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

Joan Margalef†

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Abstract

This paper develops a model to estimate investors' disaster probabilities from yield curve data. Integrating a theoretical asset pricing model with Datastream yield curve data, I uncover daily disaster probabilities for 60 countries from 2000 to 2023. These probabilities can be used to evaluate investors' forecasting abilities and help identify effective policies for stabilizing markets. I demonstrate these applications with case studies, including the Russian-Ukrainian war and Mario Draghi's "whatever it takes" speech. Additionally, the model can be used to provide insights into the nature of disasters as they unfold. 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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†Universitat Autònoma de Barcelona and Barcelona School of Economics (joan.margalef@bse.eu)

1 Introduction

Investors' beliefs are not innocuous. They can have real economic effects and serious welfare implications. If investors suspect that a government might default, they will demand higher returns, increasing the debt burden, 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] This is particularly relevant for economic disasters, such as defaults, wars, or depressions, where even minor fears can have large consequences. For these reasons, authorities try to manage public perceptions through effective communication and policy interventions.[3] The challenge is that investors' beliefs are not directly observable. However, since asset prices are influenced by these beliefs, they can be used to reveal investor's perceived disaster risk.[4]

This paper provides a model to extract investors' disaster probabilities from yield curve data. The yield curve is a graph that plots government bonds' yield against their maturity dates. 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.[5] By integrating a structurally theoretical asset pricing model with Datastream yield curve data, I estimate disaster probabilities for around 60 countries from 2000-2023, available at a daily frequency. These probabilities can be applied in various ways. First, to evaluate the predictive power of investors' beliefs. 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. Second, to identify how government policies influence investors' beliefs. Clear central bank communication and announcements regarding monetary policy, such as interest rate decisions, can significantly influence market expectations. However, the market's reaction is not always predictable or fully aligned with central bank intentions.[6] By analyzing investor beliefs through this model, we can better understand the effectiveness of such interventions. Additionally, the model can be adjusted to classify the effect of the disaster once it occurs. For

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 the achievement of 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."

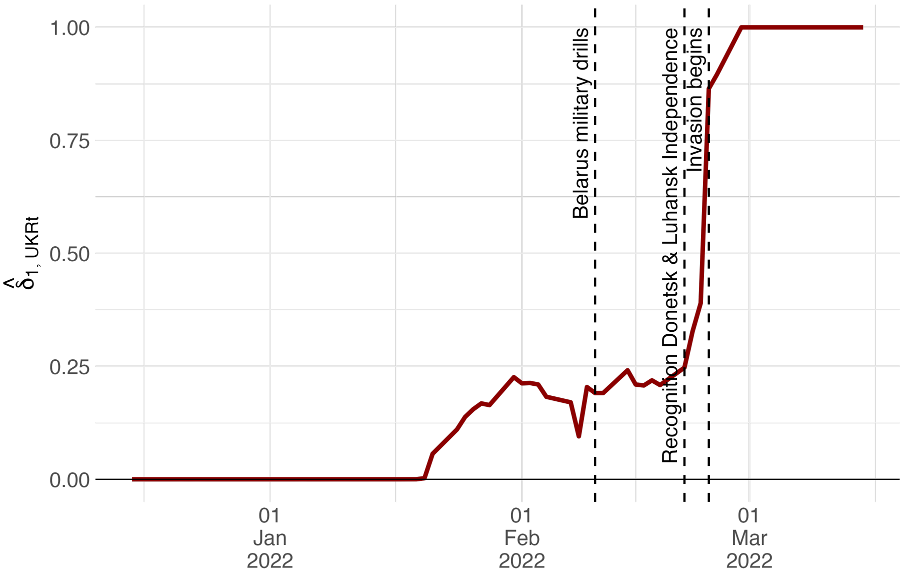
5. Substantial empirical evidence suggests that the yield curve is one of the most informative indicators, particularly for forecasting economic downturns (Estrella and Hardouvelis 1991; Estrella and Mishkin 1998; Ang, Piazzesi, and Wei 2006). Even the Federal Reserve Bank of New York has a webpage dedicated 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).

6. 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.

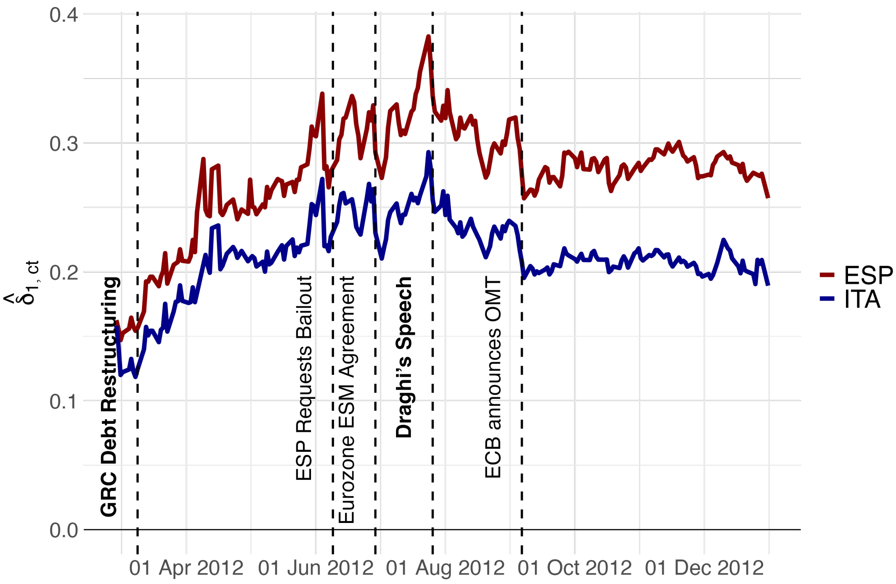
instance, it is ambiguous whether a pandemic is a disaster that will increase or decrease bond prices. The model can help to clarify this.

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 tell that prices depend on the expectation of consumption growth, inflation, and sovereign default. The occurrence of a disaster affects the law of motion of these variables by inducing "jumps". Then, 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: interstate wars, sovereign defaults or consumption disasters. The model tells 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. Since the difference between the observed and theoretical prices captures the disaster wedge, I regress the observed prices on computed theoretical prices using multiple fixed-effect regression. The fixed-effect estimates are used to infer the disaster wedge for each country over time. Finally, for a given disaster type, I estimate the disaster probabilities from the disaster wedge. The type of disaster is set according to the specific context of each country.

The model estimates disaster probabilities for approximately 60 countries from 2000 to 2023, with updates available on a daily basis. I showcase studies to illustrate the model's capabilities, see Figure 1 for a preview. First, investors assigned a relatively low probability to the Russian-Ukrainian war. The estimated disaster probability remained low in the months before the conflict, then jumped abruptly after the invasion began. Second, the model captures the significant impact of Mario Draghi's "whatever it takes" speech in 2012. For Italy and Spain, which were at the peak of default risk the day before the speech, the disaster risk declined on the day of the speech, reversing the upward trend. Lastly, the model can also be used to identify the "type" of a disaster once it occurs, as with the COVID-19 pandemic. The pandemic led to a general increase in perceived default risk across multiple countries. The theoretical model also explains the upward-sloping yield curve puzzle and yield curve inversion before recessions in the US.



(a) Probability of War in Ukraine



(b) Probability of Default in Italy and Spain

Figure 1: Key Results: Estimated Disaster Probabilities in Crisis Events

Notes: Panel (a) shows the estimated probability of inter-state war before the Ukrainian-Russian conflict, indicating investors' minimal anticipation. Panel (b) 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.

Source: Author's calculations using IMF and Datastream data.

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).[7] 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 analyzing the time-fixed effects from time series analysis from 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 is particularly useful due to the additional variation it provides and its well-established role as a key financial indicator. 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. For example, the model can be calibrated to capture defaults and wars, which can occur more frequently, particularly considering the extent of 60 countries. Additionally, the model aligns with theoretical literature, offering consistent explanations for well-established phenomena. Second, the paper provides valuable insights into the potential applications of the computed disaster probabilities. These probabilities can be used to assess investors' forecasting abilities and evaluate the impact of government policies. Additionally, they can be used also to classify the effects of disasters as they unfold. The computed disaster probabilities will be made available on my GitHub repository[8], enabling researchers and policymakers to incorporate them into their own analyses.

The financial literature has explored the predictive power of asset prices in forecasting economic outcomes. Beyond the yield curve, the spread between corporate bonds and treasury notes has also been explored to predict economic activity (Gilchrist and Zakrajšek 2012; Gilchrist et al. 2016). Additionally, there is related literature in corporate finance that tries to disentangle the valuation of political risks using sovereign yield spreads (Clark 1997; Bekaert et al. 2014, 2016). This paper enhances the existing literature by offering insights into leveraging the yield curve for analyzing disaster events through an economically founded structural model. However, while the existing literature shows that market fluctuations can serve as early warning signals (Schneider and Troeger 2006), a distinction must be made between the predictive power of asset prices and whether investors' beliefs, as inferred from asset prices, actually prove to be correct. The accuracy of these investor predictions, particularly in the context of disasters, has only recently gained attention.

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

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

8. https://github.com/joanmargalef

2 Model Setup

The model follows Rietz (1988) and Barro (2006), which I extend by including time-varying probabilities of disasters and inflation.

The representative consumer maximizes a time-additive utility function:

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

where

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

β is the time discount factor and θ is the coefficient of relative risk aversion. At each period, agents can invest in government nominal zero-coupon bonds, each of which will pay out one unit of currency when reaching its maturity. Q_{Nt} is the price of a bond that matures in N periods, and X_{Nt} is the amount bought. The government can partially default on its obligations, where F_{Nt} represents the fraction of the bond that is repaid ($F_{Nt} = 1$ when no default occurs). 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.[9] 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 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 decreases in expected consumption growth and inflation. Since the bond is a mechanism to transfer

9. 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.

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 expected value of the bond.

Following the standard approach in asset pricing research, I will analyze this equilibrium price equation using exogenous processes for the fundamentals: consumption growth, inflation, and the face value of bonds.[10]

In every period, a disaster can happen or not. For simplicity, each disaster is considered independent from the others. $\delta_{\tau,t}$ 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 probablity. This allows expressing 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

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

Therefore, the disaster affects consumption growth through V_{t+1}. When the disaster does not occur, the process defaults to the log of consumption growth following an AR(1) process. $J_G > 0$ represents the "jump" in consumption growth induced by the disaster. A $J_G = 0.98$ implies that disaster lowers consumption growth by 2%.

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

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

with $J_\Pi > 0$ representing the "jump" in inflation induced by the disaster.

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

10. See Cochrane (2009).

the face value of the bond is given by

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

with

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

and $J_F \in [0,1]$ denoting 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 more risky since can suffer several haircuts.

Note that independence between disasters implies that $V_t \perp V_{t'}, W_{t'}, Z_{t'}$ for $t' \neq t$. However, V_t, W_t, and Z_t are perfectly correlated through the disaster event. Considering this, equation (2) can be rewritten as

$$Q_{Nt} = Q_{Nt}^{ND} DW_{Nt} = Q_{Nt}^{ND} \prod_{\tau=1}^{N} \underbrace{\left(1 + \delta_{\tau,t}\left(J_{\tau,N} - 1\right)\right)}_{DW_{\tau,Nt}} \tag{14}$$

where

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

and

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

Therefore, the price of a bond is composed of its price when there are no disasters, Q_{Nt}^{ND}, times the product of the disaster wedge, DW_{Nt}. $DW_{\tau,Nt}$ represents the specific disaster wedge from the disaster in τ periods. $J_{\tau,N}$ is the "overall effect" of a disaster happening in τ periods to a bond that matures in N periods. Q_{Nt}^{ND} accounts for expectations driven by the current business cycle, since it internalizes the effect of current consumption growth and inflation on the bond price.

This model provides tractable solutions that allow us to analyze how beliefs regarding disasters influence bond prices. Ignore for a moment that the disaster probabilities are connected through Equation 7. An increase in $\delta_{\tau,t}$ increases prices if and only if $J_{\tau,N} > 1$, which implies

$$\log(1-\gamma J_F) - \log(J_\Pi)\sum_{\tau=1}^{N+1-\tau}\phi_\Pi^{\tau-1} - \theta\log(J_G)\sum_{\tau=1}^{N+1-\tau}\phi_G^{\tau-1} < 0 \tag{17}$$

This implies that bond prices rise with the probability of a disaster, driven by the interplay between jumps in consumption growth, inflation, and default risk, which may offset each other. Since the overall effect depends also on the persistencies, short-term and long-term bonds may move in opposite directions. Note also that the summation in the exponent of the J_G and J_Π includes more components as the difference between the period when the disaster occurs (τ) and when it matures (N) increases. This implies that long-term bonds accumulated more effects due to the persistence of the fundamentals' process.

Accounting for the fact that the disaster probabilities move together through Equation 7,

Proposition 1 *Q_{Nt} is increasing in $\delta_{1,t}$ if and only if*

$$\sum_{\tau=1}^{N} \frac{\phi_\delta^{\tau-1}\left(J_{\tau,N}-1\right)}{1+\phi_\delta^{\tau-1}\left(J_{\tau,N}-1\right)} > 0 \tag{18}$$

The proof is in the Appendix A. A sufficient condition for this proposition to hold is that $J_{\tau,N} > 1$ for all τ and N. If $\delta_{1,t}$ increases, then all $\delta_{\tau,t}$ increase, and since all $J_{\tau,N}$ are greater than 1, then Q_{Nt} increases. However, since it is possible that the sign of $J_{\tau,N}$ changes for some maturities, it is not guaranteed that Q_{Nt} increases with $\delta_{1,t}$.

3 Estimating Investor's Disaster Probabilities

The model, summarized by Equation 14, shows that government bond prices can be decomposed by 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 equation to the data by running a fixed-effect regression to attribute part of the difference between the observed prices and the theoretical ones to the disaster wedge. Finally, specifying the disaster type, I determine the probability of the disaster.

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

Datastream, provided by Refinitiv, 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.[11]

I retrieved the computed benchmark yield curve, which is based on benchmark bonds.[12] These reflect the experience of the average bondholder, focusing on 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.[13] These cover standard government bonds with fixed rates and fixed maturity dates, while excluding bonds with variable rates, and other features that distort predictability.[14] 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.[15]

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, 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's International Financial Statistics (IMF/IFS) and annual data from the World Bank's World Development Indicators (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 choice of these two data sources is driven by their complementary strengths. The IMF provides quarterly data, which allows me to increase the updating frequency of the model by inputting per-period consumption growth and inflation. This higher frequency is crucial for aligning the macroeconomic variables with the financial data. I use the countries to match the financial data from the same time horizon (if available). On the other hand, the annual World Bank data offers more comprehensive data with a longer time span, which is particularly useful for estimating the laws of motion of consumption growth and inflation, as well as the effects of disasters over an extended period. I use annual data covering 189 countries from 1989 to 2023.

Finally, to link economic effects to inter-state wars, I utilize battle-related fatality data from the

11. To see a list of all the countries involved and their respective time horizons, see Table X in the appendix.

12. These are based on Refinitiv Government Bond Indices, which are calculated using methodologies recommended by the European Federation of Financial Analysts Societies (EFFAS).

13. 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.

14. Excluded bonds include those with inflation-linked, floating rate, convertible, and bonds with embedded options or warrants.

15. 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.

Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP/GED). I aggregate this data to the country-year level, which allows me to quantify the intensity of conflicts in each country annually. 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 involves setting parameters for the utility function, and those governing the laws of motion for consumption growth and inflation, and disaster-related parameters.

3.2.1 Utility and Law 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 of consumption growth and inflation are country-specific. To estimate them, I use annual data from the World Bank's World Development Indicators (WB/WDI) from 1989 to 2021. By taking logs on Equation 8 and 10, the laws of motion are transformed into a linear equation. In the absence of disaster shocks, these equations represent an AR(1) process. Using OLS on countries' time series, I estimate the constant parameters (α_G and α_Π), the persistence parameters (ϕ_G and ϕ_Π), and the standard deviations (σ_ε and σ_η), for each country. For the period-specific consumption growth and inflation, G_t and Π_t, I use data from the IMF's International Financial Statistics (IMF/IFS), which provides quarterly year-over-year rates.

With all these parameters, I can compute the theoretical non-disaster prices, Q_{Nt}^{ND}, for each country and period. Importantly, theoretical prices do not incorporate disaster risk; they reflect prices based purely on expectations driven by the current values of the economic fundamentals and their projected evolution according to the country's laws of motion.

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. I define three types of disasters: inter-state war, sovereign default, and the classic consumption disaster. While the first two are central to deriving disaster probabilities in this paper, the consumption disaster is included to connect with the disaster literature and demonstrate how the theoretical model can also explain empirical phenomena, such as the upward-sloping yield curve and its inversion before recessions.

For inter-state wars, the haircut when default J_F is 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 the jumps in consumption growth and inflation, I conducted a two-way fixed-effects analysis using WDI/WB data.[16] The results show that an year in war reduces consumption growth by 2% and increases inflation by 2%. Therefore, I set $J_G = 0.98$ and $J_\Pi = 1.02$.

For default as the disaster type, the objective is to capture the probability of default using $\delta_{1,t}$, allowing me to omit the parameter γ. The parameter J_F is set to 0.44, as the average haircut for sovereign defaults is 44% (Meyer, Reinhart, and Trebesch 2022).

The consumption disaster is widely used in macroeconomic literature to explain asset pricing puzzles (Rietz 1988; Barro 2006; Gabaix 2012; Barro and Liao 2021). It represents a severe drop in consumption growth, which also carries default risk. Following Barro (2006), I set J_G to 0.71, γ to 0.4, and J_F to 0.29.

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 $\hat{J}_{\tau,cN}$. Finally, I set the persistency parameter of the disaster probability $\phi_\delta = 0.5$ for all disaster types. Table 1 provides a summary of the disaster definitions.

Table 1: Summary of Disaster Definitions and Calibrations

Disaster Type	$\hat{J}_G$	$\hat{J}_\Pi$	$\hat{\gamma}$	$\hat{J}_F$	Source
Inter-State War	0.98	1.02	0.5	0.56	Von Laer & Bartels (2023) and author's calculations
Sovereign Default	-	-	-	0.44	Meyer et al. (2022)
Consumption Disaster	0.71	-	0.4	0.29	Barro (2006)

Notes: The jumps in consumption growth and inflation are denoted by J_G and J_Π, respectively. The haircut for partial default is J_F. The default probability is γ.
Source: Barro (2006), Luckner et al. (2023), and Meyer, Reinhart, and Trebesch (2022) and author's calculations.

Figure 2 shows the simulated impact of a $\delta_{1,t} = 0.25$ for each disaster type on the log price curve for the US calibration. The figure shows that for inter-state war, the inflationary/default risk outweighs the recessionary effect, leading to a price drop across all maturities. Default has the strongest negative impact. In contrast, the consumption disaster has the largest impact and is the only one that raises prices. The sharp drop in consumption makes the recessionary effect outweigh default concerns, prompting individuals to invest to smooth consumption.

16. 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.

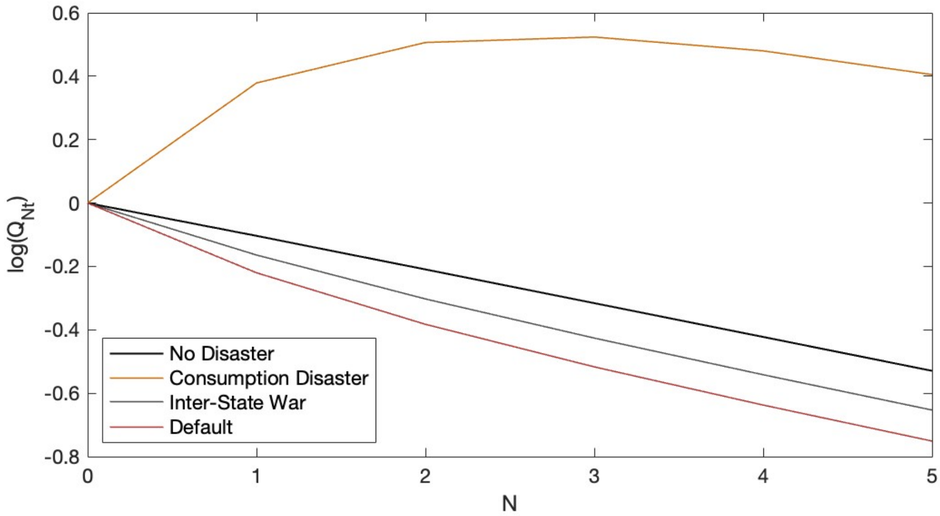


Figure 2: Comparative Statics of Disaster Shocks

Notes: The figure presents simulated price curves for each disaster type, using a calibration for the US with $\delta_{1,t} = 0.25$, $\phi_\delta = 0.5$, and the remaining disaster parameters taken from Table 1. I set $G_t = \Pi_t = 1.02$.
Source: Author's calculations.

3.3 Bringing the model to the data

To account for the panel data structure, I introduce the country index c into Equation 14:

$$Q_{Nct} = Q_{Nct}^{ND} \prod_{\tau=1}^{N} \left(1 + \delta_{\tau,ct}\left(J_{\tau,cN} - 1\right)\right) \tag{19}$$

Q_{Nct} is the observed prices for country c at time t, and Q_{Nct}^{ND} is the theoretical price. Taking logarithms,

$$q_{Nct} = q_{Nct}^{ND} + \sum_{\tau=1}^{N} \log\left(1 + \hat{\phi}_\delta^{\tau-1}\delta_{1,ct}\left(\hat{J}_{\tau,cN} - 1\right)\right) \tag{20}$$

with $q_{Nct} = \log(Q_{Nct})$ and $q_{Nct}^{ND} = \log(Q_{Nct}^{ND})$. Therefore, the disaster wedge is captured in the difference between the log of the computed theoretical prices and the observed prices. I bring this equation to the data by estimating the following regression:

$$q_{Nct} = \beta q_{Nct}^{ND} + \chi_N + \chi_c + \chi_t + \kappa_{Nc} + \kappa_{Nt} + \kappa_{ct} + u_{Nct} \tag{21}$$

where χ_N, χ_c, χ_t are fixed effects for maturity, country, and time, respectively. κ_{Nc}, κ_{Nt} and κ_{ct} are interaction terms, and u_{Nct} is the error term. The interpretation of this equation is that observed prices can be explained by the theoretical price, which accounts for expectations driven by the current business cycle, plus a set of unobserved factors that vary at different levels. Table 2 presents the regression results for the full sample and when applied exclusively to the USA time series.

Table 2: Fixed Effect Regression

	Observed Price (q_{Nct})	USA Observed Price (q_{NUSAt})
Non-Disaster Price (q^{ND}_{Nct})	0.099***	1.388***
	(0.010)	(0.524)
Country FE	Y	-
Maturity FE	Y	Y
Time FE	Y	Y
Country-Time FE	Y	-
Country-Maturity FE	Y	-
Maturity-Time FE	Y	-
Observations	26,811	528
Adjusted R^2	0.972	0.885

Note: *p<0.1; **p<0.05; ***p<0.01
Source: Author's calculations using IMF and Datastream data.

The first testable hypothesis is on the model's ability to explain observed bond prices. If the model perfectly captures the data-generating process of bond prices, the estimated β should be close to 1. In both specifications, the estimated β is positive and significant, indicating that the theoretical price moves in the expected direction. For the full sample with all fixed effects, $\hat{\beta} = 0.1$, which is notably far from 1, justifying the inclusion of additional fixed effects to capture unobserved factors not accounted for by the theoretical model. However, given that bond prices are typically close to 1, a $\hat{\beta}$ of 0.1 does not imply major deviations. In the USA-only specification, $\hat{\beta} = 1.388$, which is closer to 1, but the adjusted R^2 is substantially lower than in the full sample. Another observation is that the coefficient of the fixed effect for maturity decreases over the horizon, indicating that the theoretical model tends to overestimate prices more for long-term bonds.

Given $\delta_{1,ct}$ varies at the country-time level, it is captured in κ_{ct} as the common unobserved factor at 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 alone would suggest. Conversely, a significantly negative $\hat{\kappa}_{ct}$ implies that this unobserved factor is reducing bond prices. I assume this unobserved factor is disaster risk. Specifically, it is the average effect of disaster risk across all maturities, i.e.,

$$\hat{\kappa}_{ct} = \frac{\sum_{N \in \mathcal{N}(c,t)} q_{Nct} - \hat{\beta}\hat{q}^{ND}_{Nct} - \hat{\chi}_N - \hat{\chi}_c - \hat{\chi}_t - \hat{\kappa}_{Nc} - \hat{\kappa}_{Nt}}{|\mathcal{N}(c,t)|} \tag{22}$$

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. Figure 3 plots the evolution of $\hat{\kappa}_{ct}$ for Switzerland, Spain, Greece, Ireland, Italy, Portugal, Ukraine, and the USA with a 95% confidence interval. The red line at -0.1 represents a reference threshold. While the US and Switzerland managed to keep the disaster risk above the threshold, the other European countries failed during the European debt crisis, and Ukraine when the war started. To see the evolution of $\hat{\kappa}_{ct}$ overtime for the rest of the countries, see Figure A1, A2, A3, and A4 in the Appendix B.

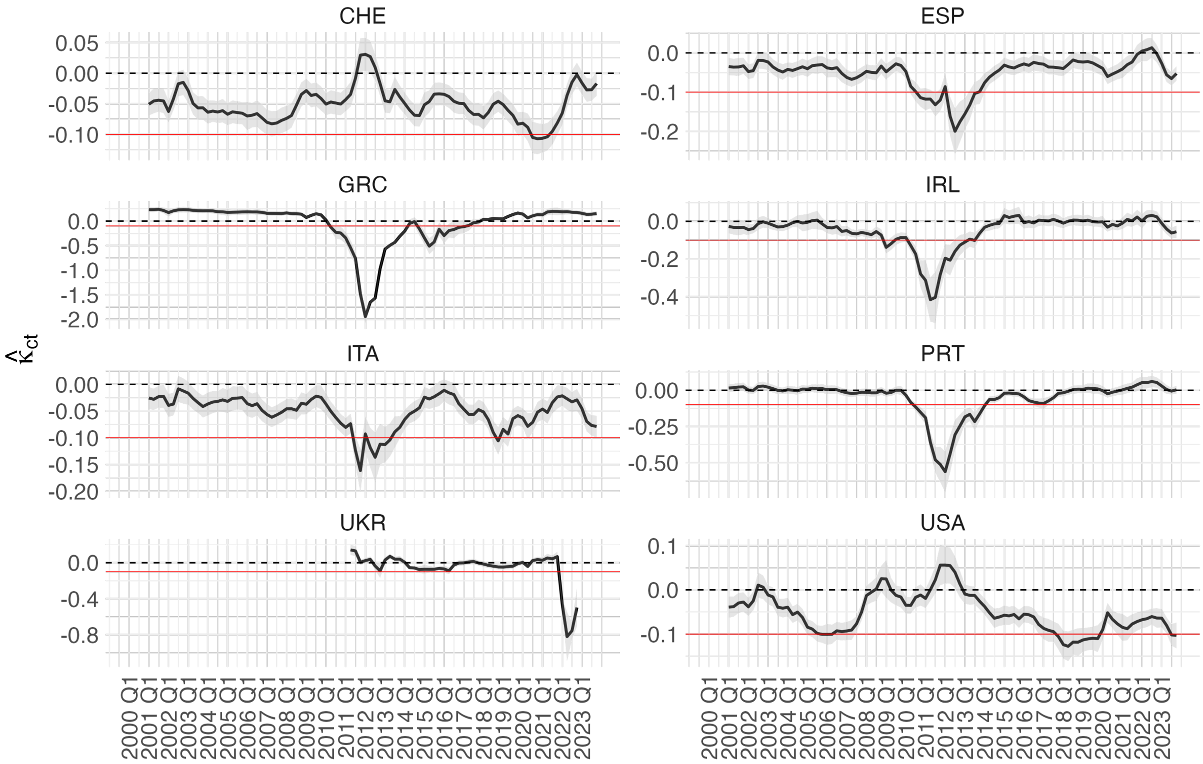


Figure 3: $\hat{\kappa}_{ct}$ for Selected Countries
Notes: The figure shows the disaster wedge with 95% confidence intervals for the selected countries (Spain, Greece, Italy, Portugal, Ukraine, and the USA). The red line at -0.1 represents a reference threshold. The values are estimated based on quarterly data.
Source: Author's calculations using IMF and Datastream data.

Given that the elements in the summation are the specific impact on each maturity, the effect of disaster risk on each maturity, $\hat{\kappa}_{ct(N)}$, is given by

$$\hat{\kappa}_{ct(N)} = q_{Nct} - \hat{\beta}\hat{q}^{ND}_{Nct} - \hat{\chi}_N - \hat{\chi}_c - \hat{\chi}_t - \hat{\kappa}_{Nc} - \hat{\kappa}_{Nt} \quad \forall N \in \mathcal{N}(c,t) \tag{23}$$

According to the assumption that $\hat{\kappa}_{ct}$ is the disaster wedge, the theoretical form of the disaster wedge is linked to the estimation through

$$\hat{\kappa}_{ct(N)} = \sum_{\tau=1}^{N} \log\left(1 + \hat{\phi}_{\delta}^{\tau-1}\delta_{1,ct}\left(\hat{J}_{\tau,cN} - 1\right)\right) \quad \forall N \in \mathcal{N}(c,t) \tag{24}$$

Equation 24 represents a system of $|\mathcal{N}(c,t)|$ with $\delta_{1,ct}$ being the unknown. I estimate it by minimizing the square distance between $\hat{\kappa}_{ct(N)}$ and the disaster wedge, i.e.,

$$\hat{\delta}_{1,ct} = \underset{\delta_{1,ct}}{\operatorname{argmin}} \sum_{N=1}^{\mathcal{N}(c,t)} \left(\hat{\kappa}_{ct(N)} - \sum_{\tau=1}^{N} \log\left(1 + \hat{\phi}_{\delta}^{\tau-1} \delta_{1,ct} \left(\hat{J}_{\tau,cN} - 1\right)\right)\right)^2 \tag{25}$$

Note that the disaster probability is estimated based on a specific disaster effect calibration. If two different disasters have a similar effect on bond prices, the model cannot differentiate between them. Therefore, identifying the type of disaster ultimately relies on the country's specific context. To enhance this identification process, an NLP (Natural Language Processing) model could be used in parallel to analyze news articles, reports, and other text data, providing insights into the specific events of concern for each country and moment in time.

4 Results

Based on the yield curve model estimation process detailed in the previous section, I can now estimate disaster probabilities for each country and period for a given disaster type, allowing us to draw several key insights. First, the model enables an assessment of investors' disaster forecasting abilities, shedding light on how market expectations adjust in response to evolving risks. Second, it provides a tool for identifying effective policy interventions aimed at stabilizing markets in times of crisis. To demonstrate these applications, I will analyze several case studies.

4.1 Evaluating Investors' Forecasting Abilities: the Ukrainian-Russian War

Financial markets are well-suited to reveal true perceptions of war risk, as they aggregate the opinions of participants who have a financial incentive to estimate risks accurately. However, while existing literature shows that market fluctuations can serve as early warning signals (Schneider and Troeger 2006), the accuracy of investors' war predictions has only recently gained attention.

I estimated the probability of an inter-state war in Ukraine. Figure 4 illustrates the evolution of the estimated probability from December 2021 to March 2022, with key events marked by dashed vertical lines. The figure reveals that, despite years of geopolitical tensions, investors largely did not anticipate the likelihood of an inter-state war two months before the invasion, and only showed some concern in the last month and a half. Even after the Belarus military drills on February 10, and Russia's recognition of the independence of Donetsk and Luhansk on February 21, investors' perceptions of an imminent conflict remained relatively low. It was only after the invasion began on February 24, that the estimated probability of an inter-state war rose sharply, indicating a rapid adjustment in investor expectations in response to the unfolding events.

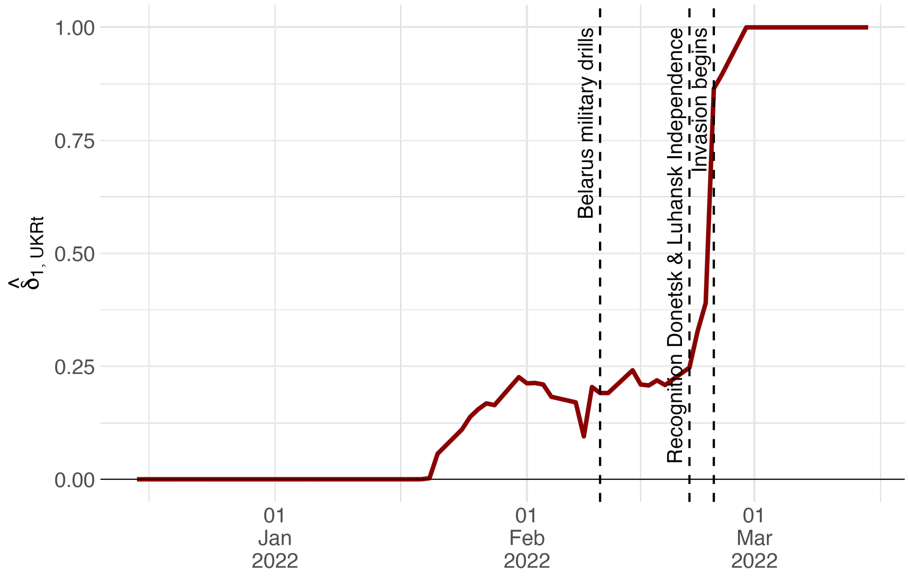


Figure 4: Evolution of Probability of Inter-State War

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 using IMF and Datastream data.

This finding indicates that the market largely failed to anticipate the outbreak of the Ukrainian-Russian war, as demonstrated by the model's estimation of a low probability before the conflict and the strong reaction that followed its onset. If financial markets accurately anticipated the onset of war, there would be no strong reaction once it starts because the risk would have already been priced in. 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 based on a strong yield reaction. This model extends the analysis by not just examining yield reactions, but by estimating the underlying investors' probability of war, accounting for the business cycle through country-specific laws of motion and other factors using fixed effects.

4.2 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 (also known as the PIIGS). These countries underwent multiple rounds of bailouts and austerity measures imposed by the IMF, the ECB, and the European Commission. I particularly analyze the case of Spain and Italy, which were in a different context than Portugal, Greece, and Ireland since they did not have an IMF bailout.

Figure 5 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 previously upward trend into a downward one. 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.

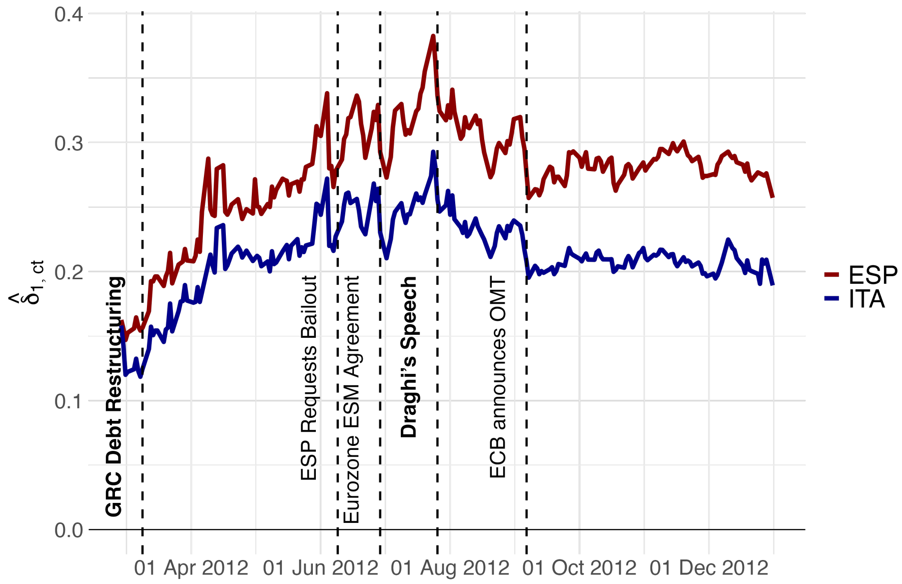


Figure 5: Evolution of Probability of Default for Spain and Italy
Notes: The figure shows the evolution of the probability of default for Spain and Italy. The values are estimated by interpolating economic quarterly data. Vertical lines represent relevant events.
Source: Author's calculations using IMF and Datastream data.

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 investor sentiment and expectations.

4.3 Additional Applications and Theoretical Insights

Beyond estimating disaster probabilities, the model offers a range of practical applications and theoretical insights. I can assess the nature of specific disasters as they unfold, such as the COVID-19 pandemic. Furthermore, consistent with the disaster literature, the model enables me to explain asset pricing phenomena, including the upward-sloping yield curve puzzle and yield curve inversion before recessions in the US.

4.3.1 COVID-19, a disaster of default risk

The COVID-19 pandemic significantly impacted global financial markets, creating uncertainty in bond prices that could either decrease or increase. One mechanism through which the crisis could reduce bond prices involves heightened government default risks, as fiscal pressures intensify with increased spending to manage the pandemic and reduced tax revenues. Additionally, inflationary concerns might arise if government stimulus leads to an oversupply of money, prompting investors to demand higher yields to offset expected losses in purchasing power, further depressing bond prices. On the other hand, the pandemic might trigger a recessionary shock that increases asset prices. Investors, anticipating low economic growth and limited consumption opportunities, may flock to the safety of government bonds. This surge in demand, coupled with increased savings channeled into securities, could drive up their prices.

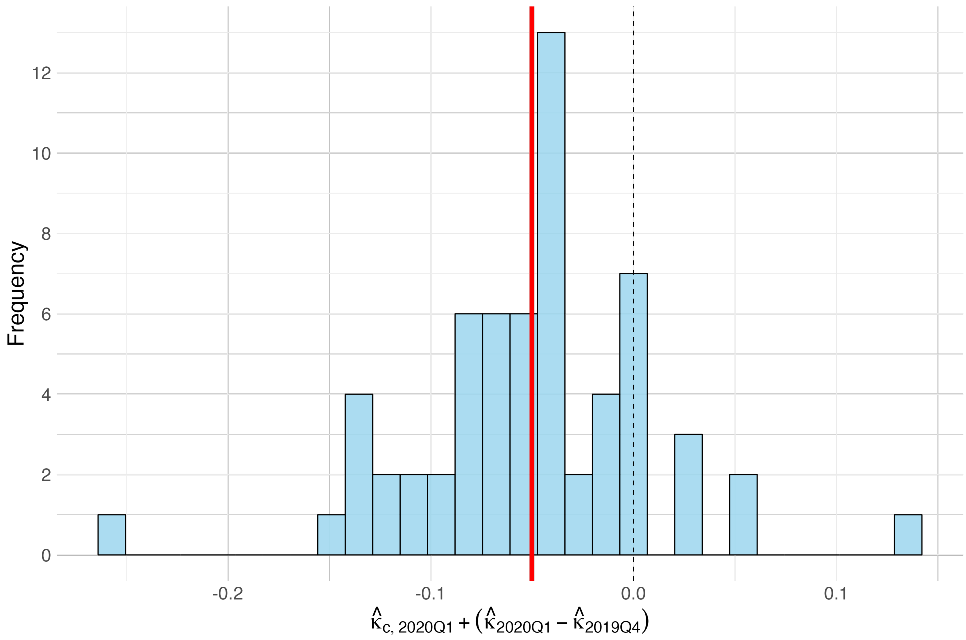


Figure 6: Distribution of Disaster Risk due to Covid-19

Notes: The figure shows the distribution of disaster risk due to COVID-19 for all countries in the sample. The values are estimated based on quarterly data. The red line at -0.05 represents the mean value.
Source: Author's calculations using IMF and Datastream data.

Figure 6 displays the distribution of estimated disaster risk across all countries during the first quarter of the COVID-19 pandemic (2020Q1). Given that the pandemic was a global event, its impact is likely reflected in the estimated time-fixed effect ($\hat{\kappa}_t$) instead of in the country-time fixed effect ($\hat{\kappa}_{ct}$). Consequently, I have adjusted the model to include the difference in time fixed effects between the pre-pandemic period and the onset of the pandemic, i.e., $\hat{\kappa}_{2020Q1} - \hat{\kappa}_{2019Q4}$, with a minor positive correction factor of 0.0016. The mean disaster risk level, marked by a red line at -0.05, indicates that the COVID-19 pandemic was a shock that reduced bond prices, reflecting heightened default risk and inflationary concerns. However, the sample shows significant variation, with 10 countries experiencing a disaster risk effect below -0.1, while a small subset showed an increase in bond prices.

My findings align with Arellano, Bai, and Mihalache (2024), which emphasizes the significant increase in default risk during pandemic crises. However, my results suggest that the COVID-19 pandemic was perceived as a less severe default shock compared to the more pronounced impacts identified in their analysis.

4.3.2 Theoretical Insights: Yield Curve Puzzle and Inversion for the US

Using the calibration for the US economy,[17] 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; Gabaix 2012), I set the probability of a consumption disaster to 0.02, which is constant over time. 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. 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 presents a novel method to extract disaster risk from yield curve data, providing a structured approach to analyze investor expectations regarding macroeconomic shocks, such as wars, financial crises, and pandemics. By integrating a classic asset pricing model with time-varying disaster probabilities and using high-frequency yield curve data, the model captures how changes in investor expectations about consumption growth, inflation, and sovereign default risk influence bond prices.

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

The application of the model to a diverse panel of 60 countries over two decades reveals several key insights into investor behavior. Firstly, the model demonstrates that financial markets largely failed to anticipate the Russian-Ukrainian war, with disaster probabilities only spiking after the invasion began. This highlights the inherent challenges of predicting geopolitical risks in financial markets, despite years of rising tensions. Secondly, the model captures the significant impact of Mario Draghi's "whatever it takes" speech in 2012 on reducing perceived default risk in Southern European countries. 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 investor sentiment, especially during periods of financial instability. Finally, the analysis shows that the COVID-19 pandemic led to a marked increase in perceived default risk across many countries, as reflected by a general decline in bond prices. While the pandemic's impact was less severe than that of previous crises, such as the European debt crisis, it nonetheless highlighted the vulnerability of sovereign debt markets to sudden and unexpected shocks.

Overall, this study contributes to the literature on disaster risk and financial markets by offering a theoretically grounded and empirically robust method for estimating investor expectations of disaster probabilities. By incorporating both macroeconomic fundamentals and disaster probabilities into a unified framework, the model provides a valuable tool for understanding how investors respond to extreme events. It also offers policymakers insights into how their actions, such as communication strategies and fiscal measures, can shape market perceptions during crises.

Further research could expand the model by incorporating additional asset classes, such as equities and corporate bonds, and developing a general equilibrium framework to more accurately capture the data-generating process, thereby improving the theoretical price estimations and enhancing identification. Moreover, it would be beneficial to refine the model by addressing potential measurement errors in the estimation process and accounting for heterogeneity in disaster impacts across different countries and events. For instance, the severity of a conflict could be influenced by its outcome, which might be better captured through a contest function that reflects the varying impacts on economies depending on the results of the war. Additionally, 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. This multi-faceted approach would improve the model's ability to differentiate between various disaster scenarios and their potential effects on investor expectations.

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Appendices

A Derivations and Proofs

A.1 Derivation of the Price Equation

Take 1-year bond, then

$$\begin{aligned}
Q_t^{(1)} &= \beta \mathbb{E}_t \left[\frac{1}{G_{t+1}^{\theta} \Pi_{t+1}} \right] = \beta \mathbb{E}_t \left[\frac{1}{(C_G G_t^{\phi_G} \varepsilon_{t+1} V_{t+1})^{\theta} C_\Pi \Pi_t^{\phi_\Pi} \eta_{t+1} W_{t+1}} \right] \\
&= \beta \frac{1}{(C_G G_t^{\phi_G})^{\theta} C_\Pi \Pi_t^{\phi_\Pi}} \mathbb{E}_t \left[\frac{1}{\varepsilon_{t+1}^{\theta}} \right] \mathbb{E}_t \left[\frac{1}{\eta_{t+1}} \right] \mathbb{E}_t \left[\frac{1}{V_{t+1}^{\theta} W_{t+1}} \right] \\
&= \beta \frac{1}{(C_G G_t^{\phi_G})^{\theta} C_\Pi \Pi_t^{\phi_\Pi}} \mathbb{E}_t \left[e^{-\log(\theta \varepsilon_{t+1})} \right] \mathbb{E}_t \left[e^{-\log(\eta_{t+1})} \right] \left(1 - \delta_{t+1} + \delta_{t+1} \frac{1}{J_G^{\theta} J_\Pi} \right) \\
&= \beta \frac{1}{(C_G G_t^{\phi_G})^{\theta} C_\Pi \Pi_t^{\phi_\Pi}} e^{\frac{1}{2}\left((\theta \sigma_\varepsilon)^2 + \sigma_\eta^2\right)} \left(1 + \delta_{t+1} \left(\frac{1}{J_G^{\theta} J_\Pi} - 1 \right) \right)
\end{aligned} \tag{26}$$

Take 2-year bond, then

$$\begin{aligned}
Q_t^{(2)} &= \beta^2 \mathbb{E}_t \left[\frac{1}{G_{t+1}^{\theta} G_{t+2}^{\theta} \Pi_{t+1} \Pi_{t+2}} \right] \\
&= \beta^2 \mathbb{E}_t \left[\frac{1}{G_{t+1}^{\theta} (C_G G_{t+1}^{\phi_G} \varepsilon_{t+2} V_{t+2})^{\theta} \Pi_{t+1} (C_\Pi \Pi_{t+1}^{\phi_\Pi} \eta_{t+2} W_{t+2})} \right] \\
&= \beta^2 \frac{1}{(C_G^{2+\phi_G} G_t^{\phi_G + \phi_G^2})^{\theta} C_\Pi^{2+\phi_\Pi} \Pi_t^{\phi_\Pi + \phi_\Pi^2}} \mathbb{E}_t \left[\frac{1}{\varepsilon_{t+1}^{(1+\phi_G)\theta}} \right] \mathbb{E}_t \left[\frac{1}{\varepsilon_{t+2}^{\theta}} \right] \mathbb{E}_t \left[\frac{1}{\eta_{t+1}^{1+\phi_\Pi}} \right] \mathbb{E}_t \left[\frac{1}{\eta_{t+2}} \right] \mathbb{E}_t \left[\frac{1}{V_{t+2}^{\theta} W_{t+2}} \right] \\
&= \beta^2 \frac{1}{(C_G^{2+\phi_G} G_t^{\phi_G + \phi_G^2})^{\theta} C_\Pi^{2+\phi_\Pi} \Pi_t^{\phi_\Pi + \phi_\Pi^2}} e^{\frac{1}{2}\left((1+(1+\phi_G)^2)\theta^2 \sigma_\varepsilon^2 + (1+(1+\phi_\Pi)^2)\sigma_\eta^2\right)} \\
&\left(1 - \delta_{t+1} + \delta_{t+1} \frac{1}{J_G^{(1+\phi_G)\theta} J_\Pi^{1+\phi_\Pi}} \right) \left(1 - \delta_{t+2} + \delta_{t+2} \frac{1}{J_G^{\theta} J_\Pi} \right)
\end{aligned} \tag{27}$$

Take 3-year bond, then

$$\begin{aligned}
Q_t^{(3)} &= \beta^3 \frac{1}{(C_G^{3+2\phi_G+\phi_G^2} G_t^{\phi_G + \phi_G^2 + \phi_G^3})^{\theta} C_\Pi^{3+2\phi_\Pi+\phi_\Pi^2} \Pi_t^{\phi_\Pi + \phi_\Pi^2 + \phi_\Pi^3}} \\
&e^{\frac{1}{2}\left((1+(1+\phi_G)^2+(1+\phi_G+\phi_G^2)^2)\theta^2 \sigma_\varepsilon^2 + (1+(1+\phi_\Pi)^2+(1+\phi_\Pi+\phi_\Pi^2)^2)\sigma_\eta^2\right)} \\
&\left(1 - \delta_{t+1} + \delta_{t+1} \frac{1}{J_G^{(1+\phi_G+\phi_G^2)\theta} J_\Pi^{1+\phi_\Pi+\phi_\Pi^2}} \right) \left(1 - \delta_{t+2} + \delta_{t+2} \frac{1}{J_G^{(1+\phi_G)\theta} J_\Pi^{1+\phi_\Pi}} \right) \left(1 - \delta_{t+3} + \delta_{t+3} \frac{1}{J_G^{\theta} J_\Pi} \right)
\end{aligned} \tag{28}$$

Then, for the N-period bond

$$Q_t^{(N)} = \beta^N \frac{1}{\left(C_G^{\sum_{i=1}^N i\phi_G^{N-i}} G_t^{\sum_{i=1}^N \phi_G^i}\right)^\theta C_\Pi^{\sum_{i=1}^N i\phi_\Pi^{N-i}} \Pi_t^{\sum_{i=1}^N \phi_\Pi^i}} e^{\frac{1}{2}\left(\sum_{i=1}^N (\sum_{j=0}^{i-1} \phi_G^j)^2 \theta^2 \sigma_\varepsilon^2 + \sum_{i=1}^N (\sum_{j=0}^{i-1} \phi_\Pi^j)^2 \sigma_\eta^2\right)}$$
$$\prod_{i=1}^N \left(1 - \delta_{t+i} + \delta_{t+i} \frac{1}{J_G^{\sum_{j=1}^{N+1-i} \theta\phi_G^{j-1}} J_\Pi^{\sum_{j=1}^{N+1-i} \phi_\Pi^{j-1}}}\right) \tag{29}$$

A.2 Proof of Proposition 1

A

B Appendix Figures

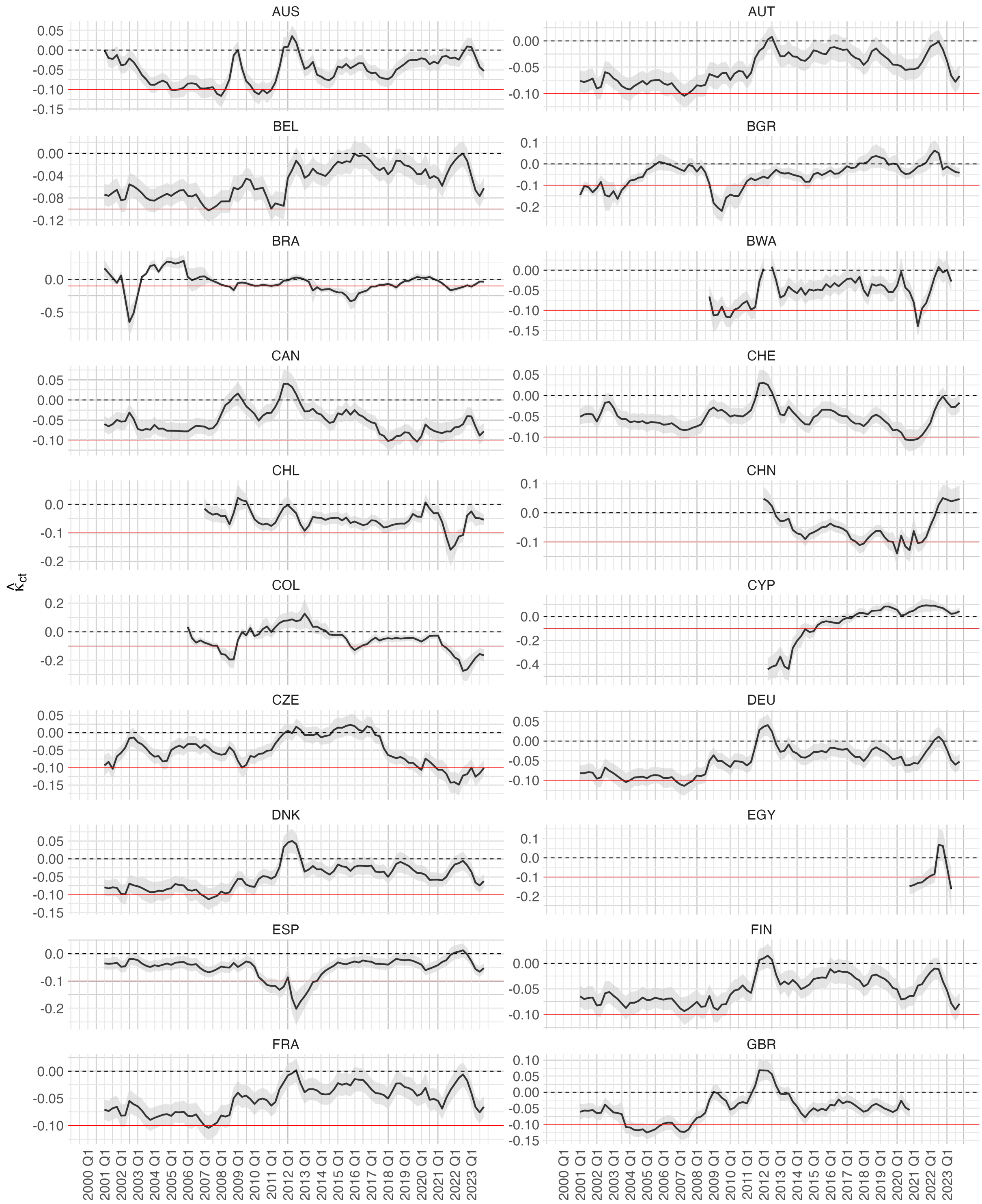

Figure A1: $\hat{\kappa}_{ct}$

Notes: The figure shows the disaster wedge with 95% confidence intervals. The red line at -0.1 represents a reference threshold. The values are estimated based on quarterly data.

Source: Author's calculations using IMF and Datastream data.

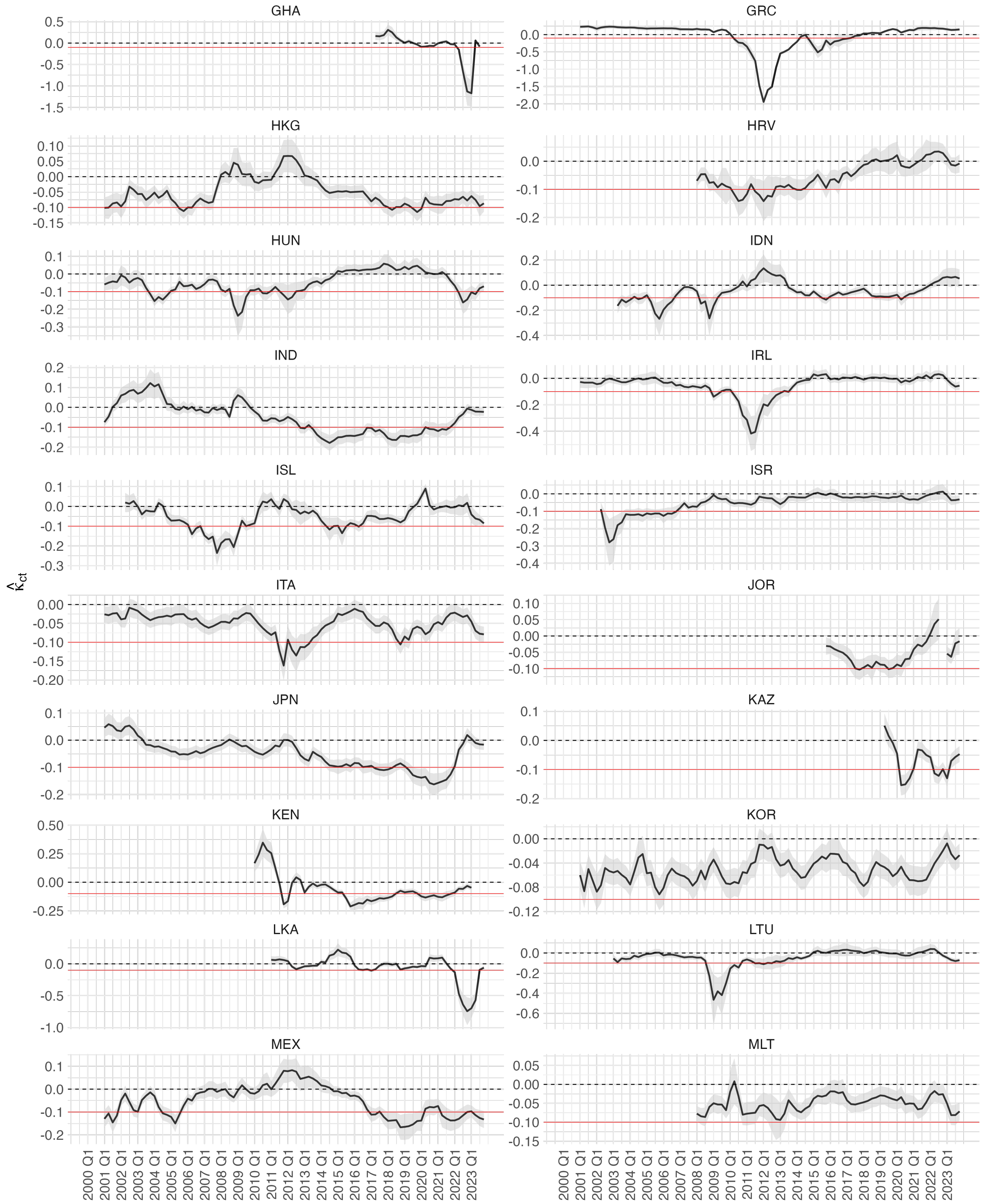

Figure A2: $\hat{\kappa}_{ct}$

Notes: The figure shows the disaster wedge with 95% confidence intervals. The red line at -0.1 represents a reference threshold. The values are estimated based on quarterly data.

Source: Author's calculations using IMF and Datastream data.

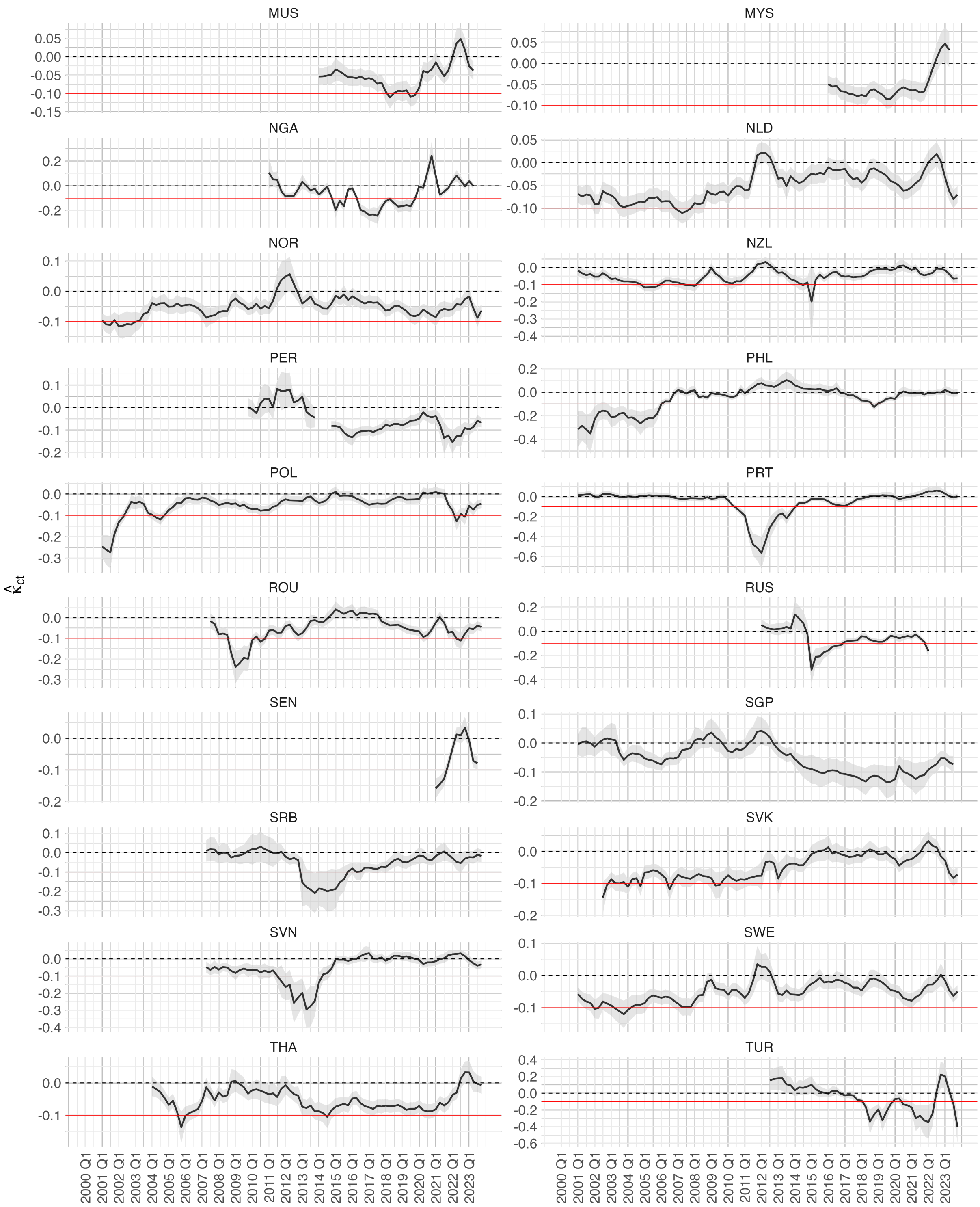

Figure A3: $\hat{\kappa}_{ct}$

Notes: The figure shows the disaster wedge with 95% confidence intervals. The red line at -0.1 represents a reference threshold. The values are estimated based on quarterly data.

Source: Author's calculations using IMF and Datastream data.

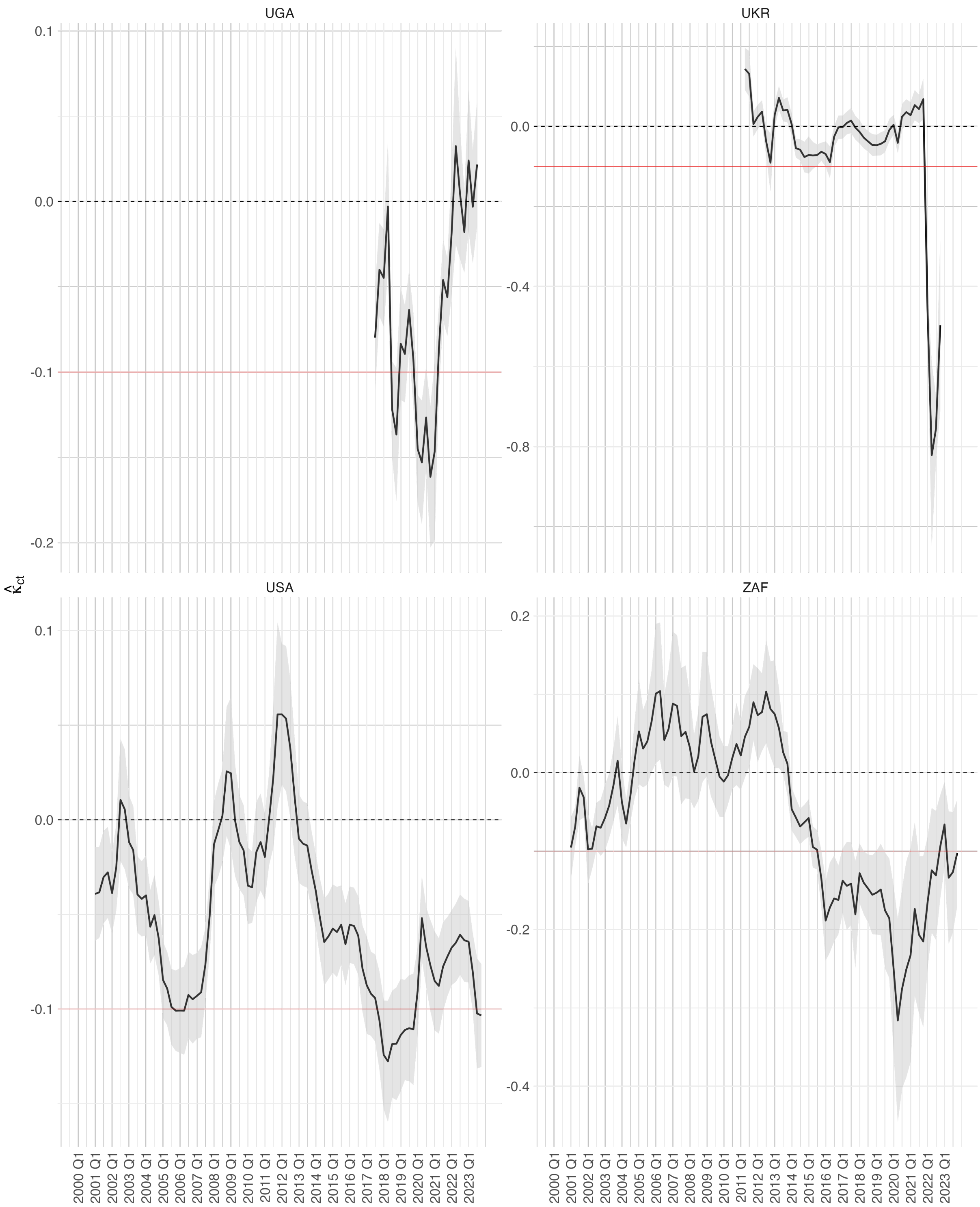

Figure A4: $\hat{\kappa}_{ct}$

Notes: The figure shows the disaster wedge with 95% confidence intervals. The red line at -0.1 represents a reference threshold. The values are estimated based on quarterly data.
Source: Author's calculations using IMF and Datastream data.

C Appendix Tables