-effects regression. This approach corrects for potential model misspecifications and more effectively isolates key interactions essential for estimating the disaster wedge. Finally, by specifying a certain type of disaster based on the specific context of each country, I estimate the disaster probability.

Using the estimated probabilities, I explore case studies to showcase the model's capabilities. I examine the impact of Mario Draghi's "whatever it takes" speech and the market's anticipation of the Ukrainian-Russian war. Figure 1 shows a preview of the results. Spain and Italy were at peak default risk the day before Draghi's speech, but disaster risk declined sharply on the day of the speech, reversing the prior upward trend. Regarding the war, investors recognized the risk of conflict before the onset; however, the abrupt increases in probability suggest that investors may have underestimated the immediacy of the escalation.

This paper mainly relates to the macroeconomic literature on "(rare) disasters" or "tail events". The early disaster literature was theoretical, addressing asset pricing puzzles—such as the risk-free rate premium—by introducing the concept of a low-probability of a "consumption" disaster (Rietz 1988; Barro 2006; Gabaix 2008; Backus, Chernov, and Martin 2011; Gourio 2012; Gabaix 2012; Wachter 2013; Farhi and Gabaix 2016).[8] More recently, advancements in econometric techniques and the availability of richer datasets have fueled a new wave of research focused on empirically identifying disaster risk from the data (Berkman, Jacobsen, and Lee 2011; Ross 2015; Schreindorfer 2020). A closely related study that merges a theoretical model with fixed effect estimation is found in Barro and Liao (2021). In their approach, they extract consumption disaster probabilities by examining the time-fixed effects from a time series analysis of several European countries. This paper contributes both methodologically and through its practical applications. First, it introduces a structural model to estimate disaster probabilities from high-frequency yield curve data. The yield curve data I use is particularly insightful due to its panel data structure, including a maturity dimension, and its well-established role as a key financial indicator.

8. Julliard and Ghosh (2012) argue that rare events alone cannot adequately explain asset pricing puzzles like the equity premium.

The model is flexible enough to be calibrated for a wide range of countries, offering daily updates, and it can account for different types of disasters, not just consumption disasters. This is important because consumption disasters are rare and may not be the most salient risk. The model can be calibrated to capture defaults and wars, which can occur more frequently, especially considering the broad sample of 60 countries. Second, the paper provides valuable insights into the potential applications of the computed disaster probabilities. These probabilities can be used to evaluate the impact of government policies and assess investors' forecasting abilities. The computed disaster probabilities will be made available on my GitHub repository[9], enabling researchers and policymakers to incorporate them into their own analyses. Finally, the theoretical framework also aligns with the theoretical literature explaining the upward-sloping yield curve puzzle and yield curve inversion before recessions in the US.

The financial literature has long explored the predictive power of asset prices in forecasting economic outcomes, with particular attention given to the yield curve and the spread between corporate and government bonds as indicators of economic activity (Gilchrist and Zakrajšek 2012; Gilchrist et al. 2016). In addition, the corporate finance literature has examined the valuation of political risks using sovereign yield spreads (Clark 1997; Bekaert et al. 2014, 2016). This paper adds to this body of research by leveraging the yield curve in a structural model. Computing the theoretical non-disaster price that accounts for current business cycle conditions, I "control" for factors unrelated to disasters that also influence yields. This approach addresses the limitation of relying solely on the yield spread, which ignores the fact that countries differ in their business cycle conditions, and not all of the spread is due to default risk. Furthermore, it's important to differentiate between the predictive power of asset prices and whether the beliefs inferred from these prices are ultimately accurate, a distinction that has only recently begun to receive attention.

This paper is structured as follows. The next section outlines the asset pricing model. In Section 3, I present the methodology for estimating investors' probability of a disaster. In Section 4, I discuss the results, followed by the conclusions in the final section.

2 Model setup

The model follows Rietz (1988) and Barro (2006), which I extend by including time-varying probabilities of disasters. It will later be calibrated separately for 64 countries, but for clarity and simplicity, the country-specific indices are omitted in this section.

The representative consumer maximizes a time-additive utility function:

$$\mathbb{E}_t \sum_{t=0}^{\infty} \beta^t U\left(C_t\right), \tag{1}$$

9. https://github.com/joanmargalef

where β is the time discount factor and the period utility function, $U(C_t)$, takes the CRRA form

$$U(C_t) = \frac{C_t^{1-\theta}}{1-\theta} \tag{2}$$

θ is the coefficient of relative risk aversion. In each period, agents can invest in government nominal zero-coupon bonds, each of which will pay out one unit of currency at maturity. Q_{Nt} is the price at t of a bond that matures in N periods, and X_{Nt} is the amount bought. The government can default on its obligations and pay a fraction F_{Nt} of the bond's face value. F_{Nt} represents the recovery rate. $F_{Nt} = 1$ indicates full payment with no default, and $F_{Nt} = 0.8$ implies that the government pays 80% of the bond's face value. The budget constraint of the agents is given by

$$P_t C_t = W_t - \sum_{N=1}^{H} Q_{Nt} X_{Nt} \quad \forall t \tag{3}$$

where P_t is the price of consumption and W_t corresponds to the wealth if no bond is bought, which includes the payments from previously purchased bonds.[10] H represents the maximum maturity. Using the usual first-order conditions, I derive the fundamental asset pricing equation:

$$Q_{Nt} = \beta^N \mathbb{E}_t \left[\frac{U'(C_{t+N}) P_t}{U'(C_t) P_{t+N}} \right] \tag{4}$$

The relationship between bond prices and bond yields is given by

$$Y_{Nt} = \left(\frac{1}{Q_{Nt}} \right)^{\frac{1}{N}} - 1 \tag{5}$$

where Y_{Nt} is the yield of a bond that matures in N periods at time t. The yield curve is the graph that plots Y_{Nt} against N. This equation allows us to translate bond prices to yields and vice versa.

Substituting in the functional form of the marginal utilities of consumption, Equation 4 can be rewritten as

$$Q_{Nt} = \beta^N \mathbb{E}_t \left[\frac{F_{Nt}}{\prod_{j=1}^{N} G_{t+j}^{\theta} \Pi_{t+j}} \right] \tag{6}$$

with $G_{t+1} = C_{t+1}/C_t$ being consumption growth and $\Pi_{t+1} = P_{t+1}/P_t$ being inflation. Note that bond prices decrease in expected consumption growth and inflation. Since the bond is a mechanism to transfer consumption to the future, there are fewer incentives to buy the bond if consumption is expected to be high. Higher expected inflation diminishes the real value of the bond. The price also decreases as the expected recovery rate decreases.

Following the standard approach in asset pricing research, I will analyze this equilibrium price equa-

10. The model shows a closed economy, where all that is produced is consumed. The BIS report Fang, Hardy, and Lewis (2022) shows that the majority of government bonds are held by domestic investors, especially during crises.

tion using exogenous processes for consumption growth, inflation, and the recovery rate.[11]

In each period, a disaster may or may not occur. For simplicity, disasters are assumed to be independent of one another. $\delta_{\tau,t}$ denotes the probability at t of a disaster happening in τ periods s.t.

$$\delta_{\tau+1,t} = \phi_\delta \delta_{\tau,t} \tag{7}$$

with $\phi_\delta \in [0, 1]$ being the persistence parameter of the disaster probability. This allows us to express all disaster probabilities in terms of $\delta_{1,t}$ since $\delta_{\tau,t} = \phi_\delta^{\tau-1}\delta_{1,t}$.

The law of motion of consumption growth is

$$G_{t+1} = \alpha_G G_t^{\phi_G} \varepsilon_{t+1} V_{t+1} \tag{8}$$

where α_G is a constant term, ϕ_G represents a persistence parameter, $\varepsilon_{t+1} \overset{\text{iid}}{\sim} \log N(0, \sigma_\varepsilon^2)$ is white noise, and $V_{t+\tau}$ is the "disaster impact factor on consumption growth" s.t.

$$V_{t+\tau} = \begin{cases} 1 & \text{if no disaster at } t+\tau \\ J_G & \text{if disaster at } t+\tau \end{cases} \tag{9}$$

Therefore, the disaster affects consumption growth through V_{t+1}. When the disaster does not occur, the log of consumption growth follows an AR(1) process. $J_G > 0$ represents the "jump" in consumption growth induced by the disaster. A value of $J_G = 0.98$ implies that the disaster reduces consumption growth by 2%. Note that the disaster directly impacts consumption growth in the same period it occurs and indirectly affects future ones. If the disaster occurs at $t + 1$, it will directly impact G_{t+1} through V_{t+1}. Additionally, it will indirectly affect $G_{t+2}, G_{t+3}, \ldots$ through their dependence on G_{t+1}.

Analogously, the process of inflation is

$$\Pi_{t+1} = \alpha_\Pi \Pi_t^{\phi_\Pi} \eta_{t+1} W_{t+1} \tag{10}$$

where α_Π is a constant term, ϕ_Π is the persistence parameter, $\eta_{t+1} \overset{\text{iid}}{\sim} \log N(0, \sigma_\eta^2)$ is white noise, and $W_{t+\tau}$ is the "disaster impact factor on inflation" s.t.

$$W_{t+\tau} = \begin{cases} 1 & \text{if no disaster at } t+\tau \\ J_\Pi & \text{if disaster at } t+\tau \end{cases} \tag{11}$$

$J_\Pi > 0$ represents the "jump" in inflation induced by the disaster. A $J_\Pi = 1.05$ means the disaster increases inflation by 5%. As with consumption growth, the disaster directly affects inflation in the same period it occurs and indirectly affects future ones.

11. See Cochrane (2009).

When a disaster occurs, there is a probability γ that it will lead to a sovereign default, which I model as an equal haircut across all bonds. When there is no disaster, the probability of default is zero. Then, the recovery rate is given by

$$F_{Nt} = 1 \cdot \prod_{\tau=1}^{N} Z_{t+\tau} \tag{12}$$

with $Z_{t+\tau}$ being the "disaster impact factor on the recovery rate" s.t.

$$Z_{t+\tau} = \begin{cases} 1 & \text{if no disaster at } t+\tau \\ 1 & \text{if disaster but no partial default at } t+\tau \\ 1-J_F & \text{if disaster and partial default at } t+\tau \end{cases} \tag{13}$$

$J_F \in [0,1]$ denotes the size of the haircut. A $J_F = 0.2$ means that the government does not pay 20% of the face value of the bond. A $J_F = 1$ is full default. The product of $Z_{t+\tau}$ over all periods until maturity implies that haircuts are cumulative, making long-term bonds riskier since they can suffer several haircuts.

Note that independence between disasters implies that the disaster impact factors are independent across periods, i.e., $V_t \perp V_{t'}, W_{t'}, Z_{t'}$ for $t' \neq t$. However, V_t, W_t, and Z_t are perfectly correlated through the disaster event.

Given this, the bond price from Equation 6 can be expressed as

$$Q_{Nt} = \underbrace{Q_{Nt}^{ND}}_{\text{Non-Disaster Price}} \underbrace{\prod_{\tau=1}^{N} \left(1 + \phi_\delta^{\tau-1} \delta_{1,t} \left(J_{\tau,N} - 1\right)\right)}_{\text{Disaster Wedge}} \tag{14}$$

Q_{Nt}^{ND} represents the bond price in the absence of disasters, and $J_{\tau,N}$ synthesizes all the jump effects of a disaster happening in τ periods to a bond that matures in N periods. I refer to $J_{\tau,N}$ as the "overall jump". Remember that $\delta_{1,t}$ is the probability at t of a disaster happening in 1 period. Thus, the price of the bond consists of the non-disaster price, Q_{Nt}^{ND}, multiplied by a "disaster wedge" that accounts for the risks of all disasters that may occur before the bond reaches maturity. This wedge depends on the disaster probabilities for all periods before maturity, $\delta_{\tau,t} = \phi_\delta^{\tau-1}\delta_{1,t}$ for $\tau \in [1, N]$, and the potential impact of each, summarized in $J_{\tau,N}$. For example, a 2-period bond is affected by the risk of a disaster happening in 1 and 2 periods, but not after, as it will have already matured. The term $1 + \phi_\delta^{\tau-1}\delta_{1,t}\left(J_{\tau,N} - 1\right)$ is the specific disaster wedge induced by the disaster in τ periods. Long-term bonds accumulate more elements in the product, as they are exposed to more periods where disasters could occur.

The functional form of the non-disaster price is

$$Q_{Nt}^{ND} = \beta^N \frac{e^{\frac{1}{2}\left(\sum_{i=1}^{N}(\sum_{j=0}^{i-1}\phi_G^j)^2\theta^2\sigma_\varepsilon^2 + \sum_{i=1}^{N}(\sum_{j=0}^{i-1}\phi_\Pi^j)^2\sigma_\eta^2\right)}}{\left(\alpha_G^{\sum_{i=1}^{N} i\phi_G^{N-i}} G_t^{\sum_{i=1}^{N}\phi_G^i}\right)^\theta \alpha_\Pi^{\sum_{i=1}^{N} i\phi_\Pi^{N-i}} \Pi_t^{\sum_{i=1}^{N}\phi_\Pi^i}} \tag{15}$$

This incorporates the expectations based on current business cycle conditions since it contains the effect of current consumption growth (G_t) and inflation (Π_t).

Finally, the functional form of $J_{\tau,N}$ is

$$J_{\tau,N} = \frac{1-\gamma J_F}{J_G^{\sum_{j=1}^{N+1-\tau}\theta\phi_G^{j-1}} J_\Pi^{\sum_{j=1}^{N+1-\tau}\phi_\Pi^{j-1}}} \tag{16}$$

This illustrates that the effect of a disaster depends on the interplay between jumps in consumption growth (J_G), inflation (J_Π), and default risk (γ and J_F), which may offset each other. As the gap between the disaster's occurrence (τ) and bond maturity (N) increases, the summations in the exponents include more components. This means long-term bonds have more effects by a single disaster due to the persistence of the underlying variables' processes (ϕ_G and ϕ_Π). As a result, short- and long-term bonds may behave very differently, even in opposite directions. For example, if a disaster causes a sharp drop in consumption growth and moderate inflation, but consumption growth is less persistent, the recessionary impact will be strong initially, leading to an increase in short-term bond prices. However, as the effect fades quickly and inflation persists, long-term bond prices will eventually decrease as inflation outweighs the recessionary impact.

This model offers tractable solutions for decomposing bond prices and allows us to analyze how disaster probabilities influence them.

Proposition 1 *The bond price with maturity N at time t, Q_{Nt}, decreases with the probability of a disaster occurring in the next period, $\delta_{1,t}$, if and only if*

$$\sum_{\tau=1}^{N} \frac{\phi_\delta^{\tau-1}(J_{\tau,N}-1)}{1+\phi_\delta^{\tau-1}(J_{\tau,N}-1)} < 0 \tag{17}$$

A sufficient condition for this to hold is that $J_{\tau,N} < 1$ for all τ.

The proof is in the Appendix A. When $\delta_{1,t}$ increases, all $\delta_{\tau,t}$ increase due to its persistence parameter, $\phi_\delta \in [0,1]$. The overall effect is ambiguous because, $J_{\tau,N}$ may be greater than or less than 1 for different values of τ. However, if $J_{\tau,N} < 1$ for all periods τ, then Q_{Nt} will decrease as $\delta_{1,t}$ increases.

3 Estimating investors' perceived probability of disaster

The model, summarized by Equation 14, shows that government bond prices can be decomposed into a non-disaster theoretical price and a disaster wedge. To estimate disaster probabilities, I first calibrate the model for every country to compute the theoretical non-disaster prices for each country and period. Then, I bring the model to the data by running a fixed-effect regression to attribute part of the difference between the observed prices and the computed theoretical ones to the disaster wedge. Finally, I determine the probability of the disaster, based on a specific disaster type.

3.1 Data

For the estimation, I use yield curve data from Datastream, macroeconomic data from the International Monetary Fund's International Financial Statistics (IMF/IFS) and World Bank's World Development Indicators (WB/WDI), and conflict data from the Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP/GED).

3.1.1 Yield curve data

Refinitiv's Datastream provides daily government bond yields for a wide range of countries, including both developed and developing economies. The availability of bond data varies by country; more developed nations typically offer a greater variety of bonds and longer maturity horizons. The analysis includes 64 countries over various time horizons.[12]

I retrieved the daily "benchmark" yield curve, which is based on "benchmark" bonds.[13] These are the most liquid government bonds, which are particularly relevant for analyzing investor expectations, as they capture actively traded securities that swiftly respond to market developments.[14] These cover standard government bonds with fixed rates and fixed maturity dates while excluding bonds with variable rates and other features that distort predictability.[15] All the bonds are denominated in the local currency of the issuing country, aligning with the model specification. I use the yield curve data provided directly by Refinitiv without any time lags.[16]

Finally, I restrict the sample to bonds with maturities between 1 and 10 years for two main reasons. First, this range aligns with the year-over-year growth rates of the macroeconomic variables. Second,

12. To see a list of all the countries involved and their respective time horizons, see Table X in the appendix.
13. These are based on Refinitiv Government Bond Indices, which are calculated using methodologies recommended by the European Federation of Financial Analysts Societies (EFFAS).
14. The Refinitiv Government Bond Indices include three main types: All Traded Index, which includes all eligible bonds, providing comprehensive market coverage; Tracker Index, a sample of bonds that closely tracks overall market performance; and Benchmark Index, focusing on the most liquid bonds.
15. Excluded bonds include those with inflation-linked, floating rate, convertible, and bonds with embedded options or warrants.
16. Refinitiv also offers computed yield curves for third parties, which may have pricing lags, meaning they are imputed after the actual time period has passed.

these maturities are more frequently available in the dataset, ensuring adequate data coverage and consistency in the analysis.

3.1.2 Economic and conflict data

The economic variables of interest in this study are consumption growth and inflation, which I sourced from quarterly data from the IMF/IFS and annual data from the WB/WDI. In both datasets, consumption growth is proxied by GDP growth in constant local currency units. Inflation is measured using the Consumer Price Index (CPI).

The IMF data, which provides quarterly updates, allows me to run the model at a quarterly frequency by inputting per-period consumption growth (G_t) and inflation (Π_t). I retrieve data for the 64 countries matching the financial data. In contrast, the annual World Bank data offers more comprehensive coverage over a longer time span, which is especially useful for estimating the parameters of the laws of motion for consumption growth and inflation, as well as the disaster parameters. This dataset includes 189 countries from 1989 to 2023.

Finally, to link economic effects to inter-state wars, I utilize battle-related fatality data from the UCDP/GED. I aggregate this data to the country-year level. This dataset is essential for calibrating the "jumps" associated with wars in the model's parameters. This includes 180 countries from 1989 to 2023.

3.2 Calibration

Calibrating the model for all countries requires setting parameters for the utility function, the laws of motion for consumption growth and inflation, and disaster-related parameters. See Table 1 and Table 2 for a summary of the calibration.

3.2.1 Utility function and laws of motion

I derive the utility function parameters from established literature. Following the methodology posited by Barro (2006), I set the discount factor, β, to 0.97 per year, and the coefficient of relative risk aversion, θ, to 4, which are common to all the countries.

The laws of motion for consumption growth and inflation are represented by Equation 8 and 10. Taking logs transforms the laws of motion into a linear form, which, in the absence of disaster shocks, follows an AR(1) process. For each country c, I estimate the constant parameters ($\alpha_{G,c}$ and $\alpha_{\Pi,c}$), the persistence parameters ($\phi_{G,c}$ and $\phi_{\Pi,c}$), and the standard deviations ($\sigma_{\varepsilon,c}$ and $\sigma_{\eta,c}$) using OLS on WB/WDI time series from 1989 to 2023. The distribution of the estimated parameters shows that the constant parameters are around 1.02 for both variables. Both log consumption growth and log inflation exhibit mean reversion. The inflationary process is more persistent, with an average persistence of 0.5, compared to 0.2 for consumption growth. See Figure B1 in Appendix B for kernel density plots of these estimates. For the period-specific consumption growth and inflation, G_{ct} and Π_{ct}, I use quarterly year-over-year data from IMF/IFS.

With all these parameters, I can compute the theoretical non-disaster prices, $\hat{Q}^{ND}_{Nct}$, for each maturity N, country c, and period t. As only G_{ct} and Π_{ct} vary over time, the non-disaster price is updated quarterly. See Table 1 for a summary of the calibration of the utility function and the laws of motion.

Table 1: Summary of calibration: utility function and laws of motion

Variable	**Value**	**Source**
	Utility function	
Time preference (β)	0.97	Barro (2006)
Risk aversion (θ)	4	Barro (2006)
	Laws of motion	
Consumption growth (G_{ct})	Country-specific	IMF/IFS
Inflation (Π_{ct})	Country-specific	IMF/IFS
Constant of consumption growth ($\alpha_{G,c}$)	Country-specific	Estimated from WB/WDI
Constant of inflation ($\alpha_{\Pi,c}$)	Country-specific	Estimated from WB/WDI
Persistence of consumption growth ($\phi_{G,c}$)	Country-specific	Estimated from WB/WDI
Persistence of inflation ($\phi_{\Pi,c}$)	Country-specific	Estimated from WB/WDI
S.d. of consumption growth ($\sigma_{\varepsilon,c}$)	Country-specific	Estimated from WB/WDI
S.d. of inflation ($\sigma_{\eta,c}$)	Country-specific	Estimated from WB/WDI

Notes: The time preference and risk aversion parameters follow Barro (2006). The consumption growth and inflation values (G_{ct} and Π_{ct}) are taken from the IMF/IFS on a quarterly basis. The laws of motion for consumption growth and inflation are estimated as AR(1) processes using OLS on country-specific time series data from WB/WDI.
Sources: Barro (2006), IMF/IFS, WB/WDI, and author's calculations.

3.2.2 Disaster parameters

The disaster parameters to be calibrated include the jumps in consumption growth (J_G) and inflation (J_Π), the probability of default during a disaster (γ), and the haircut size (J_F). These parameters are calibrated specifically for each type of disaster and are the same for all countries. I define two types of disasters: inter-state war and sovereign default.

For inter-state wars, I conducted a two-way fixed-effects analysis using WDI/WB data.[17] The results show that a year in war reduces consumption growth by 2% and increases inflation by 2%. Therefore, I set $J_G = 0.98$ and $J_\Pi = 1.02$. The regression results are presented in Table C1 in the appendix. I set the default haircut, J_F, to 0.56, based on the haircut analysis from Luckner et al. (2023), which uses historical data on sovereign defaults triggered by geopolitical disasters. Given that they recorded 45 defaults resulting from 95 inter-state wars, I set the probability of default γ to 0.5.

For default as the disaster type, the objective is to capture the probability of default using $\delta_{1,t}$. Thus, the conditional probability of default given a disaster, γ, becomes redundant, so I set it to 1. The parame-

17. To match the conflict size with Luckner et al. (2023), I define war as having more than 1,000 deaths per year using UCDP data.

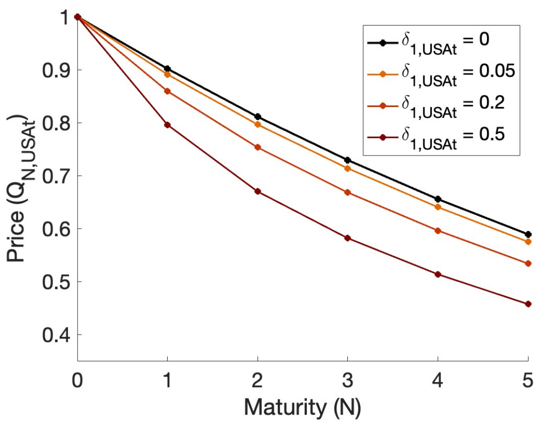
ter J_F is set to 0.44, as the average haircut for sovereign defaults is 44% (Meyer, Reinhart, and Trebesch 2022).

Table 2: Summary of calibration: disaster parameters by disaster type

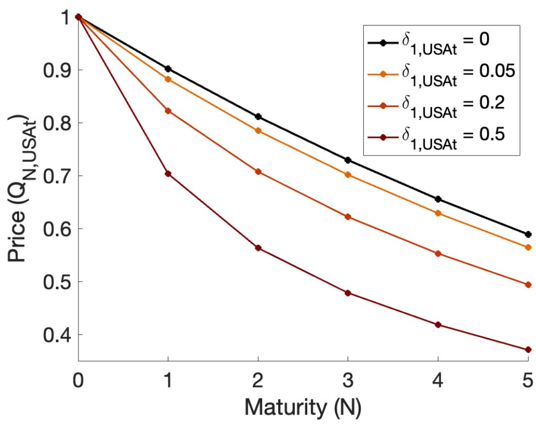
Disaster type	J_G	J_Π	γ	J_F	**Source**
Inter-state war	0.98	1.02	0.5	0.56	Von Laer & Bartels (2023), author's calculations
Sovereign default	1	1	1	0.44	Meyer et al. (2022)

Notes: J_G and J_Π are the jumps in consumption growth and inflation, respectively. γ is the probability of default when a disaster occurs, and J_F is the haircut size. $\phi_\delta = 0.5$ for all disaster types.
Source: Barro (2006), Luckner et al. (2023), and Meyer, Reinhart, and Trebesch (2022) and author's calculations on WB/WDI and UCDP/GED data.

Using the calibrated values for the disaster type along with the country's law of motion parameters as described in the previous section, I can construct the estimate of the disaster overall jump, $\hat{J}_{\tau,cN}$. Finally, I set the persistency parameter of the disaster probability $\phi_\delta = 0.5$ for all disaster types. Table 2 provides a summary of the disaster definitions.



(a) Inter-State War



(b) Sovereign Default

Figure 2: Comparative Statics of Disaster Probabilities

Notes: The figure presents simulated price curves for each disaster type, calibrated for the US with varying disaster probabilities, $\delta_{1,t}$. The persistence parameter is set to $\phi_\delta = 0.5$, and other disaster parameters are from Table 2. I set $G_t = \Pi_t = 1.02$.
Source: Author's calculations.

Figure 2 illustrates the simulated impact of $\delta_{1,t} = 0.25$ for each disaster type on the price curve using the US calibration. The results show that the likelihood of either inter-state war or default leads to a price drop across all maturities. For inter-state war, the inflationary and default risks outweigh the recessionary effects, causing a consistent decline in prices. Default has a stronger negative impact.

3.3 Bringing the model to the data

Building on the calibration, I bring the theoretical model to the data to estimate investors' perceived probability of disaster. Incorporating the panel structure using the country index c and taking logs, Equation 14 transforms into

$$q_{Nct} = q_{Nct}^{ND} + \sum_{\tau=1}^{N} \log\left(1 + \phi_\delta^{\tau-1} \delta_{1,ct} \left(J_{\tau,cN} - 1\right)\right) \tag{18}$$

with $q_{Nct} = \log(Q_{Nct})$ and $q_{Nct}^{ND} = \log(Q_{Nct}^{ND})$. The difference between the observed log price and the theoretical log price captures the disaster wedge. I bring this equation to the data by employing a fixed-effects regression. The regression model is specified as:

$$q_{Nct} = \beta \hat{q}_{Nct}^{ND} + \kappa_{Nc} + \kappa_{Nt} + \kappa_{ct} + u_{Nct} \tag{19}$$

where κ_{Nc}, κ_{Nt} and κ_{ct} represent fixed effects for country-maturity, maturity-time, and country-time interactions, respectively, and u_{Nct} is the error term. q_{Nct} is the observed log price of a bond sourced from Datastream. $\hat{q}_{Nct}^{ND}$ is the computed non-disaster theoretical log price derived from the model's calibration. While observed bond prices are available daily, the computed theoretical prices are updated quarterly based on economic data. To align frequencies, I interpolate the quarterly theoretical prices to a daily level. Results remain consistent when using the quarterly model, which uses quarterly averages of observed prices.

This equation suggests that observed bond prices can be explained by the non-disaster theoretical price, which reflects expectations based on the current business cycle, plus a set of unobserved factors varying at different levels. Fixed effects regression offers several advantages. First, it corrects for potential model misspecifications. Comparing Equation 18 with the regression equation, if the model perfectly captures the bond price data-generating process, $\hat{\beta}$ would approximate 1. However, allowing it to deviate provides a more accurate reflection of the relationship and serves as a measure of model fit. Second, because $\delta_{1,ct}$ varies at the ct level, the model's country-time interaction term, κ_{ct}, isolates variations in country-specific factors over time, which is essential for estimating disaster probabilities. Finally, the model's other fixed effects address structural and temporal influences, which enhance identification. The country-maturity interaction term, κ_{Nc}, captures structural yield curve differences across countries, reflecting time-stable variations potentially due to regulatory or market-specific conditions. The maturity-time interaction term, κ_{Nt}, controls for maturity-specific factors impacting all countries in a given period, such as global shifts in demand for certain maturities or adjustments in term premiums.

Table 3 presents the regression results from different specifications, which vary in the fixed effects included. The favorite specification, from which I estimate the disaster probabilities, includes all fixed effects. Across all specifications, $\hat{\beta}$ is positive and significant, showing that the theoretical price moves in the same direction as observed prices. However, the values are below 1 in all specifications and generally decrease as more fixed effects are added—from 0.316 (only κ_{ct}) to 0.108 (with all fixed effects).[18] This

18. Given that bond prices are close to 1, a $\hat{\beta}$ on log prices of 0.1 does not indicate major deviations.

Table 3: Fixed effect regression

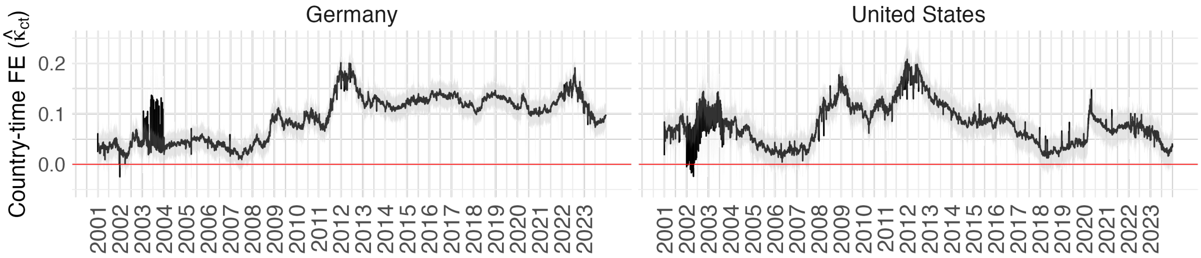
	Observed price (q_{Nct})				
	(1)	(2)	(3)	(4)	(5)
Non-disaster price ($\hat{q}_{Nct}^{ND}$)	0.109***	0.206***	0.218***	0.312***	0.292***
	(0.001)	(0.001)	(0.0004)	(0.0002)	(0.0002)
Country-time FE	✓	✓	✓	✓	
Maturity-country FE	✓	✓			
Maturity-time FE	✓		✓		
Observations	1,765,539	1,765,539	1,765,539	1,765,539	1,766,001
Adjusted R^2	0.973	0.946	0.850	0.831	0.350

Note: This table presents a fixed-effect regression of the observed log bond price ($q_{Nct} = \log(Q_{Nct})$) on the log of the theoretical non-disaster price ($q_{Nct}^{ND} = \log(Q_{Nct}^{ND})$). Fixed effects are denoted as κ_{Nc} (Maturity-country), κ_{Nt} (Maturity-time), and κ_{ct} (Country-time). Models differ by their inclusion of these fixed effects. Robust standard errors are reported in parentheses, with $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$ indicating significance levels.
Source: Datastream data for observed prices, and author's calculations for theoretical prices based on WB/WDI, IMF/IFS, and UCDP/GED data.

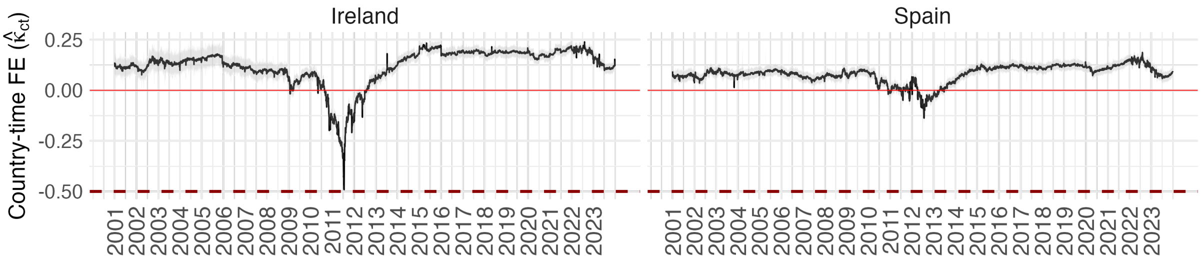
pattern supports including additional fixed effects to capture unobserved factors beyond the theoretical model, enhancing model fit as indicated by the significant increases in the adjusted R^2 with each additional fixed effect. Almost identical results are found when using the quarterly frequency model, see Table C2 in the appendix.

Given that $\delta_{1,ct}$ varies at the country-time level, it is captured in $\hat{\kappa}_{ct}$ as the common unobserved factor at the ct level. Its interpretation is as follows: if $\hat{\kappa}_{ct}$ is significantly positive, it indicates that there is an unobserved factor at the country-time level causing bond prices to be higher than what the current business cycle, and the other factors controlled by the other fixed effects, would suggest. Conversely, a significantly negative $\hat{\kappa}_{ct}$ implies that this unobserved factor is reducing bond prices. Since disaster risk reduces bond prices across maturities, as shown in Figure 2, a negative $\hat{\kappa}_{ct}$ may indicate that the unobserved factor is disaster risk.

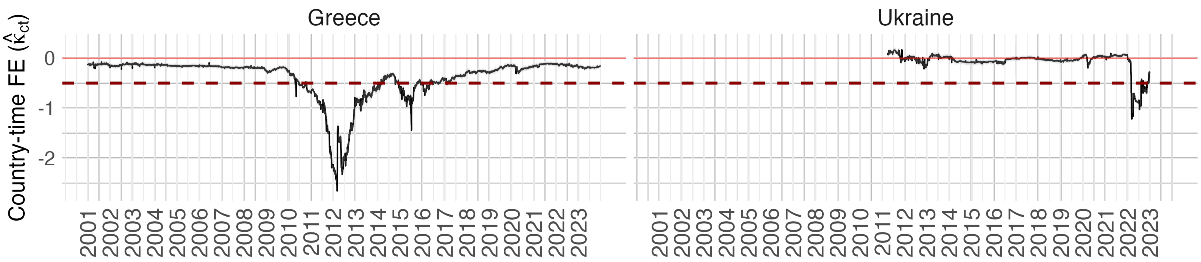
Figure 3 illustrates the evolution of $\hat{\kappa}_{ct}$ for six representative countries selected for their distinct levels of disaster risk. Germany and the United States represent stable countries with no significant disaster risk. Ireland and Spain exemplify relatively stable countries that experienced periods of disaster risk (default risk during the European debt crisis) that ultimately did not materialize. In contrast, Greece and Ukraine represent countries where disaster risk materialized, including Greece's default in 2013 and Ukraine's inter-state conflict in 2023. The horizontal lines at 0 and -0.5 serve as reference thresholds to facilitate comparison of $\hat{\kappa}_{ct}$ values across countries.



(a) No disaster risk



(b) Disaster risk with no disaster



(c) Disaster risk with disaster

Figure 3: Evolution of $\hat{\kappa}_{ct}$ for Selected Countries

Notes: The figure shows the evolution of $\hat{\kappa}_{ct}$ with 95% confidence intervals for selected countries: Germany, the United States, Ireland, Spain, Greece, and Ukraine. The red lines at 0 and -0.5 represent reference thresholds.
Source: Author's calculations.

Stable countries with no significant disaster risk, such as Germany and the USA, generally exhibit $\hat{\kappa}_{ct}$ values that remain positive or only briefly touch the zero baseline. This pattern extends to other economically robust regions, including Australia, the United Kingdom, Scandinavian countries (e.g., Sweden, Norway, Denmark), and stable European economies like Austria, the Netherlands, and Switzerland. Likewise, leading Asian economies such as Japan, South Korea, and Singapore also display this pattern.

Relatively stable countries that experienced periods of known disaster risk, such as Ireland and Spain, typically display positive $\hat{\kappa}_{ct}$ values with only shallow dips into negative territory (above -0.5) during times of financial instability. Ireland's lowest $\hat{\kappa}_{ct}$ point occurs in mid-2011, aligning with austerity measures and bailout negotiations during the peak of the European debt crisis. Spain similarly reaches a minimum in mid-2012, reflecting peak financial strain in this period. Comparable patterns are seen in other southern European countries, including Portugal, Italy, and Cyprus. Other notable examples of brief negative dips without crossing the -0.5 threshold include Israel during the Second Intifada, amid severe conflict and economic disruption, and Poland in 2002, during economic adjustments following rapid liberalization and structural reforms, which led to rising unemployment, social discontent, and fiscal strain as the country transitioned to a market-based economy. Additionally, countries like Mexico and India experienced multiple brief dips into negative territory, indicating episodic financial pressures without prolonged instability.

In contrast, Greece and Ukraine exhibit severe declines in $\hat{\kappa}_{ct}$ leading up to their respective crises, with values reaching their lowest points and crossing well below the -0.5 threshold as the disasters unfolded. Greece's significant drop aligns with its 2012 default during the European debt crisis, while Ukraine's plunge reflects the escalation of inter-state conflict in 2023. Another notable decline is observed in Sri Lanka in 2022 when the country defaulted amid a severe economic and political crisis.

These patterns suggest that when $\hat{\kappa}_{ct}$ values dip into the negative range, they may be factoring in disaster risk. Figure B2 in the appendix compares the daily and quarterly models for estimating $\hat{\kappa}_{ct}$. The daily model captures more detailed variation along the same overall trend as the quarterly model, providing greater insight. For the evolution of $\hat{\kappa}_{ct}$ across the full set of countries, see Figures B3, B4, B5, and B6 in the appendix.

To derive disaster probabilities, I assume $\hat{\kappa}_{ct}$ corresponds to the disaster wedge. Specifically, $\hat{\kappa}_{ct}$ represents the average effect of disaster wedges across all maturities, i.e.,

$$\hat{\kappa}_{ct} = \frac{\sum_{N \in \mathcal{N}(c,t)} q_{Nct} - \hat{\beta}\hat{q}_{Nct}^{ND} - \hat{\chi}_N - \hat{\kappa}_{Nc} - \hat{\kappa}_{Nt}}{|\mathcal{N}(c,t)|} \tag{20}$$

where $\mathcal{N}(c,t)$ is the set of maturities available for country c at time t, and $|\mathcal{N}(c,t)|$ is the number of them. The theoretical model then implies

$$\hat{\kappa}_{ct} = \frac{\sum_{N \in \mathcal{N}(c,t)} \log\left(1 + \phi_\delta^{\tau-1}\delta_{1,ct}\left(J_{\tau,cN} - 1\right)\right)}{|\mathcal{N}(c,t)|}$$

Finally, I specify the type of disaster by inputting the estimated persistence parameter ($\hat{\phi}_\delta$) and the overall economic impact of the disaster event ($\hat{J}_{\tau,cN}$) into the previous equation, leaving $\delta_{1,ct}$ as the only variable to be determined. The type of disaster event is tailored to each country's context; for example, an inter-state war is specified for Ukraine, while a sovereign default is specified for Greece. Given that the shortest maturity bond available is a one-year bond, $\delta_{1,ct}$ corresponds to the probability of a disaster occurring within one year.

I estimate $\delta_{1,ct}$ by minimizing the squared difference between $\hat{\kappa}_{ct}$ and the theoretical form of the disaster wedge:

$$\hat{\delta}_{1,ct} = \underset{\delta_{1,ct}}{\operatorname{argmin}} \left(\hat{\kappa}_{ct} - \frac{\sum_{N \in \mathcal{N}(c,t)} \log\left(1 + \hat{\phi}_{\delta}^{\tau-1} \delta_{1,ct} \left(\hat{J}_{\tau,cN} - 1\right)\right)}{|\mathcal{N}(c,t)|} \right)^2$$

4 Results

Using the process detailed in the previous section, I can now estimate investors' perceived probability of disaster for each country and period. These probabilities offer multiple applications. First, they provide a tool for understanding how specific events and policy interventions impact investors' perceptions. Second, the model allows for an evaluation of investors' abilities to forecast disasters. To demonstrate these applications, I will analyze several case studies.

4.1 Identifying effective policies: Mario Draghi's "whatever it takes" speech

After the 2008 recession, the Eurozone faced a severe sovereign debt crisis that threatened the stability of the currency union, particularly in Spain, Italy, Portugal, Greece, and Ireland. These countries underwent multiple rounds of bailouts and austerity measures imposed by the IMF, the ECB, and the European Commission. In this analysis, I focus on the cases of Spain and Italy, which were in a different context than Portugal, Greece, and Ireland because they did not receive an IMF bailout.

Figure 4 shows the evolution of the estimated probability of default for Spain and Italy from Greece's debt restructuring in March 2012 to January 2013. Several policy actions were taken to reduce this risk. On June 9, 2012, Spain requested a bank bailout to recapitalize its banking sector, aiming to contain the crisis and prevent further contagion. Later, on June 29, the Eurozone leaders agreed to establish the European Stability Mechanism (ESM) to provide financial assistance and stabilize the banking sector across the region. While these actions provided short-term relief, they did not reverse the overall upward trend in perceived default risk, which continued to rise. The risk reached its peak just before Draghi's speech on July 26, 2012. After his commitment to do "whatever it takes" to preserve the euro, the perceived risk dropped sharply, reversing the previous upward trend. Finally, the ECB's announcement of the Outright Monetary Transactions (OMT) program on September 6, 2012, which enabled the ECB to purchase unlimited short-term government bonds, further reduced default probabilities and led to a sustained decline in risk perceptions for both Spain and Italy.

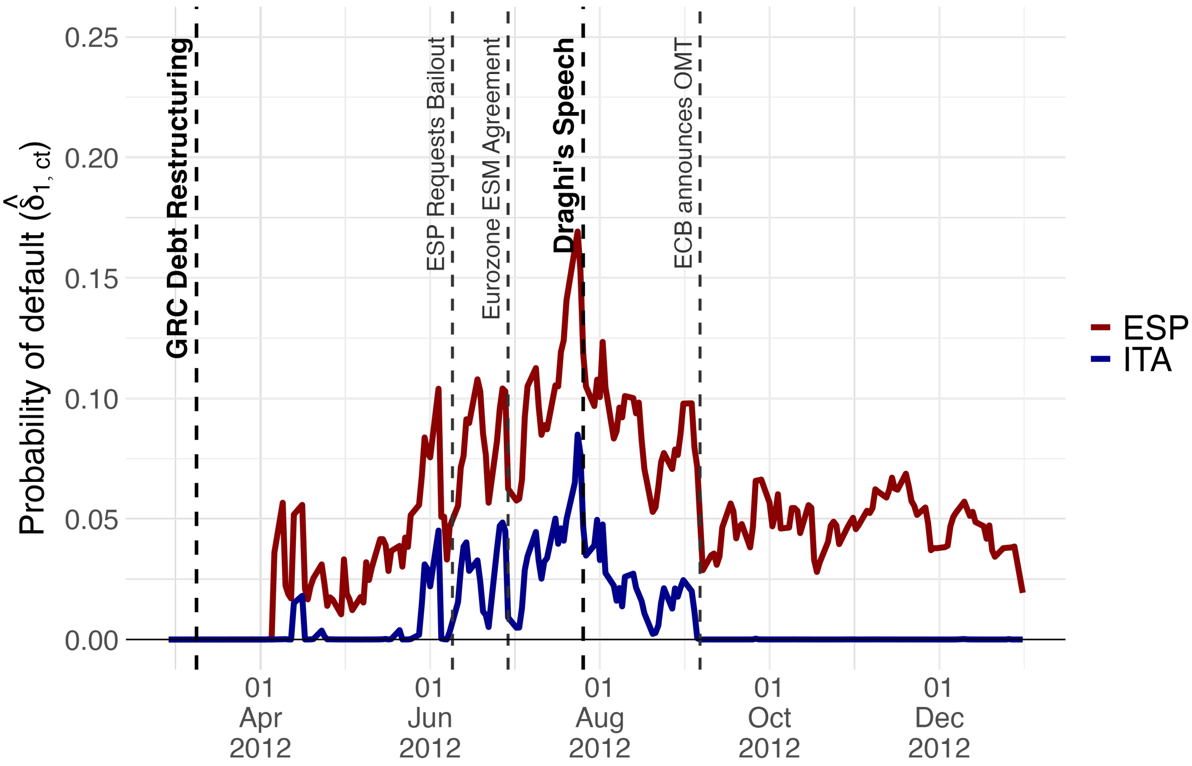


Figure 4: Evolution of probability of default for Spain and Italy

Notes: The figure shows the evolution of the probability of default for Spain and Italy. The values are estimated by interpolating economic quarterly data. Vertical lines represent relevant events.

Source: Author's calculations.

This analysis is consistent with the findings of Leombroni et al. (2021), which show that central bank communication can significantly reduce yields and risk premia, especially in times of crisis. While their study demonstrates this effect through shifts in risk premia, my analysis captures it by estimating the perceived probability of default, offering a more direct measure of investors' beliefs.

4.2 Evaluating investors' forecasting abilities: the Ukrainian-Russian war

Figure 5 illustrates the evolution of the estimated probability of an inter-state war in Ukraine and Russia, from December 2021 to March 2022, with key events marked by dashed vertical lines. Investors assigned virtually no probability to an inter-state war until approximately three months before the conflict. Starting in January, their perception of war risk began to shift, with the probability of conflict in the two countries rising gradually to around 20%. Notably, even after Belarus's military drills on February 10 and Russia's recognition of the independence of Donetsk and Luhansk on February 21, investors' probability of an imminent conflict remained relatively steady, showing little increase in perceived risk. It was only after the invasion commenced on February 24 that the estimated probability of inter-state war surged significantly.

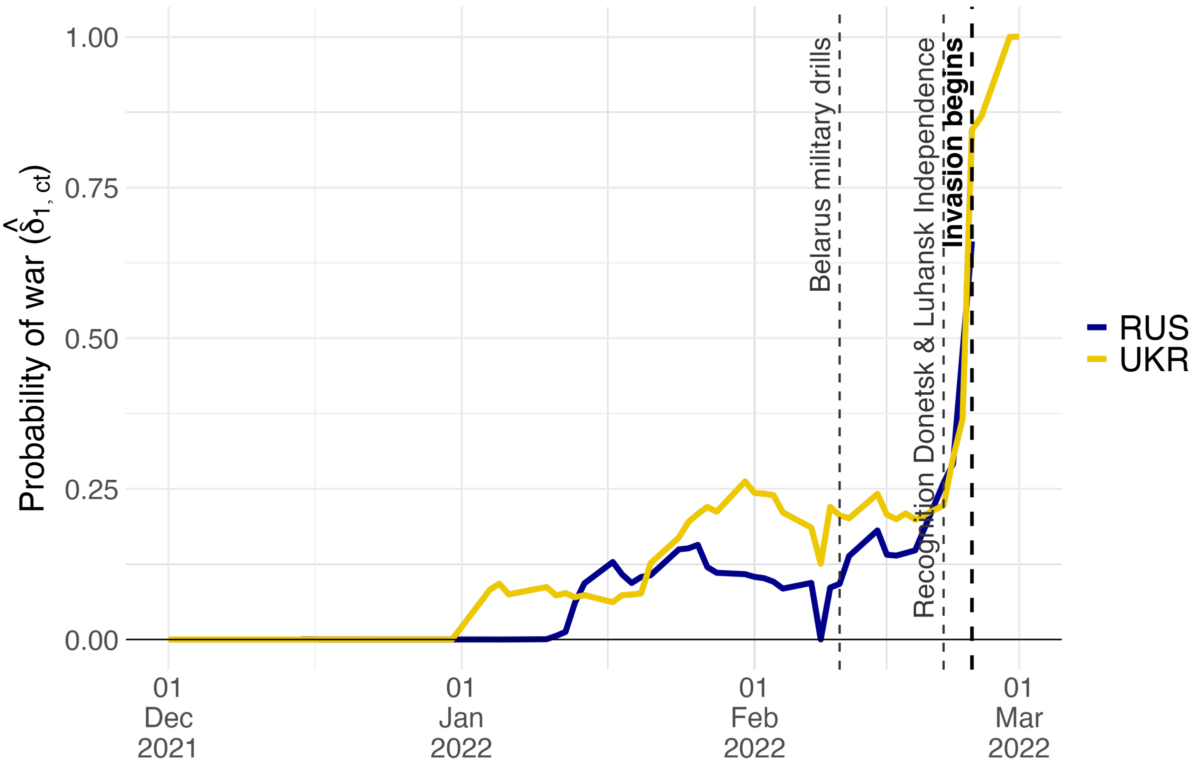


Figure 5: Evolution of probability of inter-state war for Russia and Ukraine

Notes: The figure shows the evolution of the probability of an inter-state war for Ukraine. The values are estimated by interpolating economic quarterly data.

Source: Author's calculations.

This finding suggests that the market was indeed accounting for the risk of conflict prior to its onset; however, the abrupt increase in probability implies that investors may have underestimated its immediacy. The results are consistent with Chadefaux (2017), who conducted a reduced-form analysis using government bond data and found that financial markets tend to underestimate the risk of war, as evidenced by strong yield reactions. The similar probability trajectories for both countries underscore that investors were primarily assessing the likelihood of war itself, given that both nations were implicated. Notably, Russia consistently displays a slightly lower probability, perhaps because investors expected the war to have a less severe impact on Russia than on Ukraine, despite the model's assumption that the war impact is the same for both countries. Investors may have anticipated that, in the event of conflict, Russia would likely emerge as the victor, leading to a greater haircut on Ukrainian bonds compared to Russian ones.

4.3 Theoretical Results

Using the calibration for the US economy,[19] the model captures two key phenomena: the upward-sloping yield curve puzzle and the inversion of the yield curve before recessions.

The puzzle involving the yield curve, described by Gabaix (2012), is that the nominal yield curve slopes upwards on average, with long-term yields' premium being higher than what traditional RBC models can explain. This mirrors the bond version of the equity premium puzzle noted by Campbell (2003). Following the theoretical literature on macroeconomic disasters (Barro 2006), I set the probability of a consumption disaster to 0.02, which is constant over time, the jump in consumption growth (J_G) to 0.71, the probability of default during a disaster (γ) to 0.4, and the haircut size (J_F) to 0.29. The model successfully addresses the puzzle, even without disasters. Following Gabaix (2012)'s methodology, I calculate the ratio between 5-year and 1-year bonds (Y_{5t}/Y_{1t}). The resulting ratio is close to the 0.57% obtained in Gabaix (2012), for both non-disaster (0.4%) and disaster scenarios (0.33%).

The other phenomenon is the inversion of the yield curve. The yield curve inverts when short-term interest rates are higher than long-term rates, which is often interpreted as a signal of an upcoming recession. The slope of the yield is measured by the spread between the 3-month and 10-year bonds. By approximating the 3-month yield using an interpolation between the 0-maturity bond and the 1-year bond, the model can replicate this behavior when a sufficiently high disaster probability and a recessionary jump are introduced. With parameters set at $J_G = 0.875$ and $\delta_{1,t} = 1$, the resulting spread is -1.4%.

5 Conclusions

This paper introduces a novel approach to estimating investors' perceived probability of disaster, using yield curve data. I provide daily estimates of the one-year-ahead disaster probability as perceived by investors for around 60 countries from 2000 to 2023. These probabilities are valuable for two key reasons. First, they help identify how government policies and significant events influence investors' beliefs. Second, the model enables the evaluation of investors' predictive accuracy, offering a benchmark against other forecasting methods. Furthermore, the model also aligns with theoretical literature to explain yield curve behavior.

The application of the model uncovers several key insights through case studies. First, the model captures the significant impact of Mario Draghi's "whatever it takes" speech in 2012 on reducing perceived default risk in Italy and Spain. The rapid decline in estimated disaster probabilities following this speech underscores the profound effect that central bank communication and credible policy commitments can have on investors' expectations. Second, the model shows that financial markets gradually

19. For this part of the analysis, I set $G_t = \Pi_t = 1.02$.

began to recognize the risk of an inter-state war between Ukraine and Russia, then adjusted sharply as the conflict began.

Overall, this study contributes to the literature on disaster risk by offering a theoretically grounded method for estimating investors' perceived probability of disaster. The estimated disaster probabilities will be made publicly available on my GitHub repository, enabling researchers and policymakers to incorporate them into their analyses.[20] The model can also be applied to several additional areas, which I have not yet explored, including estimating the welfare implications of policies—such as the economic savings generated by Mario Draghi's "whatever it takes" speech—and analyzing other types of disasters, such as currency crises, natural disasters, and other extreme events.

Furthermore, future research can address the model's limitations. First, there is room for improvement in the performance of the theoretical model. Expanding the model to incorporate additional instruments, such as equities and corporate bonds, and developing a general equilibrium framework could more accurately capture the data-generating process. This would improve theoretical price estimations and enhance the identification of disaster risk. Another issue is the inability to distinguish between the probability of a disaster and its effect, as the model relies on general assumptions about the magnitude of disaster-related jumps. Calibrating these jumps to be country-specific or dependent on other variables could address this limitation. Additionally, the current approach requires specifying the type of disaster based on the country's context, limiting the model's use for long-term analysis as these contexts are likely to change. Integrating an NLP model to analyze news reports and text data could help identify not only the type of disaster but also its severity, allowing for a more precise estimation of disaster risk probabilities.

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Appendices

A Derivations and Proofs

A.1 Derivation of the Price Equation

For the 1-period bond, the price is given by

$$
\begin{aligned}
Q_{1t} =& \beta \mathbb{E}_t \left[\frac{F_{1t}}{G_{t+1}^{\theta} \Pi_{t+1}} \right] = \beta \mathbb{E}_t \left[\frac{Z_{t+1}}{(\alpha_G G_t^{\phi_G} \varepsilon_{t+1} V_{t+1})^{\theta} \alpha_\Pi \Pi_t^{\phi_\Pi} \eta_{t+1} W_{t+1}} \right] \\
&= \beta \frac{1}{(\alpha_G G_t^{\phi_G})^{\theta} \alpha_\Pi \Pi_t^{\phi_\Pi}} \mathbb{E}_t \left[\frac{1}{\varepsilon_{t+1}^{\theta}} \right] \mathbb{E}_t \left[\frac{1}{\eta_{t+1}} \right] \mathbb{E}_t \left[\frac{1}{V_{t+1}^{\theta} W_{t+1}} \right] \\
&= \beta \frac{1}{(\alpha_G G_t^{\phi_G})^{\theta} \alpha_\Pi \Pi_t^{\phi_\Pi}} \mathbb{E}_t \left[e^{-\log(\theta \varepsilon_{t+1})} \right] \mathbb{E}_t \left[e^{-\log(\eta_{t+1})} \right] \left(1 - \delta_{1,t} + \delta_{1,t} \frac{1 - \gamma J_F}{J_G^{\theta} J_\Pi} \right) \\
&= \beta \frac{e^{\frac{1}{2}\left((\theta\sigma_\varepsilon)^2 + \sigma_\eta^2\right)}}{(\alpha_G G_t^{\phi_G})^{\theta} \alpha_\Pi \Pi_t^{\phi_\Pi}} \left(1 + \delta_{1,t} \left(\frac{1 - \gamma J_F}{J_G^{\theta} J_\Pi} - 1 \right) \right)
\end{aligned}
\tag{A1}
$$

For the 2-period bond, the price is given by

$$
\begin{aligned}
Q_{2t} =& \beta^2 \mathbb{E}_t \left[\frac{1}{G_{t+1}^{\theta} G_{t+2}^{\theta} \Pi_{t+1} \Pi_{t+2}} \right] \\
&= \beta^2 \mathbb{E}_t \left[\frac{1}{G_{t+1}^{\theta} (\alpha_G G_{t+1}^{\phi_G} \varepsilon_{t+2} V_{t+2})^{\theta} \Pi_{t+1} (\alpha_\Pi \Pi_{t+1}^{\phi_\Pi} \eta_{t+2} W_{t+2})} \right] \\
&= \beta^2 \frac{1}{(\alpha_G^{2+\phi_G} G_t^{\phi_G + \phi_G^2})^{\theta} \alpha_\Pi^{2+\phi_\Pi} \Pi_t^{\phi_\Pi + \phi_\Pi^2}} \mathbb{E}_t \left[\frac{1}{\varepsilon_{t+1}^{(1+\phi_G)\theta}} \right] \mathbb{E}_t \left[\frac{1}{\varepsilon_{t+2}^{\theta}} \right] \mathbb{E}_t \left[\frac{1}{\eta_{t+1}^{1+\phi_\Pi}} \right] \mathbb{E}_t \left[\frac{1}{\eta_{t+2}} \right] \\
&\mathbb{E}_t \left[\frac{Z_{t+1}}{V_{t+1}^{\theta} W_{t+1}} \right] \mathbb{E}_t \left[\frac{Z_{t+2}}{V_{t+2}^{\theta} W_{t+2}} \right] \\
&= \beta^2 \frac{e^{\frac{1}{2}\left((1+(1+\phi_G)^2)\theta^2\sigma_\varepsilon^2 + (1+(1+\phi_\Pi)^2)\sigma_\eta^2\right)}}{(\alpha_G^{2+\phi_G} G_t^{\phi_G + \phi_G^2})^{\theta} \alpha_\Pi^{2+\phi_\Pi} \Pi_t^{\phi_\Pi + \phi_\Pi^2}} \left(1 + \delta_{1,t} \left(\frac{1 - \gamma J_F}{J_G^{(1+\phi_G)\theta} J_\Pi^{1+\phi_\Pi}} - 1 \right) \right) \left(1 + \delta_{2,t} \left(\frac{1 - \gamma J_F}{J_G^{\theta} J_\Pi} - 1 \right) \right)
\end{aligned}
\tag{A2}
$$

For the 3-period bond, the price is given by

$$
\begin{aligned}
Q_{3t} =& \beta^3 \frac{e^{\frac{1}{2}\left((1+(1+\phi_G)^2 + (1+\phi_G+\phi_G^2)^2)\theta^2\sigma_\varepsilon^2 + (1+(1+\phi_\Pi)^2 + (1+\phi_\Pi+\phi_\Pi^2)^2)\sigma_\eta^2\right)}}{(\alpha_G^{3+2\phi_G+\phi_G^2} G_t^{\phi_G+\phi_G^2+\phi_G^3})^{\theta} \alpha_\Pi^{3+2\phi_\Pi+\phi_\Pi^2} \Pi_t^{\phi_\Pi+\phi_\Pi^2+\phi_\Pi^3}} \left(1 + \delta_{1,t} \left(\frac{1 - \gamma J_F}{J_G^{(1+\phi_G+\phi_G^2)\theta} J_\Pi^{1+\phi_\Pi+\phi_\Pi^2}} - 1 \right) \right) \\
&\left(1 + \delta_{2,t} \left(\frac{1 - \gamma J_F}{J_G^{(1+\phi_G)\theta} J_\Pi^{1+\phi_\Pi}} - 1 \right) \right) \left(1 + \delta_{3,t} \left(\frac{1 - \gamma J_F}{J_G^{\theta} J_\Pi} - 1 \right) \right)
\end{aligned}
\tag{A3}
$$

Then, for the N-period bond,

$$
\begin{aligned}
Q_{Nt} =& \beta^N \frac{e^{\frac{1}{2}\left(\sum_{i=1}^{N}(\sum_{j=0}^{i-1}\phi_G^j)^2\theta^2\sigma_\varepsilon^2 + \sum_{i=1}^{N}(\sum_{j=0}^{i-1}\phi_\Pi^j)^2\sigma_\eta^2\right)}}{\left(\alpha_G^{\sum_{i=1}^{N} i\phi_G^{N-i}} G_t^{\sum_{i=1}^{N}\phi_G^i}\right)^\theta \alpha_\Pi^{\sum_{i=1}^{N} i\phi_\Pi^{N-i}} \Pi_t^{\sum_{i=1}^{N}\phi_\Pi^i}} \\
& \prod_{\tau=1}^{N}\left(1+\delta_{\tau,t}\left(\frac{1}{J_G^{\sum_{j=1}^{N+1-i}\theta\phi_G^{j-1}} J_\Pi^{\sum_{j=1}^{N+1-i}\phi_\Pi^{j-1}}}-1\right)\right)
\end{aligned}
\tag{A4}
$$

A.2 Proof of Proposition 1

I use the logarithmic differentiation trick. Taking the logarithm of Equation 14:

$$
\log(Q_{Nt}) = \log(Q^{ND}) + \sum_{\tau=1}^{N}\log\left(1+\phi_\delta^{\tau-1}\delta_{1,t}\left(J_{\tau,N}-1\right)\right) \tag{A5}
$$

Then, differentiating with respect to $\delta_{1,t}$,

$$
\begin{aligned}
\frac{\partial\log(Q_{Nt})}{\partial\delta_{1,t}} =& \sum_{\tau=1}^{N}\frac{\phi_\delta^{\tau-1}\left(J_{\tau,cN}-1\right)}{1+\phi_\delta^{\tau-1}\delta_{1,t}\left(J_{\tau,N}-1\right)} \\
\frac{1}{Q_{Nt}}\frac{\partial Q_{Nt}}{\partial\delta_{1,t}} =& \sum_{\tau=1}^{N}\frac{\phi_\delta^{\tau-1}\left(J_{\tau,cN}-1\right)}{1+\phi_\delta^{\tau-1}\delta_{1,t}\left(J_{\tau,N}-1\right)} \\
\frac{\partial Q_{Nt}}{\partial\delta_{1,t}} =& Q_{Nt}\sum_{\tau=1}^{N}\frac{\phi_\delta^{\tau-1}\left(J_{\tau,cN}-1\right)}{1+\phi_\delta^{\tau-1}\delta_{1,t}\left(J_{\tau,N}-1\right)}
\end{aligned}
\tag{A6}
$$

Since $Q_{Nt} > 0$, the sign of $\frac{\partial Q_{Nt}}{\partial\delta_{1,t}}$ is determined by the sign of the second element, which proves the first part of the proposition.

Because the denominator in each term is always positive ($1+\phi_\delta^{\tau-1}\delta_{1,t}\left(J_{\tau,N}-1\right) > 0$ and $\phi_\delta > 0$), the sign of each element in the sum depends on the sign of $J_{\tau,N}-1$. The sum includes all periods until maturity, with each term weighted by a positive denominator. Therefore, if all $J_{\tau,N} < 1$, then each term in the sum is negative, and thus the price decreases with an increase in $\delta_{1,t}$.

B Appendix Figures

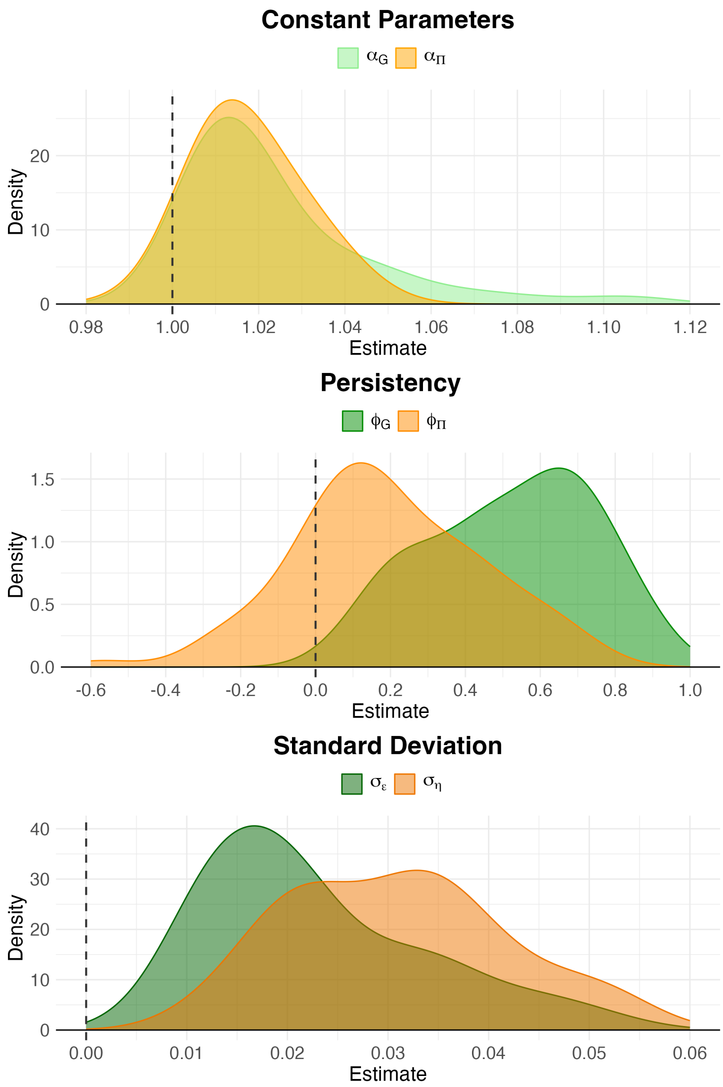

Figure B1: Distribution of Estimates from Laws of Motion

Notes: Notes: The figure shows the kernel density of the estimates for α_G, α_Π, ϕ_G, ϕ_Π, σ_ε, and σ_η. The density plots for the constant parameters use a bandwidth of 0.01, for the persistency parameters a bandwidth of 0.1, and for the residual standard deviations a bandwidth of 0.005.

Source: Author's calculations.

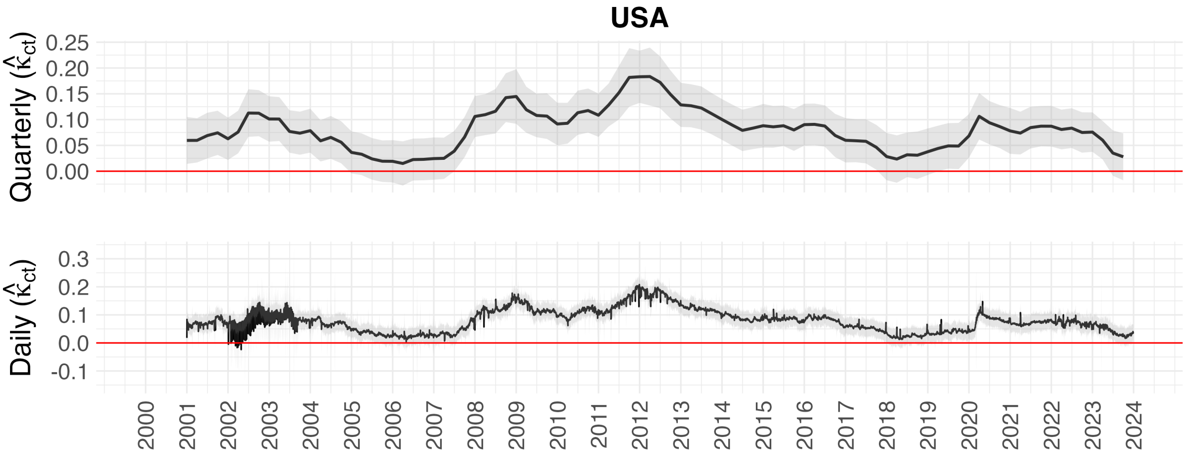

Figure B2: Comparison between Daily and Quarterly Data

Notes: The figure shows the evolution of $\hat{\kappa}_{ct}$ with 95% confidence intervals for the US using daily and quarterly data.
Source: Author's calculations.

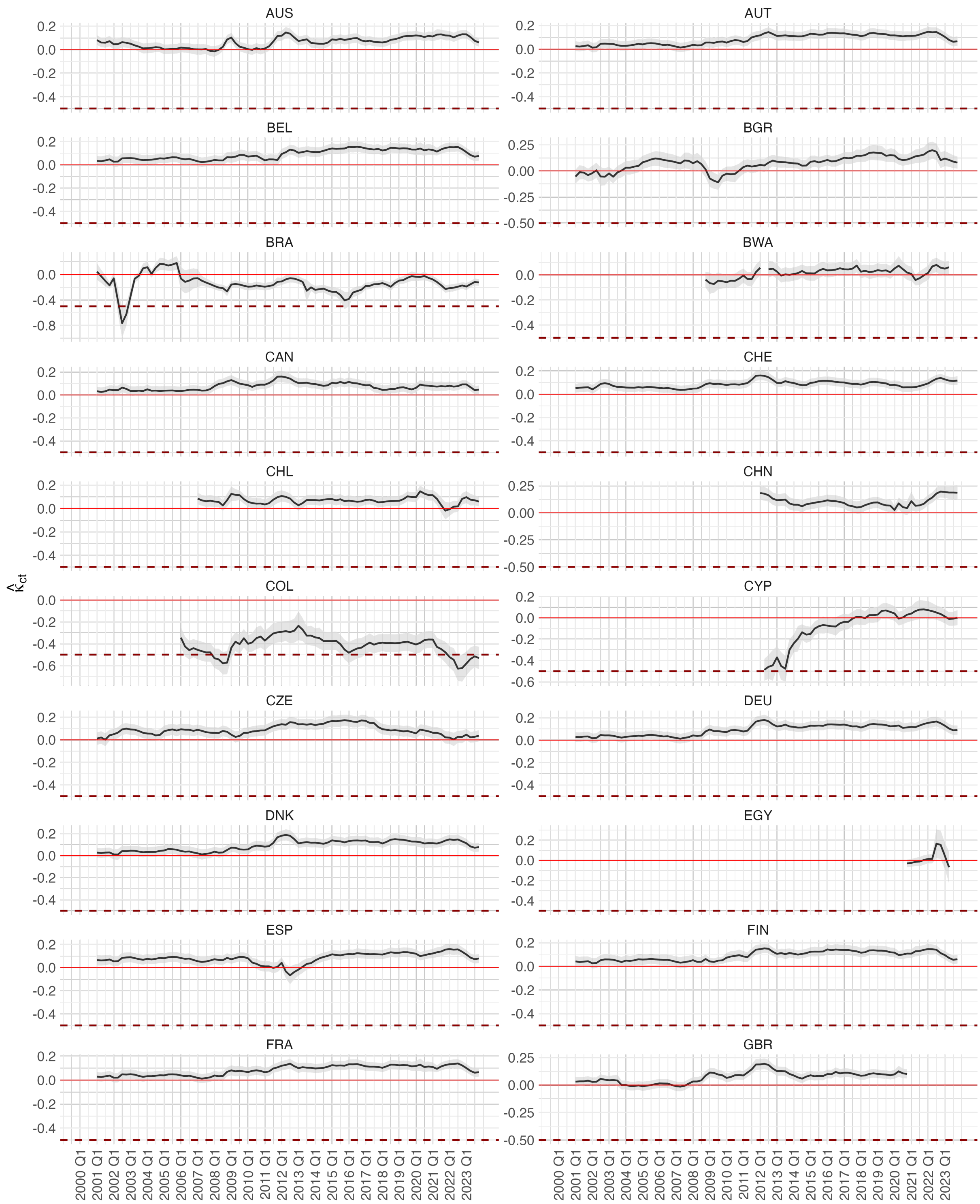

Figure B3: $\hat{\kappa}_{ct}$ for all countries - part 1

Notes: The figure shows the evolution of $\hat{\kappa}_{ct}$ with 95% confidence intervals. The red line at 0 represents a reference threshold. The values are estimated based on the quarterly model.

Source: Author's calculations.

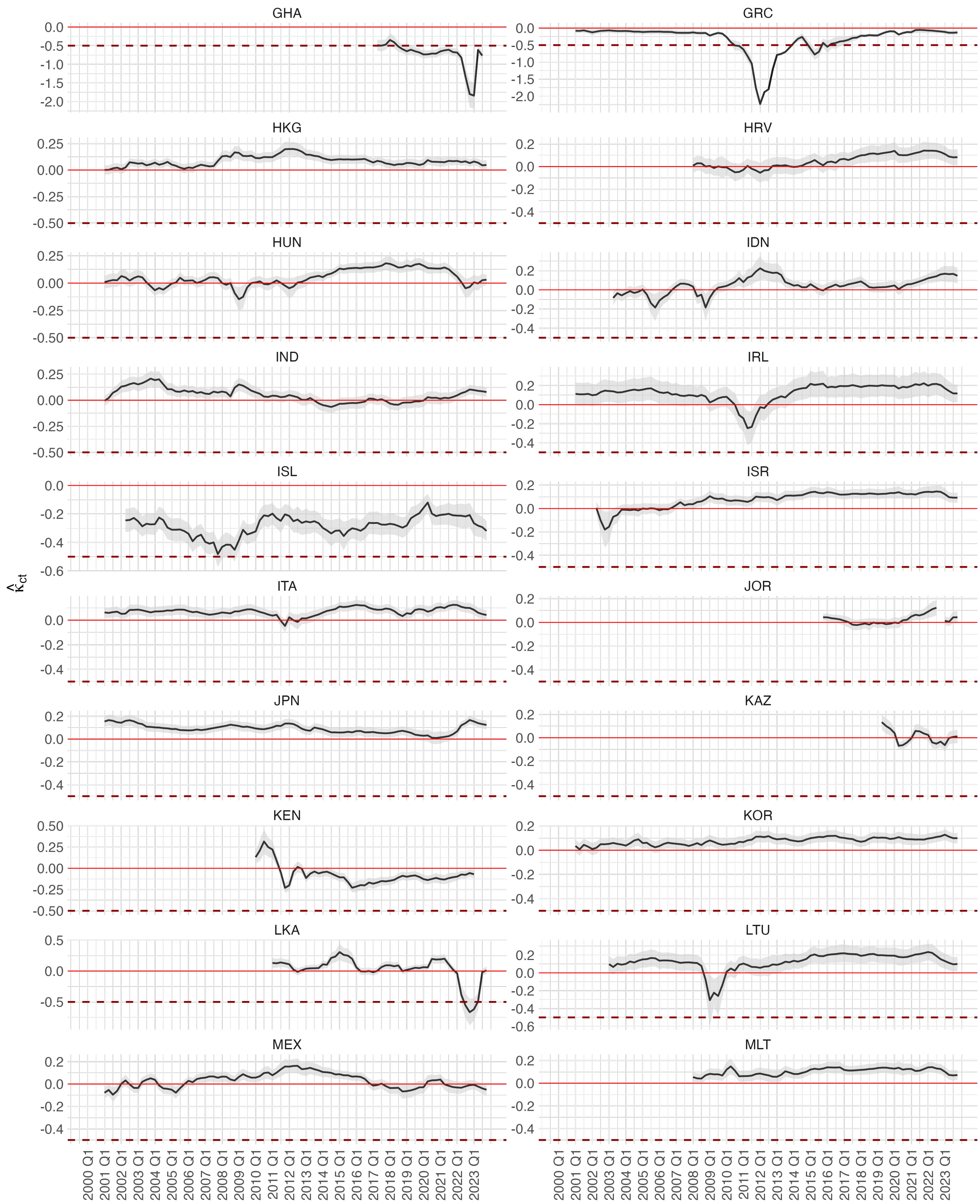

Figure B4: $\hat{\kappa}_{ct}$ for all countries - part 2

Notes: The figure shows the evolution of $\hat{\kappa}_{ct}$ with 95% confidence intervals. The red line at 0 represents a reference threshold. The values are estimated based on the quarterly model.
Source: Author's calculations.

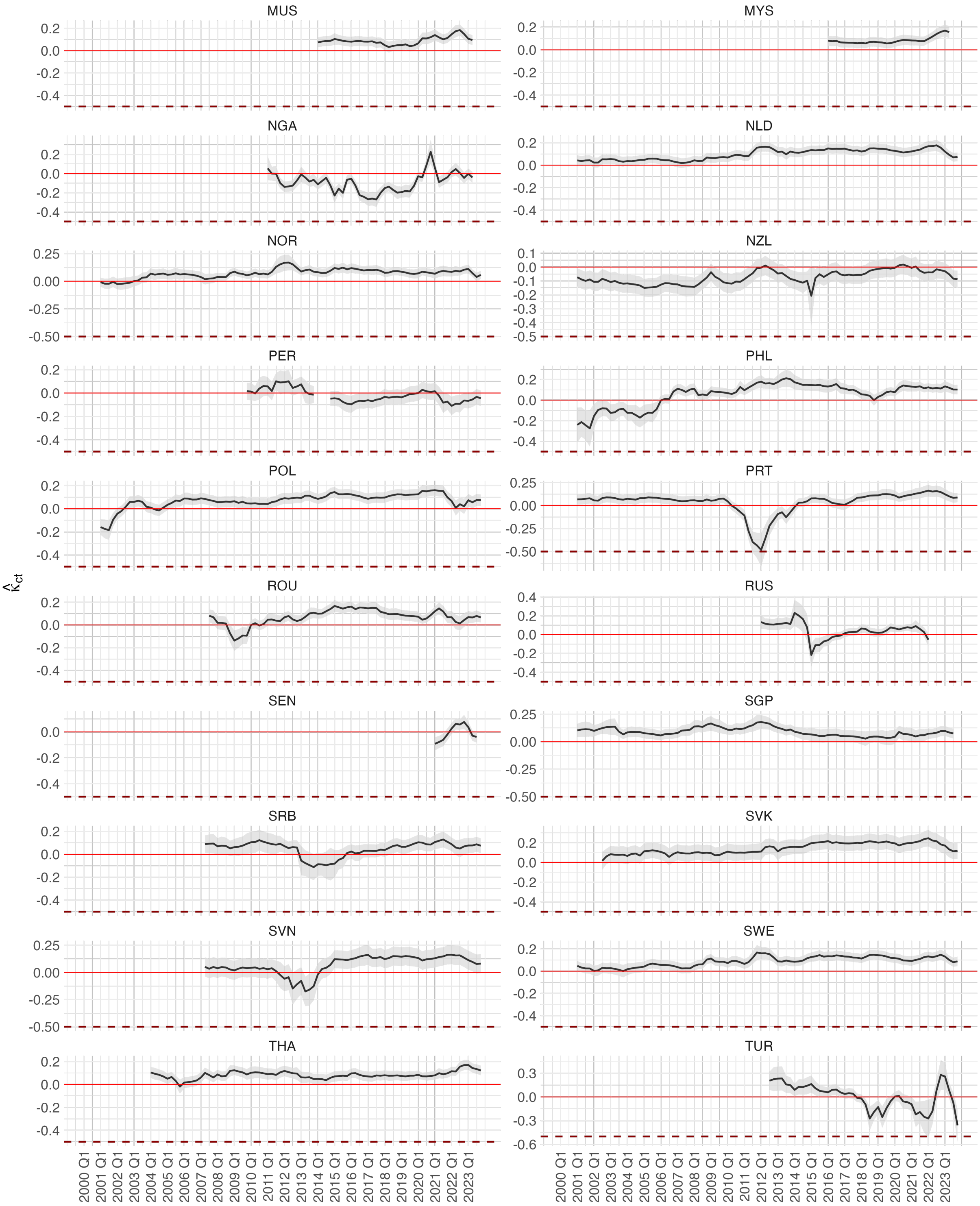

Figure B5: $\hat{\kappa}_{ct}$ for all countries - part 3

Notes: The figure shows the evolution of $\hat{\kappa}_{ct}$ with 95% confidence intervals. The red line at 0 represents a reference threshold. The values are estimated based on the quarterly model.

Source: Author's calculations.

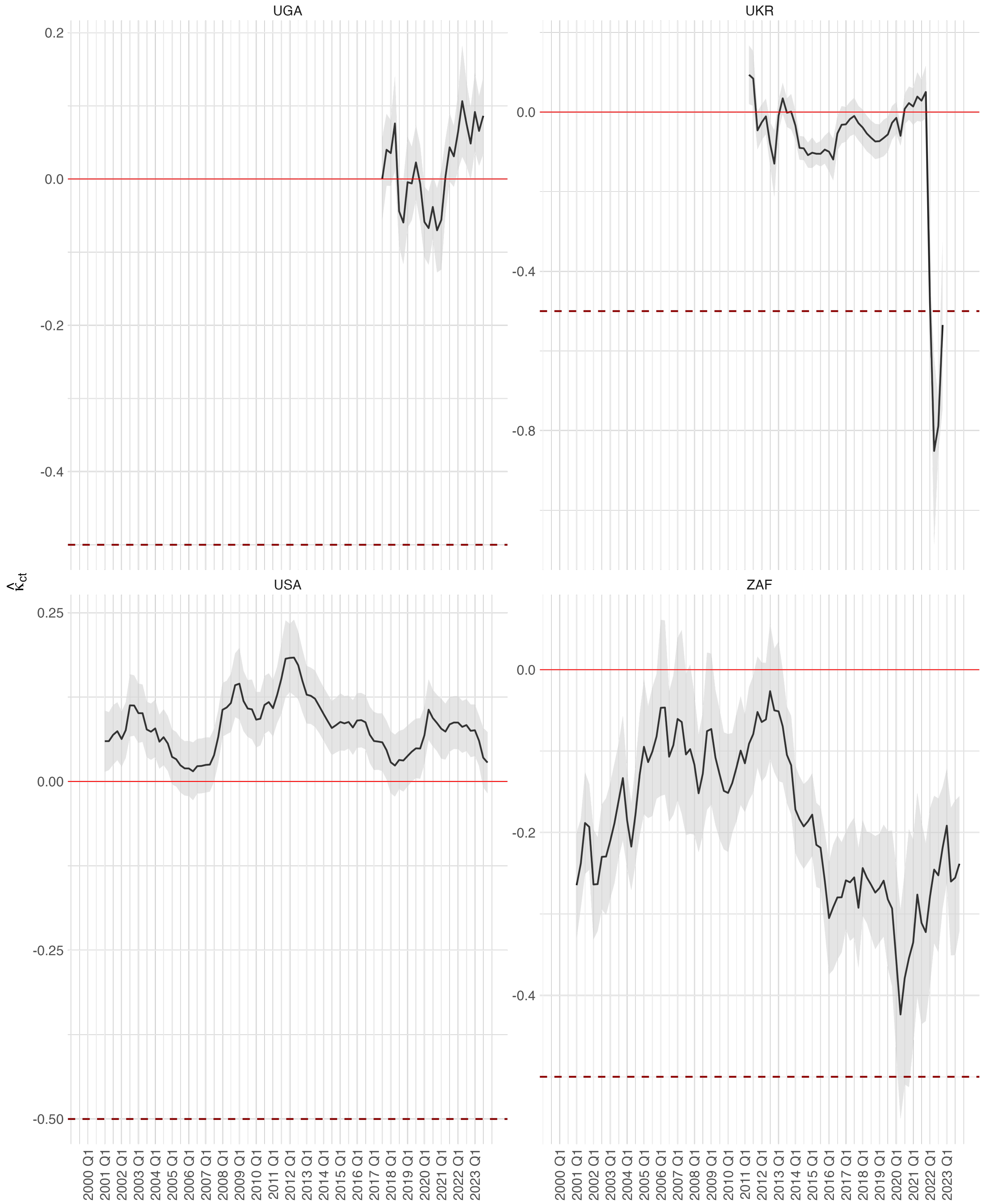

Figure B6: $\hat{\kappa}_{ct}$ for all countries - part 4

Notes: The figure shows the evolution of $\hat{\kappa}_{ct}$ with 95% confidence intervals. The red line at 0 represents a reference threshold. The values are estimated based on the quarterly model.

Source: Author's calculations.

C Appendix Tables

Table C1: Fixed effects regression: impact of war on consumption growth and inflation

	Growth_t	Inflation_t
War_t	-0.023^{***}	0.018^{***}
	(0.004)	(0.004)
Growth_{t-1}	0.164^{***}	
	(0.014)	
Inflation_{t-1}		0.526^{***}
Country FE	✓	✓
Time FE	✓	✓
Observations	5,730	5,242
Adjusted R^2	0.003	0.290

Note: This table presents fixed-effect regressions examining the impact of war on consumption growth (Growth_t) and inflation (Inflation_t). The regression equations are: $\log(\text{Growth}_t) = \beta_1^G \text{War}_t + \beta_2^G \log(\text{Growth}_{t-1}) + \kappa_c + \kappa_t + \epsilon_{it}$, $\log \text{Inflation}_t) = \beta_1^\Pi \text{War}_t + \beta_2^\Pi \log(\text{Inflation}_{t-1}) + \kappa_c + \kappa_t + \epsilon_{it}$. Robust standard errors are reported in parentheses, with $^*p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$ indicating significance levels.
Source: WB/WDI and UCDP/GED data.

Table C2: Fixed effect regression - Quarterly data

	Observed price (q_{Nct})				
	(1)	(2)	(3)	(4)	(5)
Non-disaster price ($\hat{q}_{Nct}^{ND}$)	0.108^{***}	0.206^{***}	0.213^{***}	0.316^{***}	0.294^{***}
	(0.008)	(0.010)	(0.003)	(0.001)	(0.001)
Country-time FE	✓	✓	✓	✓	
Maturity-country FE	✓	✓			
Maturity-time FE	✓		✓		
Observations	28,725	28,725	28,725	28,725	28,725
Adjusted R^2	0.973	0.947	0.846	0.828	0.351

Note: This table presents a fixed-effect regression of the observed log bond price ($q_{Nct} = \log(Q_{Nct})$) on the log of the theoretical non-disaster price ($q_{Nct}^{ND} = \log(Q_{Nct}^{ND})$). Fixed effects are denoted as κ_{Nc} (Maturity-Country), κ_{Nt} (Maturity-Time), and κ_{ct} (Country-Time). Models differ by their inclusion of these fixed effects. Robust standard errors are reported in parentheses, with $^*p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$ indicating significance levels.
Source: Datastream data for observed prices, and author's calculations for theoretical prices based on WB/WDI, IMF/IFS, and UCDP/GED data