

Rare Disasters: a Model to capture Implications, Peculiarities, and Policy Insights.

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A chi mi ha insegnato la felicità

Abstract

This thesis rigorously investigates macroeconomic and financial implications of rare disasters using a sophisticated Dynamic Stochastic General Equilibrium (DSGE) model enriched by Epstein-Zin recursive preferences. In an increasingly interconnected global economy, frequently exposed to severe shocks, such as wars, financial crises, and pandemics, the study differentiates between disaster types, capturing distinct impacts on first and second moments of macroeconomic quantities, asset prices, and risk premia.

Drawing on foundational studies by Rietz (1988), Barro (2006, 2009), and Gourio (2012), this research introduces heterogeneity in disaster shocks, calibrated through extensive empirical analysis of historical OECD data (1900–2024). The model incorporates stochastic variations in disaster severity, persistence, and probability, effectively reproducing macro-financial dynamics like countercyclical risk premia and precautionary saving behaviors. It addresses longstanding puzzles in economics, such as the equity premium puzzle and volatility clustering in asset prices, while accurately modeling significant economic downturns associated with disasters.

Moreover, the thesis evaluates targeted economic policies aimed at mitigating catastrophic impacts. By simulating policy interventions: structural preparedness for wars, regulatory frameworks for financial crises, and balanced fiscal-health strategies for pandemics, it quantifies their effectiveness in reducing volatility and enhancing resilience.

The findings highlight considerable heterogeneity in disaster impacts, underscoring the need for differentiated policy responses. This study contributes not only theoretical advancements but also practical, policy-relevant insights, guiding stabilization strategies amid extreme uncertainty.

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Glossary

AAA Highest bond rating. [8](#)

AR(1) Autoregressive Process of order 1. [2](#)

BGP Balanced Growth Path. [26](#)

CIR Cox–Ingersoll–Ross. [9](#)

CRRA Constant Relative Risk Adversion. [5](#)

DSGE Dynamic Stochastic General Equilibrium. [iii](#)

EZ Epstein-Zin. [10](#)

EZW Epstein-Zin-Weil. [6](#)

GDP Gross Domestic Product. [1](#)

HP Hodrick-Prescott. [38](#)

IES Elasticity of intertemporal substitution. [6](#)

IRF Impulse Response Function. [36](#)

OECD Organisation for Economic Co-operation and Development. [iii](#)

OLS Ordinary Least Squares. [22](#)

OTC Over the counter. [11](#)

P/D Price/Dividend. [8](#)

RBC Real Business Cycle. [8](#)

RF Risk Free Rate. [32](#)

SDF Stochastic Discount Factor. [15](#)

TFP Total Factor Productivity. 13

VAR Vector Autoregression. 34

VIX CBOE Volatility Index. 34

VOL Physical volatility of returns. 36

Introduction

In a world interconnected as never before, traveling at a speed that would not have been imagined attainable and sustainable in the past, it is necessary to incorporate the risk of rare events into the vision and evaluation of experts in every subject. Nowadays, society is suddenly faced with two wars on Europe's doorstep (the Russian-Ukrainian conflict and the Israeli-Palestinian conflict) and the impacts of climate change, where nature is beginning to present its bill after centuries of reckless and short-sighted exploitation. All this just after recovering from a global pandemic. It is therefore immediately apparent that these three examples are paradigms of the fact that the system in which humanity finds itself living faces the unexpected with a frequency that is no longer negligible or ignorable; just as it is easy to understand that the correct evaluation and incorporation of the risk of these phenomena is decisive for the preservation and progress of this system itself.

Economics is at the forefront of this mission, being the science that is responsible for adapting increasingly evolved, varied and numerous needs to an increasingly scarce pool of resources.

As Nassim Taleb famously observed in *The Black Swan* [71], modern society suffers from an illusion of predictability: we build systems, forecasts, and policies based on what we *think* we know, systematically underestimating the role of uncertainty. Rare disasters, by definition, escape the boundaries of historical data and conventional modeling. They are *outliers* that redefine what is possible, until they happen, at which point they seem inevitable in hindsight.

The Russian-Ukrainian conflict, the COVID-19 pandemic, and climate-induced catastrophes are not just isolated incidents; they are black swans in disguise, events that seem unique only until one realizes how limited and backward-looking our predictive frameworks have become. We often mistake the map for the territory, assuming linearity in a non-linear world. The goal is not just to prevent rare disasters, but to build economic systems capable of withstanding and even benefiting from them. It is increasingly necessary to evolve a system that is *antifragile*, that must accept volatility as a feature, not a bug, designing institutions that do not merely survive rare events, but evolve through them.

It would be almost self-evident to look for some reference to convince the reader of the seriousness of phenomena that can be classified as rare disasters, since it is intrinsic in the real and financial impact they entail, and which everyone becomes a direct witness. Suffice it to say that their burden is reflected in the scientific definition attributed to him from the beginning of their study: the first scientific source that has framed them was the work of Barro, defining them as events involving a decrease of at least 15% in real GDP per capita [8].

From then on, many distinguished scientists have committed themselves to incorporate the risk of rare disasters into their models in order to be able to price it or assess its impacts on the financial and real economy. Among them stands out the work of Gourio (2012)[\[38\]](#), who through a DSGE model managed to generate an empirically reasonable connection between rare disaster risk premium and output or investment. However, almost all of the most important studies on the subject have introduced the risk of rare disasters in order to solve, at least in part, long-standing problems such as the equity premium puzzle and the risk free rate, thus modeling disasters in aggregate without differentiating their impacts depending on their type. An initial suggestion for developing this research idea comes from the work of Gabaix (2012), who introduces the concept of asset resilience, which measures an asset's ability to maintain its value during a disaster [\[35\]](#). Although Gabaix does not explicitly distinguish between different types of disasters, his model suggests that investors' perceptions of resilience may vary depending on the nature of the disaster, implying that different catastrophic events could have distinct impacts on asset prices. It is, therefore, within these boundaries that the first research question guiding this thesis will be posed: to understand the differences between the impacts of different types of rare disasters on macro-financial variables and asset prices.

From the modelling of impacts, and the concept of resilience, comes directly the second objective of this study: to understand how different economic policies can best combat the gigantic impacts of disasters. Cantelmo (2022), to cite a recent example in literature, explores the impact of rare disasters on the natural interest rate and macroeconomic conditions. Using a non-linear New-Keynesian model, it simulates scenarios in which the risk of natural disasters negatively affects the natural interest rate and inflation[\[23\]](#). The results suggest that, in the presence of such risks, central banks may have to adjust their monetary policies to stabilize the economy.

In order to fill these research gaps as clearly and efficiently as possible, this work will be based on the implementation of a Dynamic Stochastic General Equilibrium (DSGE) model, which is considered better than a Real Business Cycle model, as it allows for a more accurate treatment of time-varying risk, which is a fundamental assumption for this thesis. The model incorporates permanent and transitory shocks to productivity as well as capital destruction shocks, which are only active in a state of disaster, with probability p_t , following an [AR\(1\)](#) process in logarithms. The general equilibrium is described by an Euler condition of the type:

$$\mathbb{E}_t \left[M_{t+1} \cdot R_{t+1}^K \right] = 1,$$

where the stochastic discount factor reflects the intertemporal structure of recursive preferences and risk aversion related to disaster probability. The solution of the model is obtained by non-linear numerical methods. Intermediate objectives include:

1. Estimating macro-financial effects specific to each type of disaster;
2. Quantifying the response of real variables and asset prices to changes in p_t ;
3. Simulating the comparative effectiveness of economic policies in mitigating adverse effects.

The main contribution of the paper is therefore twofold: on the one hand, to provide a theoretical microfoundation useful to explain the heterogeneity of economic impacts of rare disasters; on the other hand, to assess how targeted policy instruments can reduce the risk premium and improve macroeconomic resilience, offering relevant implications for the design of stabilization policies in extreme risk contexts.

In the following chapters, therefore, the work will be concretized: first of all, by reviewing the most important contributions from the literature on which the study of this type of phenomena is based; then proceed to the configuration and implementation of the mathematical model that will produce the results that will be carefully evaluated, compared with the literature and interpreted. Finally, they themselves will be used to draw the main conclusions of the study, with suggestions for improvement and future research.

Chapter 1

Literature Review

1.1 From Rietz's idea to Barro's empirical measurements

The first trace of the insight into the importance of rare disaster risk in the possible solution to the equity risk premium problem can be found in the work of Rietz (1988). His model represents an evolution of the Arrow-Debreu economy proposed by Mehra and Prescott (1985) [59], an evolution that is able to capture the impacts of crashes without distorting the assumptions of the original model (the economy is still a finite state version of Lucas' (1978) model [58] and still has a Debreu competitive equilibrium with non-stationary consumption levels. There are no frictions and no closed market), was able to explain both the high risk premia and the low risk-free returns [68]. In mathematical terms, the economic agent finds itself maximizing $\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\alpha}}{1-\alpha} \right]$, with the novelty of introducing a third state into the consumption growth process, a state that possesses low probability π , but strong negative impact: $x_3 = \theta(1 + \mu)$, with $\theta < 1$. The Markovian transition matrix for the three states is:

$$Q = \begin{bmatrix} 1 - \delta - \pi & \delta & \pi \\ \delta & 1 - \delta - \pi & \pi \\ \frac{1}{2} & \frac{1}{2} & 0 \end{bmatrix}$$

Where state 3 (crash) cannot recur consecutively, making the risk more plausible and persistent over time. This leads to the determination of equity pricing through the first-order condition:

$$p^e(c, i) = \beta \sum_j \phi_{ij} x_j^{-\alpha} [p^e(x_j c, j) + x_j c]$$

proving a realistic equity risk premium (6-7%) with plausible parameters relating risk aversion and time preference.

From this brilliant introduction follows the work of Barro (2006), considered the founding work of all literature on the topic. He considers correct the general reasoning behind Rietz's model, but states that the major reason for skepticism about Rietz's argument is the belief that it depends on counterfactually high probabilities and sizes of economic disasters. For this

reason he measured the frequencies and sizes of every economic disaster occurred during the twentieth century, suggesting a disaster annual probability of 1.5-2 % with a decline in GDP per capita ranging from 15 to 64 percent. Another step forward in this study is from a model of disaster as a discrete, exogenous state, to one as a continuous Poisson shock; in addition, the paper assesses the impact on assets by also considering default on risk-free securities. Barro follows Lucas' (1978) representative-agent, fruit-tree model of asset pricing with exogenous, stochastic production, in which:

- Consumption equals Output of fruit ($C_t = A_t$);
- Markets are complete, with competitive prices;
- Preferences are isoelastic CRRA (with $\gamma > 1$)

The representative consumer maximizes a time-additive utility function

$$U(C_t) = \mathbb{E}_0 \left[\int_0^\infty e^{-\rho t} \frac{C_t^{1-\gamma}}{1-\gamma} dt \right]$$

while Output of fruits follows

$$\log A_{t+1} = \log A_t + \bar{g} + u_{t+1} + v_{t+1}$$

where $u_{t+1} \sim \mathcal{N}(0, \sigma^2)$ are normal (Brownian) shocks and v_{t+1} rare disaster with:

$$\begin{cases} v_{t+1} = 0 & \text{with probability } e^{-p} \\ v_{t+1} = \log(1-b) & \text{with probability } 1 - e^{-p} \end{cases}$$

p and b are respectively the Poisson rate and severity of rare disasters. This leads to equity price under this model:

$$P_t^1 = A_t \cdot e^{-\rho(1-\gamma) + \gamma\bar{g} - \frac{1}{2}\gamma(1+\gamma)\sigma^2} \cdot \left[e^{-p} + (1 - e^{-p})\mathbb{E}[(1-b)^{1-\gamma}] \right]$$

that can be expressed in expected log returns (conditioned to $dt \rightarrow 0$) as:

$$\log \mathbb{E}[R^e] = \rho + \gamma\bar{g} - \frac{1}{2}\gamma(1+\gamma)\sigma^2 + p \cdot \left[\mathbb{E}[(1-b)^{1-\gamma}] - 1 \right]$$

The expected risk-free can be obtained as:

$$\log \mathbb{E}[R^f] = \rho + \gamma\bar{g} - \frac{1}{2}\gamma(1+\gamma)\sigma^2 + p \cdot (1-q) \cdot \left[\mathbb{E}[(1-b)^{-\gamma}] - 1 \right]$$

$$\Rightarrow \text{with premium: } \mathbb{E}[R^e] - \mathbb{E}[R^f] \approx \gamma\sigma^2 + p \cdot (\text{disaster curvature})$$

With this configuration, Barro confirms Rietz's idea: rare disasters explain equity premium puzzle, but his approach becomes quantitative and calibratable, linking historical distributions

of disasters with asset pricing. It is precisely this feature that makes this study so important as a basis for subsequent literature.

The same author, in a later study (Barro 2009) [9], incorporates aspects related to the parametrization of asset prices and the assessment of welfare cost of consumption uncertainty into the framework of the 2006 model. The first notable development refers to the change in the type of utility function to an Epstein-Zin-Weil (EZW) function [31] in order to obtain:

- A risk aversion greater than 1 ($\gamma > 1$, necessary to explain equity premia without generating counterfactual previsions;
- An Elasticity of Intertemporal Substitution greater than unit ($IES > 1$), being able to explain asset prices dynamics in a more realistic way.

Overcoming the isoelastic utility structure allows the model to avoid two counterfactual predictions typical of the power utility: an increase in aggregate uncertainty that leads to an increase in the price-dividend ratio and higher expected growth that reduces the price-dividend ratio. With EZW preferences and $IES > 1$, Barro shows instead that an increase in uncertainty reduces the value of shares, in line with empirical evidence. One of the most conceptually relevant extensions introduced by Barro (2009) to the original 2006 framework is the explicit quantification of the welfare costs associated with the existence of the risk of rare economic disasters. In particular, the author proposes to measure, in terms of equivalent output, how much a society would be willing to sacrifice each year in order to completely eliminate the uncertainty generated by catastrophic events, such as wars, extreme financial crises or pandemics. The approach followed is consistent with the principle, already emphasized by Alvarez and Jermann (2004), that any assessment of the effect of a shock on aggregate utility must be consistent with its assessment by the financial markets [3]. In the context of the Epstein-Zin-Weil preference model, the present value of the productive asset, expressed as a price/dividend ratio, is influenced by the presence of disaster risk through the following relationship:

$$\frac{1}{V} = r^* + \gamma g^* - \frac{1}{2}\gamma(1 + \theta)\sigma^2 + p \left[\mathbb{E} \left[(1 - b)^{1-\gamma} \right] - 1 + \gamma \mathbb{E}[b] \right]$$

From this formulation, Barro calculates the equivalent cost in terms of output to eliminate the risk of disaster. The quantity that measures this compensatory change is the ratio of output in a hypothetical economy without disasters to that observed in the economy with disasters, given by:

$$\frac{Y^*}{Y} = \left(\frac{V}{V^*} \right)^{\frac{1}{1-\theta}}$$

where V^* refers to the ideal economy with null disaster probability. Barro estimates that the economy would be willing to give up about 24% of its GDP each year in order to eliminate disaster risk, whereas removing only the volatility component, represented by the standard deviation, would entail a welfare cost equivalent to an annual loss of only 1.6% of GDP. This difference, robust even to parametric variation, highlights how disaster risk has a disproportionately high

impact on welfare compared to mere business cycle volatility, overturning previously accepted conclusions, such as that of Lucas (1987), that the cost of the business cycle is negligible. This result is fundamental to the objectives of the study in this thesis as it allows us to assess the economic importance of policies aimed at reducing the probability or severity of systemic disasters. Preventive interventions, financial regulation, geopolitical stabilization and public health strategies can, in the light of the model, generate extremely relevant welfare benefits even if disasters remain rare events, precisely because their expected impact is amplified by agents' strong risk aversion.

1.2 Time-varying severity and probability

One of the most innovative theoretical contributions to the literature on rare disasters is the work of Xavier Gabaix (2012), who introduces a framework capable of simultaneously addressing and solving ten historical “puzzles” in the field of asset pricing, including:

1. the equity premium puzzle;
2. the risk-free rate puzzle;
3. excess volatility;
4. the predictability of stock returns;
5. the anomalous behavior of out-of-the-money options;

The central innovation is the transition from a model in which the severity of disasters is constant (as in Barro 2006) to an environment in which it is stochastic and time-varying, thus generating risk premia that are also time-varying. This extension allows the model to generate realistic dynamics for asset prices and returns, explaining the volatility of price-dividend ratios, the cross-sectional predictability of returns, and the behavior of options and rate curves [35]. Gabaix starts from an endowment economy with an isoelastic expected utility and pricing kernel expressible as

$$\frac{M_{t+1}}{M_t} = \begin{cases} e^{-\delta} & \text{no disaster} \\ e^{-\delta} B_{t+1}^{-\gamma} & \text{disaster} \end{cases}$$

The innovative feature is definitely the introduction of an intrinsic resilience to each asset, defined as

$$H_{i,t} = p_t \mathbb{E}_t^D [B_{t+1}^{-\gamma} F_{i,t+1} - 1]$$

where $F_{i,t+1} \in [0, 1]$ the dividend recovery rate of asset i in the event of a disaster. This formulation makes it possible to distinguish between assets that are more or less exposed to tail shocks, and introduces a key element: cross-sectional heterogeneity in disaster response. $H_{i,t+1}$ dynamics are modeled by a linearity-generating process which provides closed-form analytical

solutions for asset prices. The Price of a dividend-paying stock is given by

$$P_{i,t} = \frac{D_{i,t}}{1 - e^{-\delta_i}} \left(1 + \frac{e^{-\delta_i - h_i^*} \hat{H}_{i,t}}{1 - e^{-\delta_i - \phi_H}} \right)$$

and can be approximated for short time intervals as:

$$P_{i,t} = \frac{D_{i,t}}{\delta_i} \left(1 + \frac{\hat{H}_{i,t}}{\delta_i + \phi_H} \right) \quad \text{with} \quad \delta_i = \delta - g_i^D - \ln(1 + H_i^*)$$

The expected return, conditional on the absence of disasters, becomes:

$$\tilde{r}_{i,t} = \delta - H_{i,t} \quad \Rightarrow \quad \text{Equity premium} = p_t \mathbb{E}_t^D \left[B_{t+1}^{-\gamma} (1 - F_{i,t+1}) \right]$$

The P/D ratio is thus negatively correlated with the perception of disaster risk, generating predictability of returns and excess volatility. In the model, a disaster leads to a positive jump in expected inflation, penalizing long-dated bonds, allowing it to be shown that if the nominal risk premium is stochastic, the rate curve has a positive slope and forward rates are predictable, explaining puzzles such as Fama-Bliss (1987) [32]. Using a calibration with $\gamma = 1, p = 3.36\%$ and $\mathbb{E}[B] = 0.66$ produces:

- Equity premium around 6.5%
- Risk free rate around 1%
- P/D Ratio volatility in line with USA historical data
- Bond spread volatility coherent with AAA bond behavior
- Option prices consistent with volatility smirk

This model integrates systemic and idiosyncratic risk in a single linear scheme, opening the way for analysis with multi-asset data, options and nominal instruments.

In the same year, the work of Gourio (2012) also represents one of the most significant advances in the literature on rare disasters, as it manages to integrate real macroeconomics (business cycle) with asset pricing (risk premia) in a coherent manner, within a single DSGE framework [38]. Unlike previous contributions, notably Barro (2006, 2009) and Gabaix (2012), Gourio's model innovates on both theoretical and quantitative levels, introducing disaster risk in a production economy with optimizing agents, physical capital, and recursive preferences à la Epstein-Zin. Gourio builds a complete RBC model with endogenous capital and labor accumulation. This allows us to analyze how variations in disaster risk simultaneously impact the dynamics of capital, investment and employment, as well as risk premia and asset prices. This consistency makes it possible to empirically reproduce the correlation between asset prices and real variables, such as price-to-book ratio and investment, which other models fail to do. While Barro (2006) considers instantaneous and permanent disasters, Gourio instead models disasters as events that:

- last several periods, with a certain persistence q ;
- Combine permanent and transitory shocks to productivity (θ_t and ϕ_t);
- destroy physical or qualitative capital (ξ_t), producing realistic effects on the cycle.

With regard to the time-varying aspect, in the case of Gourio(2012) it is the probability of disaster that is time-varying, following an AR(1) process with mean and variance calibrated to historical data, allowing the model to generate counter-cyclical risk premia, in accordance with empirical results. It also shows that an exogenous increase in disaster risk, even without realization generates:

- fall in investment, employment and output;
- increase in risk premium and fall in stock prices;
- fall in risk-free rates due to increased precautionary savings.

This result is achieved without the need for shocks to total factor productivity, and perfectly simulates macro developments during panic phases such as the 2008-2009 crisis. These listed aspects are the reason why this model was chosen as the skeleton for the study of this thesis, with the aim of highlighting the differences in the implications of various types of disaster and the consequent policy assessments: It is sufficiently parsimonious for quantitative analysis, but also rich enough to distinguish the effect of transitory and permanent shocks, to introduce differences between wars, pandemics, financial crises and to simulate relevant policy scenarios.

1.3 Volatility and exchange rates

In her contribution, Jessica Wachter(2013) proposes a refined extension of the rare disaster risk model, in which the probability of economic disaster evolves over time according to a stochastic process, offering a unified explanation for the equity premium puzzle, excessive stock market volatility and the predictability of stock returns. This approach overcomes the limitations of static models, which, while being able to justify a high risk premium, cannot replicate the empirical variability of stock returns nor their predictability. The probability of disaster follows a Cox-Ingersoll-Ross (CIR) process, which ensures stationarity and positivity [73]:

$$d\lambda_t = \kappa(\bar{\lambda} - \lambda_t)dt + \sigma_\lambda \sqrt{\lambda_t} dW_t^\lambda$$

The model generates an endogenous increase in equity volatility as λ_t increases, consistent with empirical evidence on the counter-cyclical behavior of volatility and the Sharpe ratio. Equity volatility intensity is an increasing and concave function of the probability of disaster. In addition, it succeeds in explaining the maturity structure of the equity premium, showing that even short-term equities incorporate a significant premium, in line with market data.

In the joint contribution by Farhi and Gabaix (2016), the authors extend the rare disaster framework to the international context, exploring the macro-financial implications that such

extreme events generate on the currency market. The work represents one of the first theoretical formalizations in which disaster risk is country-specific and can simultaneously justify the existence of currency risk premia, excessive exchange rate volatility, and the so-called forward premium puzzle [33]. Unlike the original model of Gabaix (2012), which focuses on equities in a closed economy, this version introduces a two-country environment, with representative consumers, nominal exchange rates, and imperfectly correlated disaster risks. The innovative aspect is that, even in the absence of realized disasters, the mere divergence in risk perceptions between the two countries generates:

- variations in nominal exchange rates;
- risk premiums on currencies;
- persistent distortions in forward yields.

The nominal exchange rate S_t between the currencies of two countries, Home (H) and Foreign (F), reflects differences in expected disaster risks:

$$S_t = \frac{P_{H,t}}{P_{F,t}} = \left(\frac{C_{H,t}}{C_{F,t}} \right) \times \left(\frac{F_{F,t}}{F_{H,t}} \right)$$

where $F_{i,t}$ is the risk-adjusted real exchange rate, which incorporates potential disaster-related jumps in country i . When $p_H > p_F$, country H shows a weaker currency and higher forward yields: this replicates the forward premium puzzle. The model predicts that the premium required by investors to hold foreign currency is positively correlated with local disaster risk and negatively correlated with the foreign country's exposure to disasters. Thus, cross-market consistency is generated between currency risk, bond spreads and equity premiums. Moreover allows differentiating the behavior of assets exposed to global disasters from those with domestic risk: currencies become a key tool to diversify tail risk.

1.4 A new method for estimating disaster probability

In the joint contribution by Robert J. Barro and Gordon Y. Liao published in the Journal of Financial Economics in 2021, the authors propose a new approach to estimate the objective probability of rare disasters using option price data, in particular far-out-of-the-money options. The work integrates disaster risk theory with an option pricing formula derived from recursive preferences [12]. As shown by the previous contributions reviewed, this one also starts from an EZ utility framework. The relative price of a far-out-of-the-money European put Π , with short maturity T and strike price ϵP_t , is calculated as follows

$$\Pi = \frac{P_t^{put}}{P_t} = \frac{\alpha z_0^\alpha}{(\alpha - \gamma)(1 + \alpha - \gamma)} \cdot pT \cdot \varepsilon^{1+\alpha-\gamma}$$

where

- p is the disaster probability;
- α is the tail exponent of severity distribution;
- z_0 is the minimum threshold for severity;
- γ the risk aversion coefficient.

The authors assume that the severity of economic disasters follows a Pareto distribution:

$$f(z) = \alpha z_0^\alpha z^{-(1+\alpha)}, \quad z \geq z_0 > 1$$

this choice is consistent with the empirical evidence collected in Barro and Jin (2011) [10], and is crucial for option pricing analysis, as it allows for an accurate description of the effect of thick tails on the premium demanded by investors. The model is extended to include the possibility that p_t follows a stochastic process, subject to sudden shocks. In such a case, the option price includes two components: one related to the risk of realized disaster and one to the possibility that the perception of risk increases abruptly during the life of the option:

$$\Pi = T\varepsilon^{1+\alpha-\gamma} \left[\eta_1 p_t + \eta_2 q \varepsilon^{\alpha^*-\alpha} \right]$$

where q is the probability of a sudden increase in p_t , and α^* is the tail parameter for changes in p_t . Applying the formula to data on put options on the S&P500 and six other stock indices (UK, Eurozone, Germany, Japan, Sweden, Switzerland), the authors estimate a time series of the objective probability of p_t disaster consistent with major historical events. The approach shows that option prices contain predictive information on macroeconomic tail risk: high values of p_t anticipate a higher probability of negative growth in real GDP. The method also proves to be robust using OTC data and across different maturities and exercises.

Chapter 2

Methods

2.1 The Model

The model framework starts from an agent with recursive preferences (Epstein & Zein 1989)

$$V_t = (U_t^{1-\psi} + \beta E_t(V_{t+1}^{1-\gamma})^{\frac{1-\psi}{1-\gamma}})^{\frac{1}{1-\psi}}$$

where utility follows the classical Cobb-Douglas form, consistent with balanced growth:

$$U_t = u(C_t, N_t) = C_t(1 - N_t)^u$$

while γ is the risk aversion coefficient, and ψ is inversely related to IES. To be precise, IES is $\frac{1}{\psi}$ with $\hat{\psi} = 1 - (1 + \nu)(1 - \psi)$ and $IES > 1$ when $\psi < 1$ [70].

The output function of firms is also of the Cobb-Douglas type [26]:

$$Y_t = K_t^a (z_t N_t)^{1-\alpha}$$

where the productivity z_t is formed by two components:

1. $z_{p,t}$ permanent productivity;
2. $z_{r,t}$ transitory productivity;

such that

$$\log z_t = \log z_{p,t} + \log z_{r,t}.$$

The accumulation path of capital is described by:

$$K_{t+1} = (1 - \delta)K_t + \phi\left(\frac{I_t}{K_t}\right)K_t$$

where ϕ is an increasing and concave function, which curvature captures physical adjustment costs. The resource constraint is:

$$C_t + I_t = Y_t.$$

In order to be able to further schematize the narrative of the model, two case studies will be divided, depending on whether or not the rare disaster is realized.

2.1.1 Normal times

The permanent component of productivity evolves according to a random walk with drift,

$$\log z_{p,t} = \log z_{p,t-1} + \mu + \epsilon_t,$$

where ϵ_t is the normal small shock introduced by the real business cycle theory [55]: $\epsilon_t \stackrel{\text{iid}}{\sim} \mathcal{N}(0, \sigma_\epsilon^2)$, while the transitory component reverts to 0 as $\rho < 1$: $\log z_{r,t} = \rho \log z_{r,t-1}$. This means that an economy without disaster in recent past will have $\log z_{r,t} \simeq 0$.

2.1.2 Disaster occurrence

In this framework, rare disaster is modeled as a combination of a productivity shock and a “depreciation shock” to the capital stock, that can happen each period with probability p_t and once the economy has entered in a state of disaster, can remain there next period with probability q . Capital accumulation during disasters follows:

$$K_{t+1} = \left((1 - \delta)K_t + \phi \left(\frac{I_t}{K_t} \right) K_t \right) e^{\xi_{t+1}}$$

with the depreciation shock $\xi_{t+1} \stackrel{\text{iid}}{\sim} \mathcal{N}(\mu_\xi - \frac{1}{2}\sigma_\xi^2, \sigma_\xi^2)$. Since data clearly shows that disasters occur over several years, then preceding partial recoveries, instead being instantaneous and permanent as treated by past studies, it is clear that they can be a shock to the permanent and transitory component of TFP. The permanent productivity is affected by a factor $\theta_t \stackrel{\text{iid}}{\sim} \mathcal{N}(\mu_\theta - \frac{1}{2}\sigma_\theta^2, \sigma_\theta^2)$:

$$\log z_{p,t} = \log z_{p,t-1} + \mu + \epsilon_t + \theta_t.$$

Same rules for the transitory shock $\varphi_t \stackrel{\text{iid}}{\sim} \mathcal{N}(\mu_\varphi - \frac{1}{2}\sigma_\varphi^2, \sigma_\varphi^2)$ such that:

$$\log z_{r,t} = \rho \log z_{r,t-1} + \varphi_t - \theta_t$$

These parameters make it possible to describe a U-shape pattern for productivity, which undergoes a short-term shock and then returns with speed described by ρ_z to its long-term impact. It may also happen that the long-term effects of disasters are positive, this phenomenon may be due to political and economic reactions to the disaster and can be formalized mathematically by the normal distribution of the long-term shock.

Another innovative feature of the model is that the probability of entering the disaster state is time-varying. It is a Markov chain that roughly follows an AR(1) process:

$$\log(p_t) = \rho_p \log(p_{t-1}) + (1 - \rho_p) \log \bar{p} + \varepsilon_t^p,$$

while $\varepsilon_t^p \stackrel{\text{iid}}{\sim} \mathcal{N}(0, \sigma_p^2)$

2.1.3 Model summary and assumptions

Given the information introduced above, it is possible to summarize the model as follows:

$$x_t = \begin{cases} 1, & \text{in disaster state} \\ 0, & \text{without disaster} \end{cases} \quad (2.1)$$

$$\log z_{p,t} = \log z_{p,t-1} + \mu + \varepsilon_t + x_t \theta_t, \quad (2.2)$$

$$\log z_{r,t} = \rho_z \log z_{r,t-1} + (\varphi_t - \theta_t) x_t, \quad (2.3)$$

$$K_{t+1} = \left((1 - \delta) K_t + \phi \left(\frac{I_t}{K_t} \right) K_t \right) e^{x_{t+1} \xi_{t+1}}, \quad (2.4)$$

$$\Pr(x_{t+1} = 1 \mid x_t = 1) = \max(q, p_t), \quad \text{and} \quad \Pr(x_{t+1} = 1 \mid x_t = 0) = p_t. \quad (2.5)$$

While in the neoclassical treatment rare disasters are configured by a reduction in TFP or by capital destruction, this model tries to reconcile both assumptions. Numerous studies, including that of Kehoe and Prescott (2007) [50], highlight the crucial role of total factor productivity during more pronounced economic downturns. Although the underlying causes of TFP fluctuations remain partly poorly understood, large and persistent declines in this variable can be traced back to ineffective public policies, such as overly burdensome tax regimes or trade restrictions, or to dysfunctions in the financial system that undermine the efficient allocation of capital.

In the context of wars or epidemic disasters, the physical destruction of capital is a tangible consequence. However, in periods of economic depression, it is more appropriate to interpret this concept in qualitative terms. In these cases, it is not so much a deterioration of physical capital, but rather a loss of intangible capital, such as relational value with customers and employees, that may be lost as a result of prolonged crises. Moreover, such events are frequently accompanied by increasing volatility at the microeconomic level and intense reallocation processes, which may render certain specialized capital assets obsolete or unusable. Finally, situations of expropriation or nationalization may generate effects similar to capital destruction, when capital is taken away from its previous users and used inefficiently.

The theoretical framework outlined in the previous section highlights two essential components that underpin the model's dynamics. First, disaster episodes are characterized by elevated marginal utility of consumption. Second, capital tends to yield low realized returns when such adverse events occur. These features align well with empirical observations and are consistent with economic intuition. Within a neoclassical setting, a sharp decline in total factor productivity serves as the most straightforward mechanism to capture the first effect, while modeling a shock to capital depreciation effectively accounts for the second. Nevertheless, the core implications of the model are expected to remain robust even under alternative structural specification.

2.1.4 Equilibrium

The model has 3 condition that characterize the equilibrium

$$C_t + I_t = Y_t; \quad (2.6)$$

$$-\frac{u_N(C_t, N_t)}{u_C(C_t, N_t)} = \frac{\nu C_t}{1 - N_t} = W_t = (1 - \alpha) \frac{Y_t}{N_t}; \quad (2.7)$$

$$E_t (M_{t+1} R_{t+1}^K) = 1. \quad (2.8)$$

The first equation is the resource constraint, while the second is the standard labor market condition and the third is the Euler condition with SDF M_{t+1} is the marginal rate of substitution of the household, with recursive preferences:

$$M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\psi} \left(\frac{1 - N_{t+1}}{1 - N_t} \right)^{(1-\psi)\nu} \frac{V_{t+1}^{\psi-\gamma}}{E_t (V_{t+1}^{1-\gamma})^{\frac{\psi-\gamma}{1-\gamma}}}$$

and the return on capital:

$$R_{t+1}^K = e^{x_{t+1}\xi_{t+1}} \phi' \left(\frac{I_t}{K_t} \right) \left(\frac{1 - \delta + \phi \left(\frac{I_{t+1}}{K_{t+1}} \right)}{\phi' \left(\frac{I_{t+1}}{K_{t+1}} \right)} + \alpha \frac{Y_{t+1}}{K_{t+1}} - \frac{I_{t+1}}{K_{t+1}} \right).$$

that follows (Hayashi 1982), adjusted for ξ_{t+1} [43] [49].

2.1.5 Recursive formulation

The theoretical framework of the model includes five distinct state variables, namely: the capital stock K , permanent and transitory technological factors z_p and z_r , respectively, the disaster probability p , and the disaster occurrence state $x \in \{0, 1\}$. The system is influenced by three primary stochastic disturbances: the disaster occurrence indicator in the subsequent period $x' \in \{0, 1\}$, an updated disaster probability p' , and a minor technology shock ϵ' . Conditional upon a disaster event $x = 1$, three additional random factors characterize the magnitude of the disaster: ϕ' , θ' , and ξ' .

Let $V(K, z_p, z_r, p, x)$ denote the representative household's value function. Given the homogeneity embedded in the utility specification, production function, and capital adjustment cost structure, coupled with the permanent component of productivity z_p evolving as a random walk, the model allows for a simplification of the value function into the following expression:

$$V(K, z_p, z_r, p, x) = z_p g(k, z_r, p, x)$$

where $k = \frac{K}{z_p}$, and the function g satisfies

$$g(k, z_r, p, x)^{1-\psi} = \max_{c, i, N} u(c, N)^{1-\psi} + \beta E \left(e^{(1-\gamma)(\mu + \epsilon' + x'\theta')} g(k', z'_r, p', x')^{1-\gamma} \right)^{\frac{1-\psi}{1-\gamma}}$$

with constraints:

$$c + i = k^\alpha (z_r N)^{1-\alpha}$$

$$k' = \frac{e^{x'\xi'} \left[(1 - \delta)k + \phi \left(\frac{i}{k} \right) k \right]}{e^{\mu + \varepsilon' + x'\theta'}}$$

In this equation, $c = \frac{C}{z_p}$ and $i = \frac{I}{z_p}$ represent consumption and investment normalized by the permanent component of technology, and the expectation operator accounts for uncertainty over future realizations of $x', p', \varepsilon', \phi', \theta'$, and ξ' . Employing this normalization significantly simplifies the analysis by yielding analytical tractability and facilitating computational implementation. Specifically, it ensures the stationarity of the normalized capital stock k , and reduces the dimensionality of the state space, thereby streamlining the numerical evaluation of the model.

2.1.6 Asset Prices

Given the stochastic discount factor M_{t+1} , it is relatively straightforward to determine asset prices within this economic framework. However, the empirical interpretation requires additional considerations, particularly regarding interest rates and equity valuations. Specifically, the theoretical price of a one-period real risk-free bond is expressed by the conditional expectation $E_t(M_{t+1})$. Nevertheless, identifying a real-world counterpart to this asset can be problematic, given that even sovereign bonds may default under disaster scenarios. Consistent with Barro's (2006) framework, this default scenario is modeled by assuming that during a disaster, sovereign bonds repay only a fraction $r < 1$ of their nominal value.

Therefore, the one-period government bond (or Treasury bill) price becomes:

$$Q_{1,t} = E_t [M_{t+1} (1 + x_{t+1}(r - 1))]$$

The term structure for government bond prices with maturity n is subsequently derived through the following standard recursive relationship:

$$Q_{n,t} = E_t [M_{t+1} (1 + x_{t+1}(r - 1)) Q_{n-1,t+1}], \quad \text{with} \quad Q_{0,t} = 1$$

implicitly assuming that disasters proportionally impact bonds across all maturities equally.

Shifting attention to equity valuation, consider first the market value of the aggregate capital stock, denoted by P_t . This market valuation must satisfy the standard asset-pricing equation given by:

$$P_t = E_t [M_{t+1} (D_{t+1} + P_{t+1})]$$

The term D_t , representing the dividend or net payout distributed by the representative firm, is defined as the firm's total output Y_t minus labor compensation $w_t N_t$ and investment expenditures I_t :

$$D_t = Y_t - w_t N_t - I_t$$

This expression captures the residual cash flow available to equity holders after accounting for

operational and capital costs. The asset return is then:

$$R_{t+1} = \frac{(P_{t+1} + D_{t+1})}{P_t}$$

One notable issue of this model is the fact that the volatility of profits in the model equals the volatility of output: this leads to a difference between the riskiness of cash flows observed in the data and those implied by the model (volatile and procyclical). The former turn out to be more risky. This study offers a solution by incorporating leverage in the model: each period, the firm issues 10-Year bonds in a proportion ζ to its capital stock, that default in case of a disaster with a recovery rate $r_c < r$. The leverage incorporated in the model should be interpreted not only as financial, but also as operating leverage, in accordance with (Abel 1999), (Bansal and Yaron 2004), and (Watcher 2013) [1] [7], [73]. Given that the Modigliani and Miller theorem applies in this framework, leverage affects the model exclusively by altering the payout structure and consequently influencing the characteristics of equity returns. This implies that all other conclusions and results derived from the analysis remain robust and unaffected by the inclusion of leverage [61].

2.1.7 Types of disasters and policy effects

In order to incorporate the objectives of the present study into this framework, specifically to identify the peculiarities of the impacts of individual disaster types and policy effects, a number of variables were adapted and transformed in line with the objectives.

First of all, the aggregate probability of disaster is the sum of the probabilities of the individual types of disaster: wars, financial crises and epidemics:

$$p = \sum_{i=1}^3 p_i,$$

then the variable q , representing the probability of remaining in the disaster state given its occurrence in the previous period, was adjusted. Specifically, it is the weighted average of the individual probabilities, weighted on the empirical frequencies of occurrence:

$$q = \sum_{i=1}^3 (\pi_i q_i)$$

Obviously, the variables that have been manipulated the most to reflect the impacts are the shocks on the permanent and transient probability components. The shock and volatility values of the different disaster types were calculated empirically as shown in the next chapter, and then aggregated using a calibration factor consistent with the theorized U-shape in the model, to assess impacts and recoveries.

In order to assess the impacts of policies, it was decided to simulate the model for each of the three types of disaster, then make a valuation considering impacts on quantities, asset returns and transmission mechanisms of the impacts themselves.

Chapter 3

Results

3.1 Calibration

3.1.1 Parameter Values

Table 3.1: Parameter Values for the Benchmark Model

Capital share	α	0.34	Mean permanent shock	μ_θ	-0.006
Depreciation rate	δ	0.02	Std. dev. permanent shock	σ_θ	0.091
Leisure preference	ν	2.33	Mean transitory shock	μ_φ	-0.052
Discount factor	β	0.999	Std. dev. transitory shock	σ_φ	0.041
Adjustment cost	η	1.5	Persistence of productivity	ρ_z	0.71
Trend growth of TFP	μ	0.007	Persistence of disaster state	q	0.919
Std. dev. of TFP shock	σ_ε	0.011	Persistence of $\log(p)$	ρ_p	0.90
Elasticity of substitution	$1/\hat{\psi}$	2	Std. dev. of $\log(p)$	$\frac{\sigma_p}{\sqrt{1-\rho_p^2}}$	2.80
Risk aversion	γ	4.25	Average prob. of disaster		0.72

Calibration parameters are listed in Table 3.1 and each variable is expressed in quarterly values.

Capital share, Depreciation rate, Leisure preference and Discount factor ($\alpha, \delta, \nu, \beta$) are extracted from the Real Business Cycle literature, more specifically (Prescott 1986) for α , (Cooley and Prescott 1995) for δ , (King et al. 1988) for β and (Hansen 1985) for ν [65] [27] [51] [42]. The TFP parameters (μ and σ_ε) were derived empirically from the trend rate of total factor productivity calculated by the Bureau of Labor Statistics in a dataset from January 1947 to December 2024. Capital adjustment costs are modeled using a standard quadratic specification, defined as:

$$\phi(x) = x - \frac{\eta}{2}(x - \delta - \mu)^2$$

where η is calibrated to match the observed volatility in investment dynamics, based on USA total market capitalization. The coefficient of relative risk aversion, denoted by γ , is set to 4.25 to replicate the empirical mean of the equity premium.

The intertemporal elasticity of substitution (IES) in consumption is fixed at 2. This choice

is crucial because an IES greater than one is necessary for the model to generate a decline in investment in response to rising disaster risk, which in turn drives countercyclical variation in risk premia, an empirical regularity. A lower IES would lead to counterfactual predictions. It is worth noting that the appropriate magnitude of the IES remains the subject of ongoing academic debate.

The most delicate part of the calibration was undoubtedly the choice of shock parameters (mean and standard deviation) for the distributions of the permanent and transitory components. The strategy was to build a historical disaster dataset for the OECD nations from the available data of the Penn World Table and Maddison Project Database, with particular reference to the latest versions (10.01 and 2023) [34], [20]. Using the definition formalized by Barro in 2006, I first subset the GDP per capita from 1900 to 2024 for the 38 nations of the organization; then I identified for each state the episodes with a drop greater than 15% multi-year and yearly, accurately verifying the cause in order to categorize the occurrences of disasters and 3 macro-categories (Wars, Epidemics and Financial Crises). With these criteria, it was decided to construct an additional summary dataset (reported in Table 3.2) identifying the reference country, the years of the disaster, the total and average annual impact together with the assigned category

Table 3.2: Rare Disasters Impact Dataset

Country	Years	Total Impact	Duration	Annual Impact	Category
AUS	1914–1918	-0.1121	5	-0.022420	War
AUS	1927–1931	-0.2371	5	-0.047420	Financial
AUS	1944–1946	-0.1513	3	-0.050433	War
AUT	1913–1919	-0.4121	7	-0.058871	War
AUT	1930–1933	-0.2558	4	-0.063950	Financial
AUT	1945	-0.5845	1	-0.584500	War
BEL	1917–1918	-0.3245	2	-0.162250	War
BEL	1929–1932	-0.1073	4	-0.026825	Financial
BEL	1940–1943	-0.2642	4	-0.066050	War
CAN	1918–1921	-0.3399	4	-0.084975	Epidemic
CAN	1929–1933	-0.4037	5	-0.080740	Financial
CHE	1913–1915	-0.1053	3	-0.035100	War
CHE	1917–1919	-0.1738	3	-0.057933	Epidemic
CHE	1921	-0.1853	1	-0.185300	Financial
CHE	1940–1943	-0.1260	4	-0.031500	War
CHL	1914–1921	-0.1976	8	-0.024700	War
CHL	1930–1932	-0.5851	3	-0.195033	Financial
CHL	1947–1949	-0.0171	3	-0.005700	War
CHL	1972–1975	-0.2505	4	-0.062625	War
CHL	1982–1983	-0.1932	2	-0.096600	Financial

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Table 3.2 – Continuation of previous page

Country	Years	Total Impact	Duration	Annual Impact	Category
CHL	2019–2020	-0.0897	2	-0.044850	Epidemic
COL	2020	-0.0902	1	-0.090200	Epidemic
CZE	1991	-0.1025	1	-0.102500	Financial
DEU	1914–1915	-0.2138	2	-0.106900	War
DEU	1919	-0.1331	1	-0.133100	War
DEU	1923	-0.1746	1	-0.174600	Financial
DEU	1929–1932	-0.1889	4	-0.047225	Financial
DEU	1945–1946	-0.7669	2	-0.383450	War
DNK	1915–1921	-0.0563	7	-0.008043	War
DNK	1940–1941	-0.2523	2	-0.126150	War
ESP	1930–1931	-0.0948	2	-0.047400	Financial
ESP	1936–1938	-0.3286	3	-0.109533	War
ESP	2020	-0.1179	1	-0.117900	Epidemic
EST	1990–1994	-0.4182	5	-0.083640	War
EST	2008–2009	-0.2261	2	-0.113050	Financial
EST	2020	-0.0086	1	-0.008600	Epidemic
FIN	1914–1918	-0.4040	5	-0.080800	War
FIN	1939–1940	-0.1056	2	-0.052800	War
FIN	1990–1993	-0.1176	4	-0.029400	Financial
FRA	1917–1918	-0.3355	2	-0.167750	War
FRA	1930–1932	-0.1685	3	-0.056167	Financial
FRA	1940–1944	-0.6308	5	-0.126160	War
FRA	2020	-0.0811	1	-0.081100	Epidemic
GBR	1917–1921	-0.2364	5	-0.047280	Epidemic
GBR	1944–1947	-0.1559	4	-0.038975	War
GBR	2020	-0.1141	1	-0.114100	Epidemic
GRC	1900–1901	-0.1489	2	-0.074450	Financial
GRC	1912–1913	-0.4313	2	-0.215650	War
GRC	1915–1917	-0.5159	3	-0.171967	War
GRC	1919	-0.1088	1	-0.108800	War
GRC	1938–1945	-0.9978	8	-0.124725	War
GRC	2009–2013	-0.2501	5	-0.050020	Financial
GRC	2020	-0.0881	1	-0.088100	Epidemic
HUN	1920	-0.1854	1	-0.185400	War
HUN	1930–1932	-0.1192	3	-0.039733	Financial
HUN	1946	-0.3726	1	-0.372600	War
HUN	1989–1992	-0.1945	4	-0.048625	Financial
IRL	2008–2009	-0.0969	2	-0.048450	Financial
ISL	1914–1918	-0.2417	5	-0.048340	War

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Table 3.2 – Continuation of previous page

Country	Years	Total Impact	Duration	Annual Impact	Category
ISL	1920	-0.1520	1	-0.152000	Epidemic
ISL	1948–1951	-0.1303	4	-0.032575	War
ISL	2008–2010	-0.1214	3	-0.040467	Financial
ISL	2019–2020	-0.0916	2	-0.045800	Epidemic
ITA	1914–1915	-0.1050	2	-0.052500	War
ITA	1940–1945	-0.5724	6	-0.095400	War
ITA	2020	-0.0853	1	-0.085300	Epidemic
JPN	1930–1931	-0.0943	2	-0.047150	Financial
JPN	1942–1947	-0.5390	6	-0.089833	War
KOR	1938–1939	-0.2028	2	-0.101400	War
KOR	1942–1946	-0.6514	5	-0.130280	War
KOR	1950–1951	-0.1679	2	-0.083950	War
KOR	1998	-0.0680	1	-0.068000	Financial
LTU	1989–1994	-0.5916	6	-0.098600	War
LTU	2009	-0.1387	1	-0.138700	Financial
LUX	1975	-0.0759	1	-0.075900	Financial
LUX	2008–2009	-0.0988	2	-0.049400	Financial
LVA	1991–1993	-0.5486	3	-0.182867	War
LVA	2008–2010	-0.1941	3	-0.064700	Financial
MEX	1910–1913	-0.1104	4	-0.027600	War
MEX	1927–1932	-0.3546	6	-0.059100	Financial
MEX	2019–2020	-0.1070	2	-0.053500	Epidemic
NLD	1914–1918	-0.1811	5	-0.036220	War
NLD	1929–1934	-0.1703	6	-0.028383	Financial
NLD	1940–1944	-0.6496	5	-0.129920	War
NOR	1917–1921	-0.1043	5	-0.020860	Epidemic
NOR	1931	-0.0837	1	-0.083700	Financial
NOR	1940–1944	-0.2055	5	-0.041100	War
NZL	1908–1909	-0.1081	2	-0.054050	Financial
NZL	1912–1918	-0.1102	7	-0.015743	War
NZL	1921–1922	-0.1470	2	-0.073500	Epidemic
NZL	1926–1927	-0.1183	2	-0.059150	Financial
NZL	1930–1932	-0.1883	3	-0.062767	Financial
NZL	1948–1951	-0.0020	4	-0.000500	War
POL	1930–1933	-0.2754	4	-0.068850	Financial
POL	1979–1982	-0.1415	4	-0.035375	Financial
POL	1989–1991	-0.1830	3	-0.061000	Financial
PRT	1928	-0.1081	1	-0.108100	Financial
PRT	1935–1936	-0.1519	2	-0.075950	War

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Table 3.2 – Continuation of previous page

Country	Years	Total Impact	Duration	Annual Impact	Category
PRT	2020	-0.0840	1	-0.084000	Epidemic
SVK	1990–1992	-0.2430	3	-0.081000	Financial
SVN	1987–1992	-0.3006	6	-0.050100	War
SVN	2009–2013	-0.1263	5	-0.025260	Financial
SWE	1917–1918	-0.1367	2	-0.068350	War
SWE	1940–1941	-0.1048	2	-0.052400	War
TUR	1918	-0.4352	1	-0.435200	War
TUR	1927	-0.0970	1	-0.097000	Financial
TUR	1940–1945	-0.4430	6	-0.073833	War
TUR	2001	-0.0801	1	-0.080100	Financial
USA	1907–1908	-0.1009	2	-0.050450	Financial
USA	1914	-0.1001	1	-0.100100	War
USA	1930–1933	-0.3725	4	-0.093125	Financial
USA	1945–1947	-0.1656	3	-0.055200	War

From this data, it is possible to guess the distribution of rare disasters for the selected pool of nations, but it should be added that Israel did not have any disasters in the specified time frame. The two components: a permanent shock θ and a transitory shock ϕ are calibrated to reproduce the observed path of real GDP per capita during historical episodes of large contraction with the objective of constructing an internally consistent aggregate benchmark. Given annual log GDP per capita data $y_{c,t}$ for country c and year t , each disaster is defined as a contiguous set of years $\{t_0, t_0 + 1, \dots, t_1\}$ during which output exhibits a significant and sustained contraction. For each event, we define a five-year pre-disaster window $\{t_{-5}, \dots, t_{-1}\}$ and fit a linear trend:

$$\hat{y}_t^{\text{trend}} = \alpha + \beta t, \quad t \in \{t_{-5}, \dots, t_{-1}\}$$

where α, β are obtained via OLS regression.

The observed log GDP per capita y_t is then decomposed into deviations from this pre-disaster trend. Let t_0 and t_1 be the first and last years of the disaster. The permanent shock θ is defined as the long-run deviation of output from its pre-disaster trend at the end of the disaster window:

$$\theta_i = y_{t_1} - \hat{y}_{t_1}^{\text{trend}}$$

The transitory shock ϕ is inferred as the residual deviation at the onset of the event that is not captured by the long-run loss:

$$\phi_i = y_{t_0} - \hat{y}_{t_0}^{\text{trend}} - \theta_i$$

This identification ensures that θ captures the permanent component, while ϕ captures the short-run overshooting at impact. Both are computed in natural logarithms.

Since the model is solved at quarterly frequency, the shocks must be rescaled accordingly. The raw estimates θ_i, ϕ_i are based on cumulative log deviations over the entire event duration and are originally expressed on an annual basis. To ensure numerical consistency and comparability with

existing literature, the raw values are divided by 10 (to convert from percent to log points) and normalized as follows:

$$\begin{aligned}\mu_\theta &= \frac{1}{4} \cdot \mathbb{E} \left[\frac{\theta_i}{10} \right], & \sigma_\theta &= \frac{1}{2} \cdot \text{Std} \left[\frac{\theta_i}{10} \right] \\ \mu_\phi &= \mathbb{E} \left[\frac{\phi_i}{10} \right], & \sigma_\phi &= \text{Std} \left[\frac{\phi_i}{10} \right]\end{aligned}$$

Note that μ_ϕ and σ_ϕ are not rescaled to quarterly frequency, since in the model the transitory shock is drawn from a discrete distribution with immediate and temporary effect.

To construct a benchmark distribution for the aggregate disaster risk economy, we define an "All" category that reflects the empirical distribution across all disaster events in the dataset. This is not computed as a weighted average of the type-specific parameters (wars, financial crises, epidemics), but directly estimated from the entire sample. The resulting moments are:

$$\begin{aligned}\mu_\theta^{\text{All}} &= -0.0060, & \sigma_\theta^{\text{All}} &= 0.0091 \\ \mu_\phi^{\text{All}} &= -0.0523, & \sigma_\phi^{\text{All}} &= 0.1179\end{aligned}$$

The values for μ_ϕ^{All} and σ_ϕ^{All} are in line with the calibration adopted in Gourio (2012), and ensure that the aggregate disaster dynamics are consistent with standard macroeconomic implications of large shocks. Following Gourio (2008), the distribution of ϕ is modeled as a truncated normal distribution with support on negative values only. This implies that the effective mean and standard deviation used in the simulations differ from the raw parameters. For instance, for the benchmark calibration $\mu_\phi^{\text{raw}} = -0.0523$ and $\sigma_\phi^{\text{raw}} = 0.1179$, the truncated distribution yields an effective mean of approximately -0.0523 and a standard deviation of approximately 0.0041 after truncation and normalization of probabilities. For each disaster type $k \in \{\text{Epidemic}, \text{Financial}, \text{War}\}$, we estimate type-specific parameters $\mu_\theta^k, \sigma_\theta^k, \mu_\phi^k, \sigma_\phi^k$ using the same procedure. These are then scaled proportionally to preserve the aggregate benchmark. That is, if the type-specific means are $\tilde{\mu}_\theta^k$, we apply a common multiplicative factor λ such that:

$$\mu_\theta^k = \lambda \cdot \tilde{\mu}_\theta^k \quad \text{with} \quad \mu_\theta^{\text{All}} = \sum_k \pi_k \cdot \mu_\theta^k$$

where π_k denotes the empirical frequency of type k in the dataset. A similar scaling is applied for σ_θ^k , and for ϕ .

This approach ensures internal coherence across scenarios, maintains empirical heterogeneity between disaster types, and preserves the aggregate behavior necessary to match long-run macroeconomic dynamics observed in the data and in the benchmark model. The calibrated parameters are shown in Table 3.3.

Table 3.3: Calibrated Parameters of Permanent and Transitory Disaster Shocks

Disaster Type	μ_θ	σ_θ	μ_ϕ	σ_ϕ
Epidemic	-0.0030	0.0042	-0.0199	0.0500
Financial	-0.0053	0.0063	-0.0441	0.0722
War	-0.0075	0.0107	-0.0692	0.1500
All (Aggregate)	-0.0060	0.0091	-0.0523	0.1179

Table 3.4: Pre- and Post-Truncation Parameters of Transitory Disaster Shocks (ϕ)

Disaster Type	Pre-truncation		Post-truncation		Gap	
	μ_ϕ	σ_ϕ	μ_ϕ^{eff}	σ_ϕ^{eff}	$\Delta\mu$	$\Delta\sigma$
Epidemic	-0.0199	0.0500	-0.0327	0.0203	+0.0128	-0.0297
Financial	-0.0441	0.0722	-0.0441	0.0254	0.0000	-0.0468
War	-0.0692	0.1500	-0.0635	0.0528	+0.0057	-0.0972
All	-0.0523	0.1179	-0.0555	0.0415	-0.0032	-0.0764

Table 3.4 reports both the pre-truncation parameters used to generate the discrete grid for ϕ , and the corresponding effective moments after truncation. The discrepancy illustrates how even a symmetric grid yields a left-skewed, concentrated distribution due to the removal of positive outcomes. This step is essential to replicate the behavior of Gourio’s model, where transitory shocks are assumed to generate only downward deviations in GDP per capita.

In modeling the stochastic structure of rare disasters, two key parameters are the unconditional quarterly probability of disaster onset, denoted p , and the probability of remaining in the disaster regime once it begins, denoted q . These parameters govern the timing and duration of disaster shocks in the DSGE model.

For each disaster type $k \in \{\text{Epidemic, Financial, War}\}$, the parameter p_k is estimated as the empirical frequency of disaster onsets relative to the total number of country-quarters in the sample. The persistence parameter q_k is computed from the average observed duration d_k of disaster events of type k , under the assumption that disaster durations follow a geometric distribution. Specifically:

$$q_k = \frac{d_k - 1}{d_k}$$

The unconditional probability of entering a disaster regime of type k , p_k , and the conditional probability of remaining in it, q_k , are then combined across types using empirical frequencies π_k , defined as the share of each disaster type in the total number of observed events. The aggregate parameters are computed as:

$$p^{\text{All}} = \sum_k \pi_k \cdot p_k, \quad q^{\text{All}} = \sum_k \pi_k \cdot q_k$$

Table 3.5: Calibrated Disaster Onset and Persistence Probabilities

Disaster Type	π_k (Frequency)	p_k	q_k	$p_k \cdot \pi_k$
Epidemic	0.1518	0.00109	0.875	0.000165
Financial	0.3750	0.00270	0.912	0.001012
War	0.4732	0.00341	0.933	0.001614
All (Aggregate)	1.0000	0.00720	0.919	0.007200

The results of Table 3.5 indicate that, at the aggregate level, the quarterly probability of entering a disaster is $p^{\text{All}} = 0.0072$, while the probability of remaining in the disaster state once it occurs is $q^{\text{All}} = 0.919$, consistent with the benchmark calibration in Gourio (2012) and in the assumptions

that the disaster probability does not change over time samples. These parameters ensure a realistic frequency and duration of disaster shocks in the simulated economy, while preserving heterogeneity across disaster types.

To maintain parsimony in the model, an initial simplifying assumption is made whereby capital destruction shocks ξ_t are equated to permanent productivity shocks θ_t , i.e., $\xi_t = \theta_t$. Although a more general specification allowing capital destruction to depend on both TFP component is conceptually plausible, it offers limited additional explanatory power. The qualitative behavior of the model remains valid, provided there exists a strong correlation between capital destruction and permanent productivity shocks. Despite the rich dynamic structure introduced by the disaster process and its associated parameters, the calibration is tightly anchored by a challenging empirical target: the entire path of consumption dynamics following a disaster event. As illustrated in Figure 3.1, the model succeeds in reproducing the mean response of consumption, and further, it approximately captures the cross-sample variance around that average. Additionally, it can be easy to demonstrate that the model's predictions extend reasonably to variables beyond consumption. A second pivotal aspect of the calibration concerns the persistence and volatility of the disaster probability process, as defined in

$$\log(p_t) = \rho_p \log(p_{t-1}) + (1 - \rho_p) \log \bar{p} + \varepsilon_t^p$$

While empirical studies such as Berkman, Jacobsen, and Lee (2011) provide evidence of time-varying disaster risk [17], pinning down the parameters governing its dynamics a priori is inherently difficult. Accordingly, the unconditional standard deviation of disaster probability innovations is selected to approximately replicate the observed volatility in equity returns. In line with Barro (2006), the government bond recovery rate r is modeled as being correlated with the magnitude of the disaster shock. In the event of a default, sovereign debt incurs a loss equal to 20% of the capital destruction, while corporate debt suffers a 38% loss. The issuance intensity parameter ζ is calibrated to 0.018, implying that firms issue new debt each quarter amounting to 1.8% of the market value of their total assets. This setup yields an average leverage ratio of approximately 50%, which is necessary for the model to replicate the magnitude of equity market crashes historically observed during disaster episodes. Although observed financial leverage in the data tends to be closer to 30%, the model adopts a broader interpretation of leverage. This encompasses not only financial obligations but also implicit exposure channels, such as the sensitivity of dividends and corporate profits to aggregate shocks, a perspective supported by empirical findings in Longstaff and Piazzesi (2004) [57].

3.2 Disaster realization with aggregate model

Figure 3.1 compares the model-implied path of consumption (blue line) following a disaster shock to empirical data estimates (red line), using cumulative impact relative to baseline as the metric of interest. The horizontal axis reports years since the occurrence of the disaster, while the vertical axis measures the cumulative deviation in consumption.

The model accurately captures the key empirical feature of disasters: a sharp and immediate decline in consumption. Specifically, the model predicts an initial contraction of approximately 15% in cumulative terms, closely aligned with the data. The trough occurs around year 5, after which consumption begins a slow recovery. This dynamic mirrors the empirical trajectory, both qualitatively

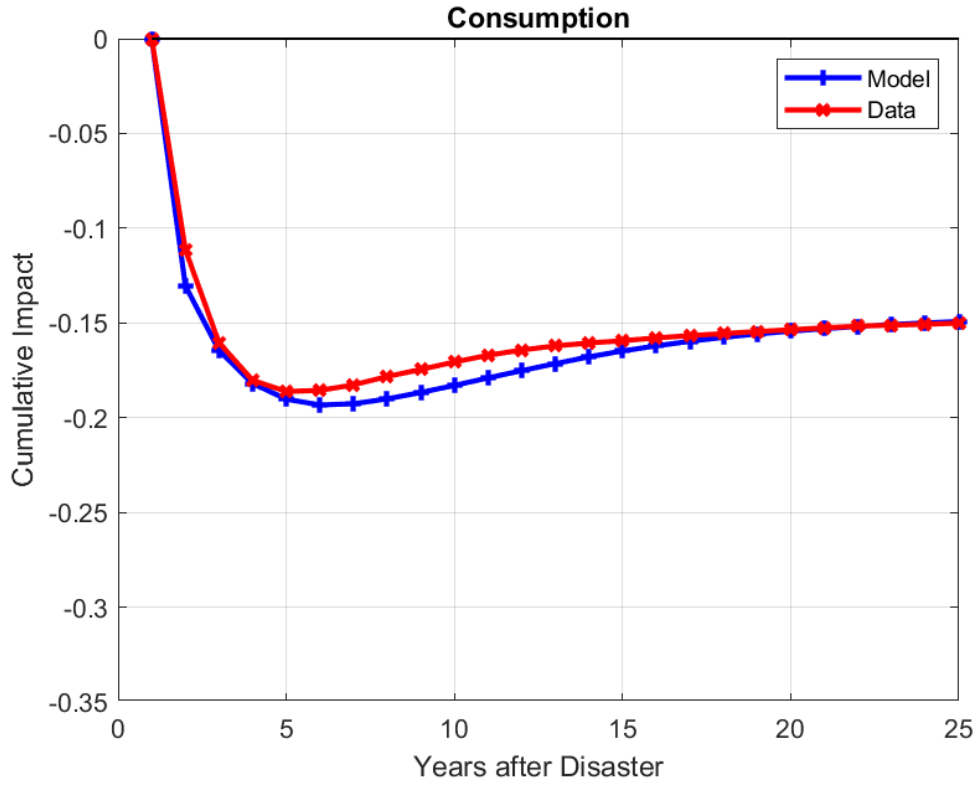


Figure 3.1: Impulse Response Function of Consumption to a Disaster Realization: Model versus Data

and quantitatively.

While the model slightly underpredicts the recovery speed, particularly between years 5 and 15, the overall path is well aligned with the observed data, especially in the long-run convergence to a persistent but attenuated consumption loss. Notably, the long-run cumulative loss remains around 15–16%, consistent with historical post-disaster trajectories.

This strong fit is particularly noteworthy given that the model was calibrated using a limited set of moments. The match supports the specification of rare disasters with persistent effects on capital and productivity as a plausible explanation for observed macroeconomic dynamics. Moreover, it validates the assumptions regarding the intertemporal elasticity of substitution and the calibration of disaster risk processes, which jointly drive the propagation mechanism of consumption shocks in the model.

Figure 3.2 displays the model's quantitative dynamics in response to a realized disaster shock. The top panel ("Quantities") illustrates the percentage deviations from the balanced growth path (BGP) for five key variables: investment i , output y , consumption c , hours worked n , and productivity z . The bottom panel ("Returns") reports quarterly percentage returns respectively for government bonds (T-Bills) and equity.

Investment exhibits the sharpest contraction, exceeding 40% on impact, which is consistent with the empirical observation that investment is the most volatile macroeconomic aggregate during crises as discovered in the work of Bloom (2009) [18]. This reflects two reinforcing mechanisms:

1. The negative productivity shock, which lowers the marginal product of capital;
2. A significant rise in perceived risk, which increases the required rate of return, thus raising the effective user cost of capital as in Gourio (2012) and Angeletos (2007) [4].

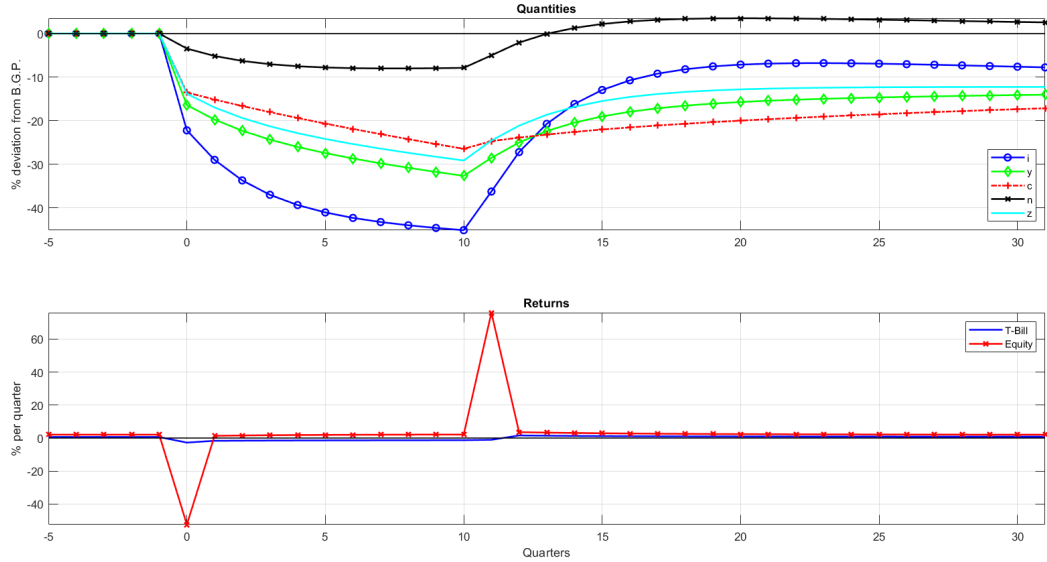


Figure 3.2: Response of macroeconomic quantities and asset returns to a typical disaster in the aggregate model

Output declines by over 30%, driven by simultaneous contractions in labor input and capital usage. This mirrors Great Depression-like dynamics, where total factor productivity and capital quality deteriorated in tandem, leading to a collapse in output (Kehoe and Prescott, 2007). Consumption falls less sharply than investment (until 25% on impact), which aligns with permanent income logic. Households smooth consumption over time, absorbing part of the shock by reducing savings and reallocating expenditure. The muted decline also reflects lower elasticity of intertemporal substitution relative to investment's sensitivity to capital risk. Labor input declines, but the fall is clearly moderate compared to capital and output, consistent with models where the income effect on labor supply partly offsets the substitution effect. The observed productivity path follows a U-shaped dynamic, reflecting the model's dual-shock structure: a persistent negative permanent shock θ and a mean-reverting transitory component ϕ , consistent with Barro et al. (2011)'s empirical findings on disaster episodes. Equity returns experience a dramatic collapse in the period of the disaster, with a drop of approximately 50%. This reflects the combination of

1. A sharp fall in the expected present value of future dividends due to declining productivity and capital;
2. A jump in the equity risk premium due to heightened macroeconomic uncertainty.

These results are consistent with documented equity market collapses during historical crises (Barro and Ursúa, 2008) [13].

Notably, a strong positive spike in equity returns occurs around after quarter 10, coinciding with the end of the disaster episode. This represents the market's reaction to the abrupt reduction in disaster risk, driving a revaluation of future cash flows and a compression in risk premia. This recovery overshoot is also observed empirically following major macro-financial shocks (Gabaix, 2012). Government bond returns (T-Bill) exhibit a mild decline during the disaster period, reflecting a flight to safety and increased demand for low-risk assets. The model incorporates partial default during disasters (as in Barro, 2006), but the relative safety of government bonds persists, yielding modestly

positive returns. This dynamic is consistent with empirical findings that long-term sovereign debt often performs well during systemic downturns, even when default risk is non-zero (Krishnamurthy and Vissing-Jorgensen, 2012) [54]. This disaster path supports Gourio’s central hypothesis: time-varying disaster risk introduces both first-moment and second-moment effects, depressing investment and output even in the absence of observed changes in total factor productivity. Importantly, the model’s ability to replicate:

- Depth and persistence of the recessionary drives;
- Volatility and cyclicalities of equity returns

demonstrates that rare disaster risk can generate quantitatively realistic business cycles endogenously linked to asset prices. Furthermore, the sharp divergence between equity and bond returns reinforces the empirical regularity of countercyclical risk premia (Lettau and Ludvigson, 2010) [56]. In line with Gourio (2012), these results suggest that models with recursive preferences and time-varying disaster probabilities provide a powerful lens to understand macro-financial interactions.

3.3 Temporary increase in Disaster Probability with aggregate model

Figure 3.3 illustrates an important experiment of the study: the impulse response of macroeconomic aggregates and asset prices to a transitory increase in the perceived probability of a rare disaster. The three-panel layout separates the evolution of disaster probability (top), the responses of key economic quantities (middle), and the asset return implications (bottom), all measured relative to the balanced growth path (BGP).

At time zero, the economy experiences an exogenous surge in the perceived probability of disaster, jumping from the baseline probability to a peak of 6% per quarter. This increase gradually decays back to the steady-state level, reflecting a persistent but temporary belief shock governed by a mean-reverting stochastic process. Such shocks capture real-world episodes of elevated macro-financial uncertainty (e.g., geopolitical crises or financial instability), where the likelihood of extreme outcomes is reassessed by agents.

Investment exhibits the most pronounced reaction, declining by over 6% on impact. This contraction reflects a sharp increase in the effective cost of capital. Firms interpret the heightened disaster probability as a deterioration in the risk-return profile of physical investment. The forward-looking nature of firms leads them to curtail capital accumulation, consistent with models of precautionary behavior under uncertainty. Aggregate output and labor input decline modestly. Output follows the drop in investment, but the reaction is more muted due to the smoother adjustment of labor. The reduction in hours worked is driven by a combination of lower expected marginal productivity and increased household aversion to supplying labor under high-risk scenarios. This response pattern mirrors empirical findings in uncertainty shock literature. Interestingly, consumption rises slightly on impact. While counterintuitive, this result is theoretically consistent with intertemporal substitution effects. Faced with increased uncertainty and reduced expected returns to investment, households optimally reduce precautionary savings and reallocate resources toward present consumption. This effect is transitory and fades as the risk subsides. A similar short-run rise in consumption in response

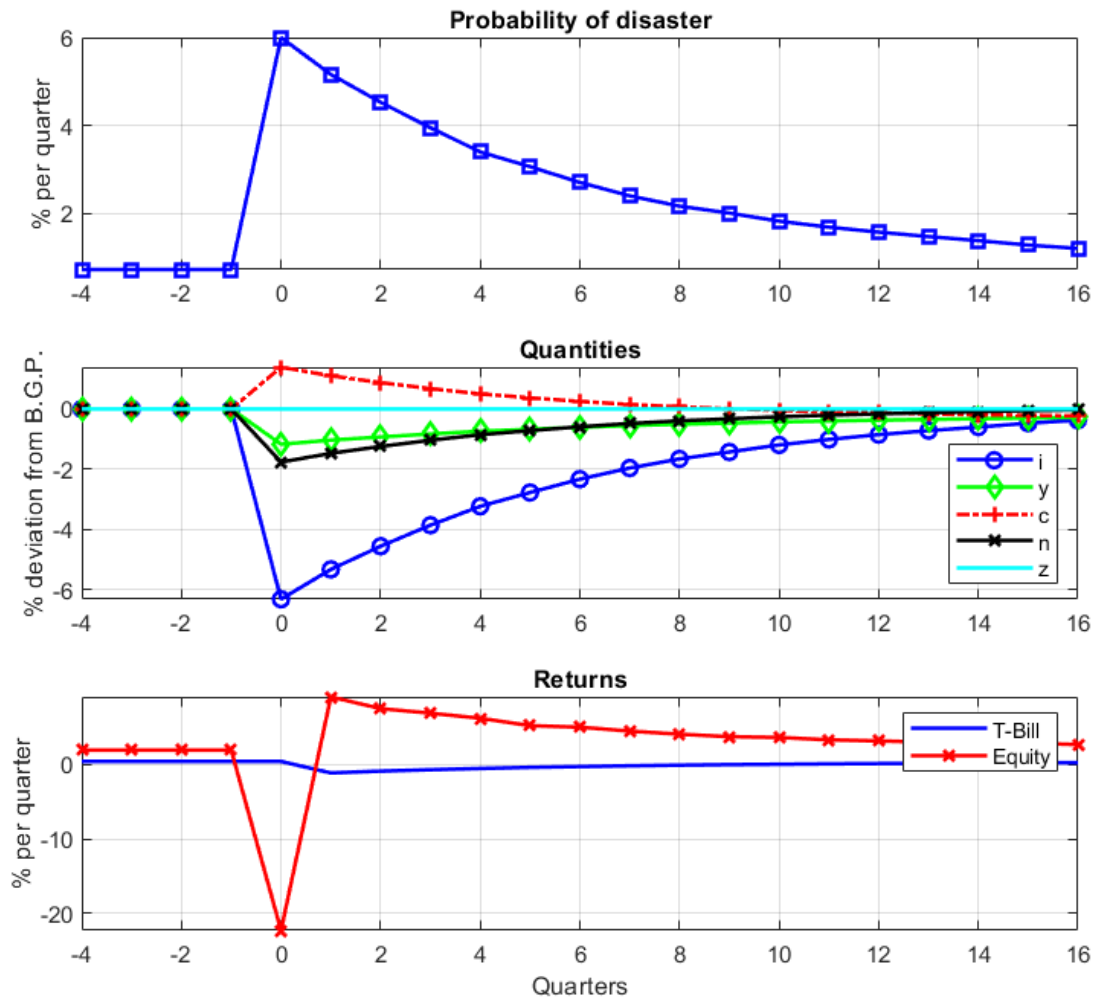


Figure 3.3: Impulse Response Function to a temporary increase in Disaster Probability

to risk shocks is also observed in models with Epstein-Zin preferences and high intertemporal elasticity of substitution (Bansal and Yaron, 2004). Productivity remains flat, confirming that the shock is purely informational and does not directly affect the production technology. This is essential to isolate the role of risk perception in driving macroeconomic dynamics, separate from fundamentals.

Equity prices experience a sharp decline, with quarterly returns plunging by over 20%. This immediate drop is driven by both a downward revision in expected future dividends (due to lower investment and output) and a sharp increase in the equity risk premium. The rise in disaster risk makes equities less attractive relative to safe assets. The path of equity returns gradually recovers in line with the decaying risk perception. These dynamics are consistent with the empirical behavior of stock markets during risk-off episodes, such as during the Global Financial Crisis or pandemic onset (Barro and Ursúa, 2008; Gabaix, 2012). Returns on short-term government bonds (T-Bills) decline mildly and temporarily. The increased demand for safe assets under elevated risk compresses yields, producing modest capital gains on existing bonds. This response is typical of “flight-to-safety” dynamics, wherein investors reallocate portfolios toward assets perceived as default-resilient. The partial government bond default mechanism built into the model moderates this effect but does not fully eliminate it, in line with real-world evidence that even sovereign debt retains relative safety during crises.

This simulation confirms a key result emphasized in Gourio (2012): an increase in disaster risk, even in the absence of any realized fundamental shock, can generate recession-like dynamics through endogenous changes in behavior. The contraction in investment and output, coupled with the sharp repricing of equity, illustrates how agents internalize higher risk into their intertemporal and intersectoral choices. Notably, these dynamics arise without any change in observed productivity or technology, demonstrating that changes in expectations about tail risk are sufficient to drive both real and financial fluctuations. This has important implications for understanding business cycles as episodes of belief-driven volatility, consistent with the growing literature on uncertainty shocks and rare disasters (Basu and Bundick, 2017) [15]. The countercyclical nature of the equity premium and the procyclicality of T-Bill returns, both endogenously generated by the model, align well with empirical findings (Lettau and Ludvigson, 2010). Additionally, the temporary but persistent nature of the shock illustrates how belief shocks can generate medium-run deviations from trend, a feature observed in post-crisis recoveries.

To conclude, figure 3.3 demonstrates the power of disaster-risk models to explain not only asset pricing anomalies but also business cycle fluctuations arising from changes in perceived, rather than realized, macroeconomic risk. The model’s responses are consistent with historical episodes of heightened uncertainty and offer a unified framework to interpret both real and financial dynamics under risk-sensitive preferences and incomplete insurance.

3.4 First and Second Moments of Quantities and Asset Returns

This section evaluates the model’s performance in replicating key statistical properties of macroeconomic aggregates and asset returns, focusing on their first and second unconditional moments. Tables

Table 3.6: Business Cycle Statistics for Consumption, Investment, Output, and Employment

	$\sigma(Y)$	$\sigma(C)$	$\sigma(I)$	$\sigma(N)$	$\rho_{C,Y}$	$\rho_{I,Y}$	$\rho_{N,Y}$
1 Data	1.12 (0.19)	0.91 (0.22)	2.36 (0.14)	1.29 (0.27)	0.69 (0.10)	0.61 (0.05)	0.81 (0.05)
2 No disasters	0.91 (0.04)	0.53 (0.03)	1.66 (0.08)	0.27 (0.01)	0.99 (0.00)	1.00 (0.00)	0.99 (0.01)
3 Constant p	0.91 (0.05)	0.52 (0.03)	1.70 (0.09)	0.28 (0.02)	0.99 (0.00)	1.00 (0.00)	0.99 (0.01)
4 Benchmark	0.94 (0.05)	0.61 (0.06)	2.27 (0.33)	0.49 (0.11)	0.68 (0.16)	0.91 (0.03)	0.78 (0.05)

Notes: All series are in growth rate. Standard errors in parentheses. Data 1947:I–2023:IV.

Table 3.7: Financial Statistics

	$E(R_f)$	$E(R_b)$	$E(R_e - R_b)$	$\sigma(R_f)$	$\sigma(R_b)$	$\sigma(R_e - R_b)$
1 Data	0.09 (0.05)	0.10 (0.05)	2.09 (0.46)	0.84 (0.05)	0.82 (0.05)	8.20 (0.37)
2 No disasters	0.68 (0.03)	0.68 (0.03)	0.07 (0.07)	0.06 (0.01)	0.06 (0.01)	1.11 (0.07)
3 Constant p	0.12 (0.03)	0.27 (0.03)	1.86 (0.02)	0.06 (0.01)	0.06 (0.01)	0.75 (0.04)
4 Benchmark	0.35 (0.21)	0.44 (0.16)	1.76 (0.32)	0.80 (0.43)	0.60 (0.32)	6.20 (1.43)

Notes: Mean and standard deviation of the risk-free, T-bill, and equity excess return. Standard errors in parentheses. Data 1947:I–2023:IV.

[3.6](#) and [3.7](#) summarize business cycle and financial statistics computed from quarterly U.S. data (1947:I–2023:IV) and compare them to various versions of the model.

The model successfully captures several stylized facts regarding the volatility and co-movement of output, consumption, investment, and employment. Empirically, investment is significantly more volatile than output, with a standard deviation of 2.36 against 1.12 for GDP, while consumption is relatively smoother at 0.91. The benchmark model replicates this ranking reasonably well, generating volatilities of 2.27 for investment, 0.94 for output, and 0.61 for consumption, closely matching the empirical ratios. In particular, the model attributes the high volatility of investment to firms’ endogenous response to fluctuations in disaster risk, an effect absent in standard RBC frameworks. Compared to the “No disasters” or “Constant pp” specifications, which generate a compressed investment volatility (1.66 and 1.70, respectively), the full model achieves higher dispersion due to the endogenous amplification from time-varying risk. Co-movements between macroeconomic variables are also well replicated. The correlation between consumption and output (0.69 in the data) remains the same in the model (0.68, reflecting the strong intertemporal smoothing inherent in recursive preferences). The correlation between employment and output is 0.78 in the benchmark case, closely approximating the data (0.81), indicating that labor dynamics are effectively mediated by disaster risk-induced changes in capital accumulation and demand for labor.

Turning to asset pricing implications, the benchmark model improves upon traditional models in reproducing the mean and volatility of excess returns. In the data, the average excess return on equity is approximately 2.09% per quarter, with a standard deviation of 8.20%. The benchmark model generates an equity premium of 1.76%, a close match, though it slightly underpredicts the volatility (6.20%). This shortfall reflects the well-known challenge of matching asset return volatility in production economies without invoking high leverage or additional frictions (Jermann, 1998; Boldrin et. al, 2001) [\[44\]](#), [\[19\]](#).

By contrast, the “No disasters” variant produces negligible equity risk premia (0.07%), confirming that variation in aggregate risk is critical to account for observed returns. Likewise, the volatility of risk-free ([R_f](#)) returns is well captured: 0.80% in the model. Importantly, the model avoids the excessive smoothness of interest rates typical in RBC settings by introducing stochastic disaster probabilities that generate time-varying discount factors and precautionary motives.

These results suggest that incorporating time-varying disaster risk significantly improves the model’s ability to reconcile real and financial data, especially in terms of matching both average returns and their dispersion. As in Barro (2006) and Gourio (2012), a small probability of large economic losses introduces a convex risk adjustment that raises the equity premium without distorting average investment or consumption paths too severely. Moreover, the model reproduces a counter-cyclical equity premium, in line with evidence from Lettau and Ludvigson (2010), where increased risk aversion in downturns translates into higher required compensation for holding risky assets. The comovement between macro quantities and expected returns thus emerges endogenously and robustly, confirming the central role of rare disaster risk in shaping the joint behavior of business cycles and asset prices.



Figure 3.4: Cross-Covariogram of (One-Sided Filtered) GDP and Excess Stock Returns in the Data, RBC and Aggregate Model

3.5 Relations between Asset Prices and Macroeconomic Quantities

3.5.1 Countercyclicalities of Risk Premia

One of the most robust empirical facts in asset pricing is that risk premia exhibit strong countercyclical behavior: expected returns on risky assets tend to increase in recessions and decline during expansions. This pattern has been dramatically illustrated during recent episodes of financial distress, in which the yield on corporate bonds and equities rose sharply, while yields on government securities simultaneously dropped, a manifestation of heightened risk aversion and a flight to safety. Importantly, this dynamic is not unique to crisis episodes, but appears to be a recurrent feature of U.S. recessions throughout the postwar period. Standard DSGE models, however, typically fail to replicate this feature. Their inability to generate endogenous variation in risk premia stems from the absence of a mechanism that links macroeconomic conditions to the stochastic discount factor in a quantitatively meaningful way. In models with expected utility and low risk aversion, asset prices move primarily in response to changes in consumption growth, with little room for time-varying expected returns. To

formally assess the model's performance on this front, we compute the covariance between detrended GDP ($\tilde{y}_t$) and future excess returns on equity, defined as

$$\text{Cov}(\tilde{y}_t, R_{t+k}^e - R_{t+k}^f) \text{ for } k = -12, \dots, +12.$$

This statistic, reported in Figure 3.4, is chosen because it captures the direction and magnitude of the interaction between output and expected returns in both model and data. Unlike correlations, covariances retain the scale of the underlying fluctuations, which is essential for quantifying asset pricing implications.

In the data (blue line), the covariance is positive for negative values of k , indicating that excess returns tend to lead GDP. This pattern is commonly interpreted as evidence that financial markets anticipate future economic conditions, potentially reflecting forward-looking information, time-to-build frictions, or slow adjustment mechanisms in the real economy. Notably, this lead-lag structure is not purely a byproduct of risk: even the RBC model without disaster risk (green line) reproduces this pattern to some extent, as higher returns are associated with positive productivity shocks, which precede above-trend output.

However, the more informative part of the figure lies in the right half (positive k), where we examine whether low output today predicts high future excess returns, that is, whether risk premia rise during downturns. Here, the benchmark model (red line) successfully generates the correct negative covariance between current output and future expected returns. This reflects the model's core mechanism: an increase in perceived disaster risk simultaneously lowers GDP (through reduced investment) and raises the marginal utility of consumption, thus pushing up the required return on risky assets.

By contrast, the RBC model shows virtually no variation in expected returns, and hence, the covariance remains close to zero. This limitation extends to most standard DSGE frameworks unless they incorporate non-standard preferences (e.g., Epstein-Zin utility) or external habit, both of which attempt to generate countercyclical risk premia through preference-based channels (Bansal and Yaron, 2004; Campbell and Cochrane, 1999) [21].

Importantly, the benchmark model links this mechanism not only to asset prices but also to investment behavior. When risk premia are elevated, firms face a higher user cost of capital, which discourages capital accumulation even when the risk-free rate is low. This helps explain the empirical puzzle of weak investment responses to low interest rates in periods of heightened uncertainty, such as during the post-2008 recovery. The model thus provides a structural rationale for why expected returns may rise precisely when economic conditions deteriorate, validating the endogeneity of risk as a key macro-financial force.

The GDP series used in this exercise is detrended via the one-sided Baxter-King filter (Baxter and King, 1999) [16], which avoids look-ahead bias and ensures that the measured comovement reflects contemporaneous expectations rather than future realizations of output. This methodological choice allows the model to be evaluated on the same empirical footing as the data.

3.5.2 Volatility, VIX and GDP

A growing body of empirical evidence has established a negative causal link between uncertainty and real economic activity. In a widely cited contribution, Bloom (2009) uses a reduced-form VAR framework to demonstrate that innovations to the VIX index, interpreted as shocks to macroeconomic

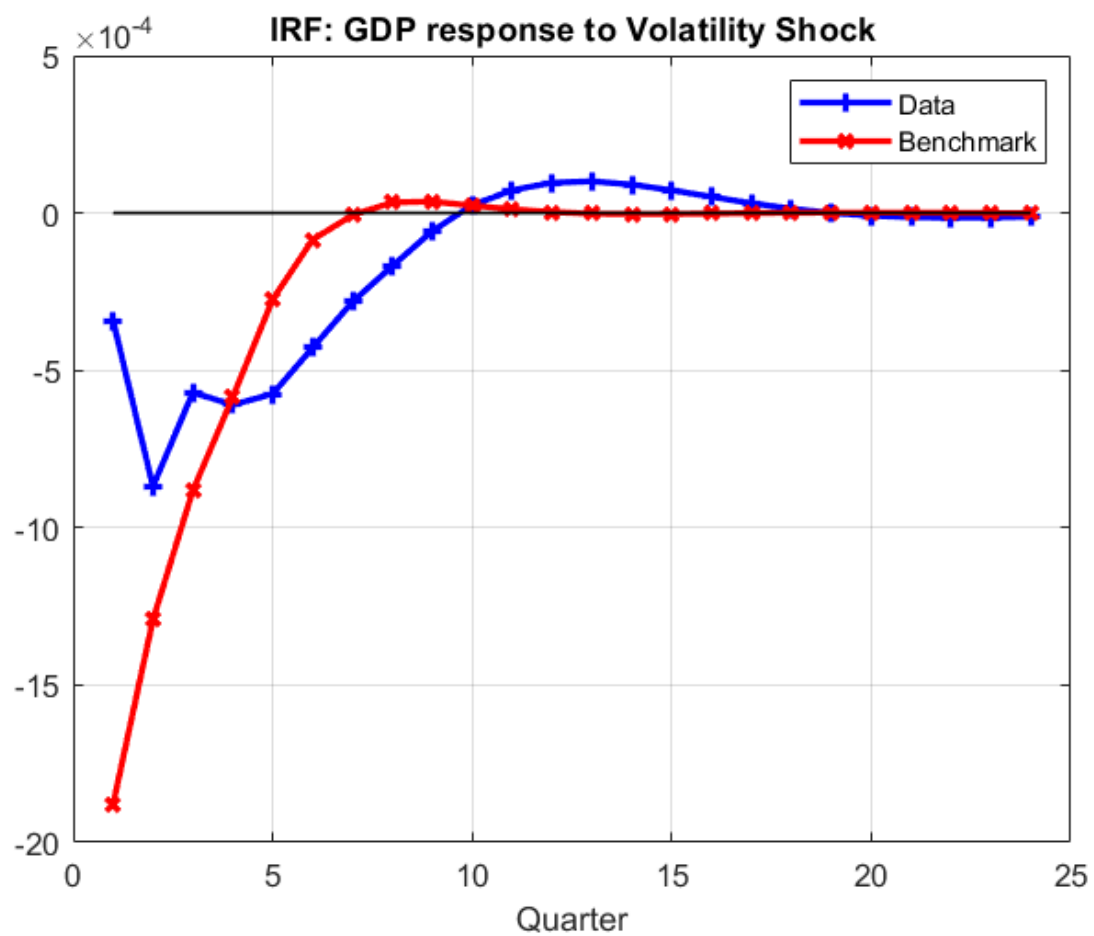


Figure 3.5: Impulse Response of GDP to a shock to VIX in a Bivariate VAR, in the Data and in the Aggregate model

uncertainty, generate significant and persistent declines in output. The VIX, constructed from S&P 500 index option prices, is often regarded as a high-frequency proxy for expected volatility under the risk-neutral measure, and is used extensively in both academic and policy applications to monitor market stress.

In this model-based experiment, we replicate Bloom’s identification strategy by computing the impulse response of output to a volatility shock, using model-simulated data and a structural VAR approach. Specifically, we feed a one-standard-deviation increase in the time-varying disaster probability pp into the model, which acts as the underlying risk state variable, and compute the resulting output response. This approach is consistent with the theoretical interpretation of the VIX as a forward-looking measure of perceived tail risk, which in our framework is nearly one-to-one with changes in pp , as in Gourio (2012).

The impulse response function (IRF) is presented in Figure 3.5. In the data (blue line), GDP declines sharply in the first two quarters following the volatility shock and then gradually recovers, exhibiting a persistent deviation from trend. This response is broadly in line with prior estimates obtained using VARs with Cholesky decompositions and four lags (Jurado et al., 2015) [47]. The initial decline in output reflects precautionary behavior by firms, including reductions in investment and hiring.

The benchmark model (red line) matches the amplitude of the initial GDP contraction quite closely. Output falls sharply on impact due to an increase in disaster probability, which raises marginal utility and suppresses investment. However, the model’s recovery dynamics differ from the data: GDP returns to trend relatively quickly, as the adjustment is nearly instantaneous. This difference stems from the model’s frictionless environment, where capital reallocations are not subject to time-to-build or irreversible investment constraints. Introducing such frictions could likely improve the model’s fit in this dimension (Arellano et al., 2019) [5].

As expected, the standard RBC model fails to generate any output response to a volatility shock, as the implied volatility of returns remains effectively constant across time. In this setup, without time-varying risk or a mechanism linking perceived uncertainty to economic behavior, the model lacks both a theoretical and quantitative counterpart to the VIX. In terms of measurement, the model-implied VIX is defined as the conditional volatility of returns under the risk-neutral measure

$$\text{VIX}_t = \sqrt{\frac{\mathbb{E}_t [M_{t+1} R_{t+1}^2]}{\mathbb{E}_t [M_{t+1}]} - \left(\frac{\mathbb{E}_t [M_{t+1} R_{t+1}]}{\mathbb{E}_t [M_{t+1}]} \right)^2}.$$

For comparison, the physical volatility of returns (VOL) is defined as

$$\text{VOL}_t = \sqrt{\mathbb{E}_t [R_{t+1}^2] - (\mathbb{E}_t [R_{t+1}])^2}.$$

In the benchmark model, both VIX and VOL respond primarily to fluctuations in p . Hence, an increase in perceived disaster probability translates directly into an increase in market volatility and a contraction in output.

This experiment illustrates that the model captures the key feature of volatility shocks, namely, their real effects, while providing a structural microfoundation for movements in VIX. The impulse response in Figure 3.5 supports the view that the VIX is not merely a reflection of realized volatility, but a forward-looking indicator of macroeconomic risk, consistent with Pastor and Veronesi (2012)

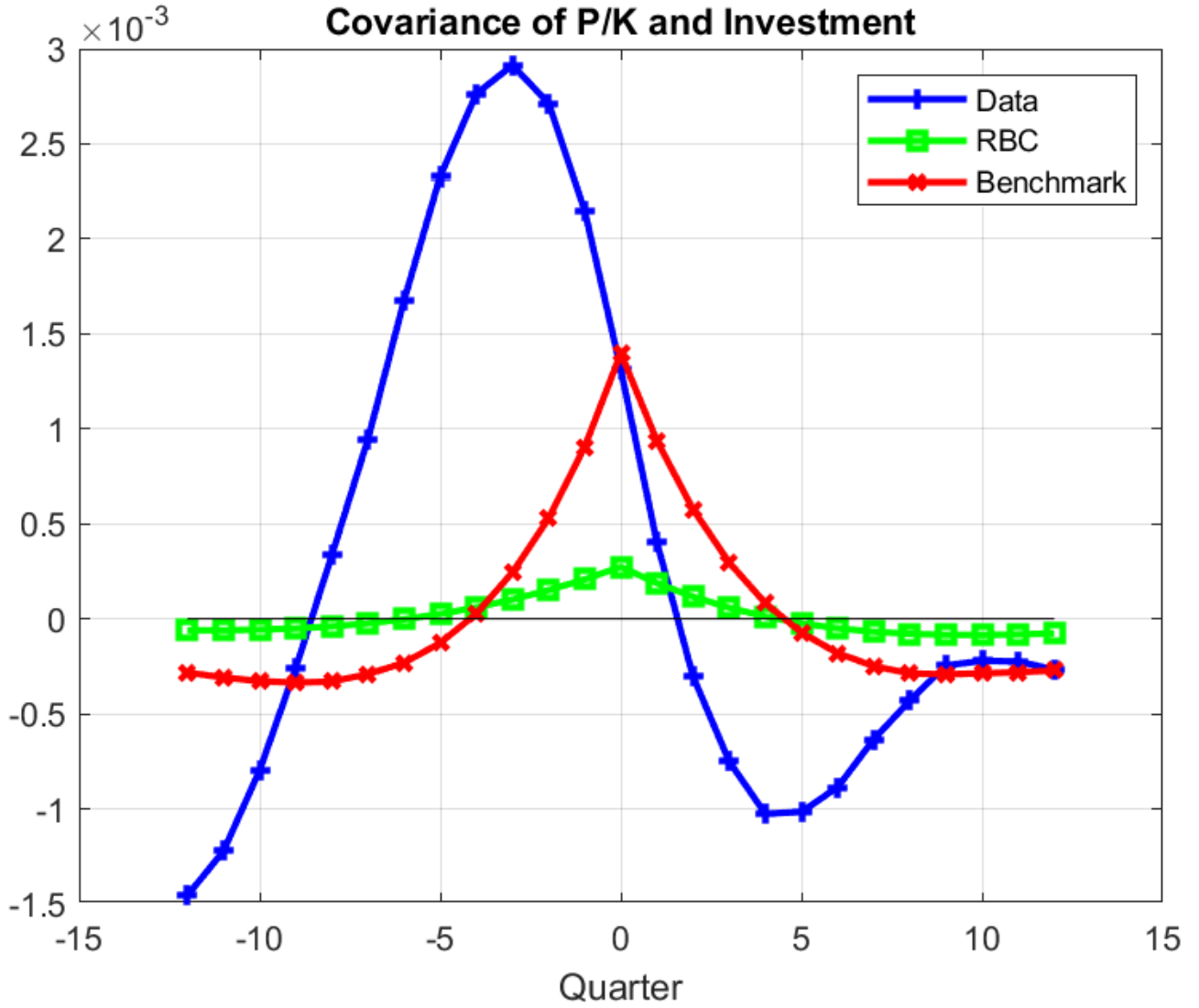


Figure 3.6: Cross-Covariogram of Investment and Price to Book Ratio in the Data, RBC and Aggregate model

[64].

3.5.3 Investment and Asset Prices

One of the enduring challenges in macro-finance is to reconcile the strong empirical link between investment and stock market valuations with the weak propagation mechanism predicted by standard neoclassical models. According to the traditional Q-theory of investment (Tobin, 1969; Hayashi, 1982) [72], investment should respond positively to increases in the market value of installed capital. While this theory correctly predicts the sign of the relationship, the magnitude observed in the data often implies implausibly large adjustment cost parameters when implemented within standard RBC frameworks (Cummins et al., 2006) [28].

In this model, however, the introduction of time-varying disaster risk creates a stronger and more realistic connection between the price of capital and investment, even with modest adjustment frictions.

Figure 3.6 reports the cross-covariogram:

$$\gamma_j = \text{Cov} \left(i_t, \log \left(\frac{P_{t+j}}{K_{t+j}} \right) \right) \text{ for } j = -12, \dots, +12.$$

where i_t is log investment and $\frac{P_t}{K_t}$ is the log price-to-capital ratio, both filtered using a one-sided HP filter to remove trends and avoid look-ahead bias. This statistic captures the dynamic relation between capital valuation and subsequent investment activity, a central test of Q-theory and of the model's ability to capture forward-looking behavior.

In the data (blue line), the covariance is clearly positive and sharply peaked around $j = 0$, confirming that investment tends to follow increases in market valuations. This pattern is consistent with the interpretation that the price-to-capital ratio contains information about expected marginal returns, and that firms react by adjusting their investment decisions accordingly.

The benchmark model (red line) replicates both the magnitude and the shape of this empirical relationship remarkably well. The cross-covariogram shows a distinct peak at $j = 0$, flanked by a decline at both leads and lags. This pattern arises because disaster risk induces time variation in expected returns: when risk declines, the valuation of capital rises, leading firms to invest more. The valuation channel thus acts as an intertemporal signal, aligning model dynamics with observed investment behavior.

By contrast, the RBC model (green line) fails to produce any substantial comovement. In that setting, asset prices are driven almost exclusively by TFP shocks, which—though they influence output—have only a muted impact on asset valuations. As a result, the model generates a flat and attenuated covariance, inconsistent with the strength of the empirical relation.

Notably, while the benchmark model replicates the overall magnitude of link between stock market and investment, it misses the slight lead of valuations observed in the data. This limitation likely reflects the absence of frictions such as time-to-build or investment gestation lags, which tend to shift the response of investment forward in time (Christiano et al., 2005) [25]. Incorporating such frictions could improve the timing match without altering the underlying mechanism.

Overall, the model demonstrates that risk-based asset valuation can act as an effective transmission channel to real investment, reinforcing the view that the financial market contains leading information about firms' future capital formation decisions.

3.5.4 Additional Asset Pricing Implications

The model offers a coherent explanation for several asset pricing regularities beyond those directly related to equity returns and macroeconomic quantities. These implications emerge naturally from the interaction between time-varying disaster risk, consumption smoothing behavior, and the pricing of long-duration cash flows.

A first result concerns the behavior of the price-dividend (P/D) ratio. In the model, this ratio (13 with a standard deviation of 0.21) reflects both the expected path of future dividends and the stochastic discount factor. As disaster risk rises, investors demand higher compensation for bearing equity risk, leading to a contraction in asset prices relative to current payouts. Consequently, the model endogenously generates a time-varying P/D ratio that responds to shifts in risk perceptions. The implied volatility of the log P/D ratio is broadly consistent with empirical evidence, suggesting

that the model captures both the level and the persistence of valuation fluctuations. This is important given the empirical finding that the log P/D ratio forecasts long-horizon returns (Cochrane, 2008).

Second, the model aligns with the notion that expected equity returns are predictable using valuation ratios. Formally, excess returns on equities satisfy the regression specification:

$$R_{t \rightarrow t+k}^e - R_{t \rightarrow t+k}^f = \alpha + \beta \cdot \frac{P_t}{D_t} + \varepsilon_{t+k}$$

Under rational expectations and a stochastic discount factor sensitive to macroeconomic risk, this regression delivers a positive slope coefficient, indicating that low P/D ratios are followed by high expected returns. This reflects the countercyclical nature of risk premia and is consistent with the model's dynamics. Moreover, the forecasting power of the P/D ratio applies to both total and excess returns, a feature supported by empirical asset pricing studies (Lettau and Ludvigson, 2001).

Third, the model offers insight into the pricing of a consumption claim: a hypothetical asset that pays the representative agent's aggregate consumption. Because aggregate consumption is smoother and less volatile than corporate dividends, the associated risk premium is lower. This result aligns with the findings of Lustig, Van Nieuwerburgh, and Verdelhan (2010), who document that claims to aggregate consumption trade at high prices precisely because they offer superior hedging properties relative to equity. In the model, the consumption claim serves as a proxy for the marginal utility-weighted pricing kernel, which fluctuates with perceived disaster risk, but less violently than the return on dividends.

Fourth, the model's treatment of consumption dynamics also helps explain a long-standing asset pricing puzzle: the low estimated intertemporal elasticity of substitution (IES) in consumption. When model-simulated data are used to estimate the IES via standard regressions of consumption growth on the risk-free rate, the coefficient is biased downward due to the omission of changes in precautionary saving motives. Specifically, variations in the probability of disaster, which are correlated with interest rates, affect consumption growth through a channel not captured by the Euler equation under certainty. This finding is consistent with Hall (1988), who estimates very low IES values in postwar US data. It suggests that precautionary behavior, induced by rare disaster risk, can rationalize empirical estimates that seem inconsistent with standard preferences.

A fifth implication pertains to the term structure of interest rates. The model generates a downward-sloping average yield curve, with a negative term premium on long-term bonds. This outcome arises because an increase in disaster probability lowers the expected future marginal utility of consumption, increasing the demand for safe, long-duration assets. Since the model assumes default risk applies uniformly across maturities, the negative term premium is not driven by differences in credit risk but rather by the hedging value of long-term bonds. In periods of elevated uncertainty, these assets serve as a store of value, pushing up their prices and lowering yields. This logic mirrors the empirical evidence that long-term government bonds hedge macroeconomic risk and offer lower average returns (Campbell et. al, 2009) [22].

Lastly, the model provides a framework to understand corporate bond spreads, as developed in Gourio (2013) [37]. The endogenous variation in disaster probability influences both the default likelihood and the risk premium demanded by investors, generating spreads that respond endogenously to the macro-financial environment. Although this mechanism is not explicitly quantified in the current implementation, it highlights the model's potential to unify explanations of equity, government, and

corporate bond pricing within a single risk-based structure.

3.6 Differences in impact between the various types of Rare Disaster

This section will present the key findings of this study: the differences in impact on macroeconomic variables and asset returns between the 3 types of rare disasters presented above:

1. Wars
2. Financial crises
3. Pandemics

The strategy was to replicate the model presented in the previous chapter, but to simulate it for each individual type, using specific probabilities and impacts instead of in aggregate form.

3.6.1 Realization impact on Macroeconomic Variables

Consumption Response

The first key dimension to consider is the response of aggregate consumption. As shown in Figure 3.7, all types of disasters induce a negative shock to consumption on impact, but the magnitude and persistence of the decline differ substantially across categories.

Wars generate the largest and most persistent contraction in consumption. Following a war-type disaster, the cumulative decline in consumption exceeds 25% relative to the pre-disaster trend. The decline deepens steadily over the first five years and only partially recovers thereafter. This pattern is consistent with the empirical observation that wars cause severe and long-lasting disruptions in both production capacity and household confidence (Barro and Ursúa, 2009).

Financial crises also lead to a significant contraction in consumption (15%), but the impact is less severe than that of wars. The immediate fall is sharp, reflecting the destruction of wealth and tightening of credit conditions, but the recovery begins earlier and is more sustained. This is in line with historical analyses of major financial panics, where although consumption is curtailed significantly, it tends to rebound faster once liquidity is restored.

Pandemics, by contrast, cause the mildest reduction in consumption (6%). The initial drop is modest and the subsequent trajectory exhibits a quicker return towards the baseline trend. This likely reflects the fact that pandemics, while disruptive to labor supply and certain sectors, do not destroy physical capital and often trigger compensatory fiscal and monetary responses aimed at stabilizing household incomes (Jordà, Singh, and Taylor, 2022) [46].

The heterogeneity in consumption responses underscores the importance of the nature of the disaster: shocks that directly impair the productive capital stock or financial system have more profound and persistent effects on household spending patterns.

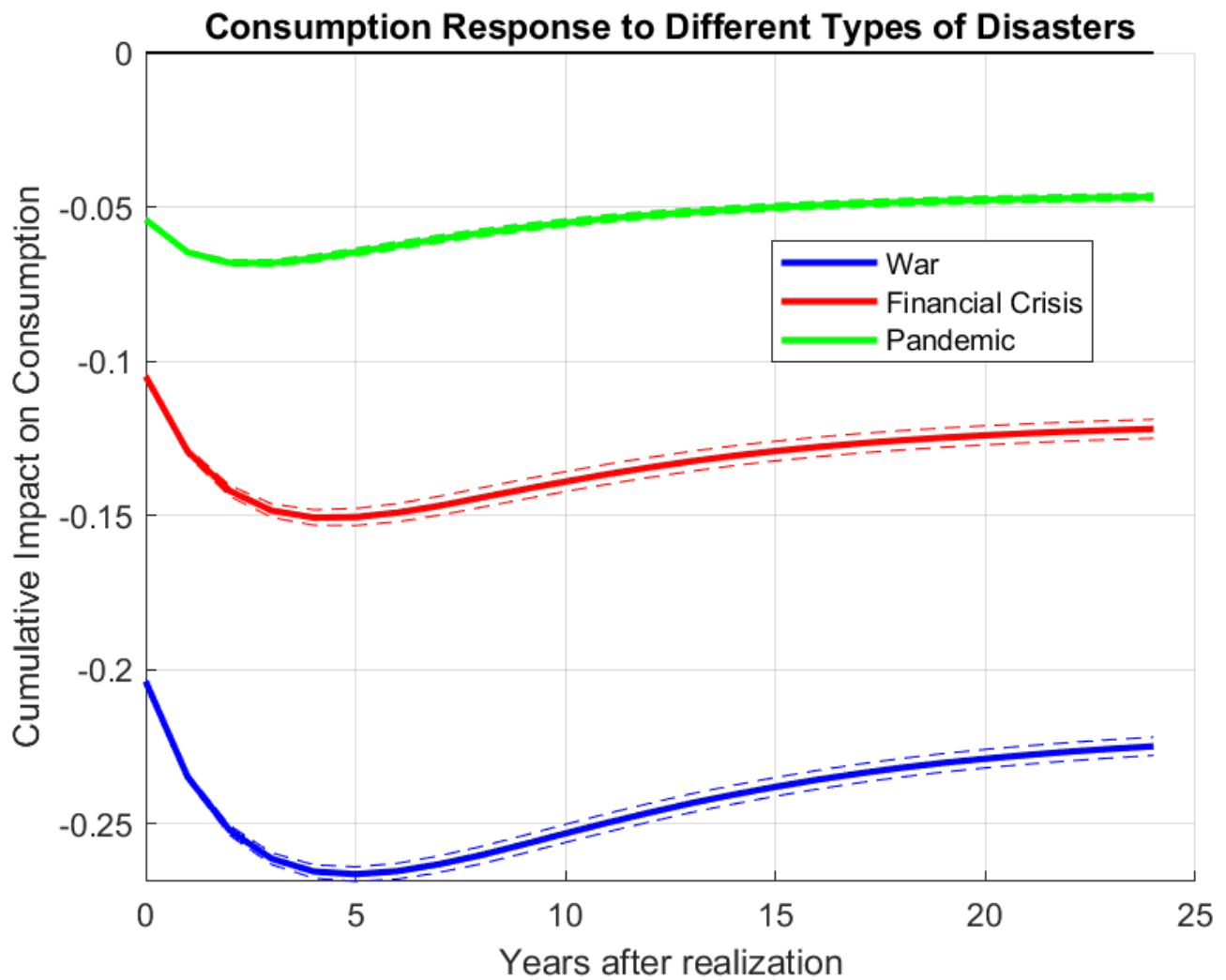


Figure 3.7: IRF of various disaster type over Consumption

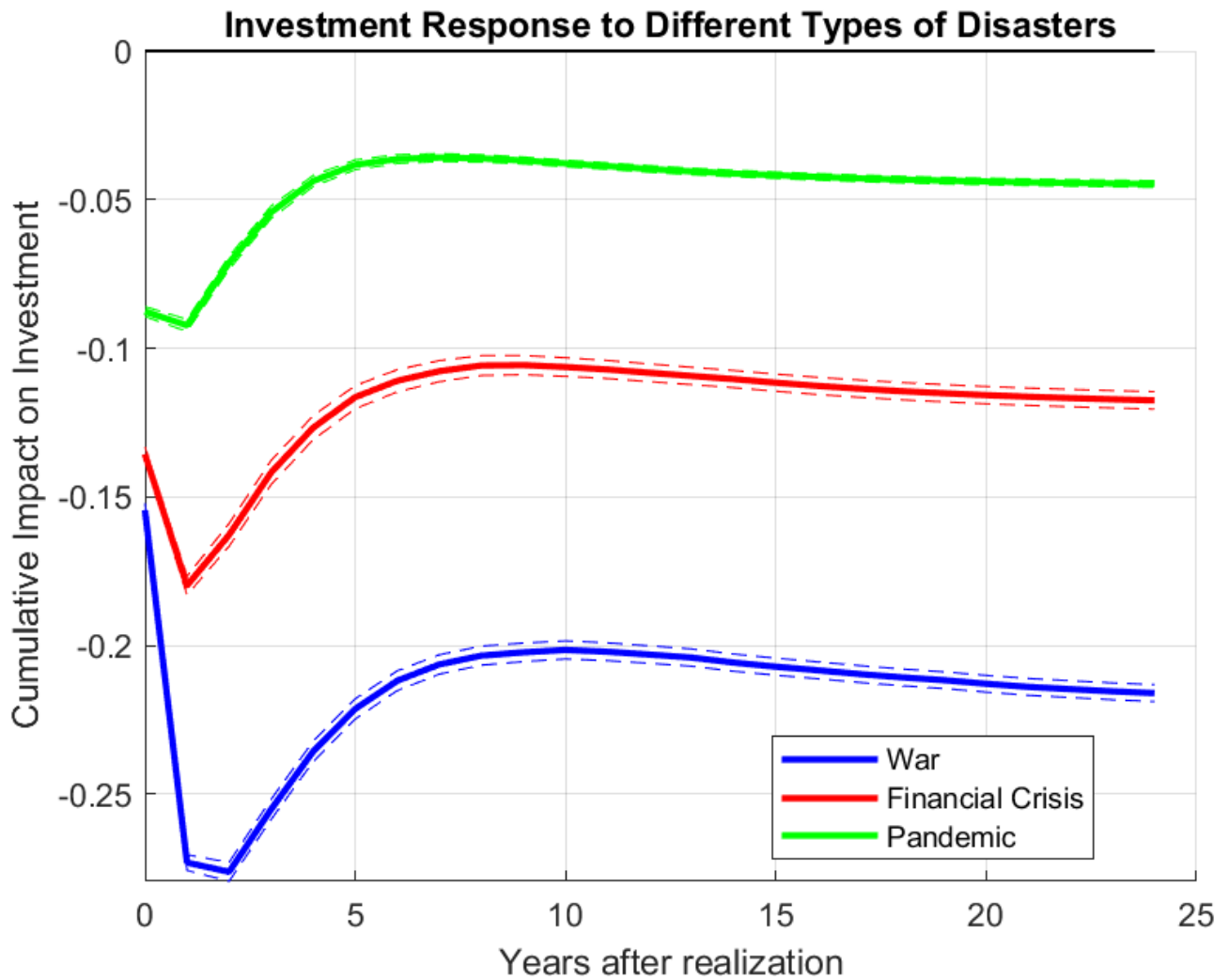


Figure 3.8: IRF of various disaster type over Investment

Investment Response

Turning to investment, the differences between disaster types are even more pronounced (Figure 3.8). Investment is highly sensitive to forward-looking expectations and risk perceptions, making it a critical margin through which disaster shocks propagate.

Following a war, investment experiences the steepest and most persistent decline, falling by more than 25% relative to trend. The IRF shows a sharp initial collapse, with no meaningful recovery even after two decades. This severe response reflects both the destruction of existing capital stock and a dramatic increase in uncertainty about future returns, consistent with the notion that wars fundamentally reshape economic structures and institutions (Cerra and Saxena, 2008) [24].

In the case of a financial crisis, investment falls sharply on impact (18%), but begins to recover within a few years. The initial contraction is driven by the tightening of credit and increased cost of capital, in line with theoretical predictions of financial accelerator models (Bernanke, Gertler, and Gilchrist, 1998) [36]. The partial recovery suggests that financial systems, while fragile, can be gradually repaired through policy interventions and market self-correction.

Pandemics generate the smallest disruption to investment. Although there is an initial contraction reflecting heightened uncertainty and temporary shutdowns, the recovery is faster and more complete. This outcome is intuitive: since pandemics tend to have temporary effects on labor supply rather than capital destruction, the expected profitability of investment projects remains more intact compared to wars or banking collapses.

Thus, investment responses differentiate sharply according to whether the disaster primarily affects physical capital (wars), financial capital (crises), or labor supply (pandemics).

Employment Response

Employment dynamics also exhibit distinctive patterns following different disasters, as seen in Figure 3.9. The IRFs suggest that although all types of disasters reduce employment initially, the medium-term adjustments vary.

After a war, employment first declines sharply (2%) but then rebounds relatively strongly over the next five to ten years. This recovery likely reflects reconstruction efforts and post-war rebuilding activities, which historically generate surges in labor demand. Nonetheless, the recovery is incomplete, indicating long-term scarring effects on the labor market.

Financial crises generate a V-shaped pattern: an initial sharp contraction (1.7%) in employment followed by a more gradual and partial recovery. Labor markets take time to adjust due to frictions such as matching inefficiencies and skills mismatches (Diamond, 2011) [30]. The persistence of higher unemployment rates after financial crises is well-documented in empirical work (Jordà, Schularick, and Taylor, 2013) [45].

Pandemics have a distinct employment trajectory: while the initial impact on employment is negative (1/%), the recovery is faster compared to wars and financial crises. However, the rebound is less pronounced in magnitude, suggesting that although labor demand returns, it does not fully restore pre-disaster employment levels. This could reflect structural shifts in labor markets induced by health crises, such as changes in the sectoral composition of demand.

Overall, the employment responses corroborate the view that the transmission of shocks to labor markets depends crucially on the underlying nature and persistence of the disaster.

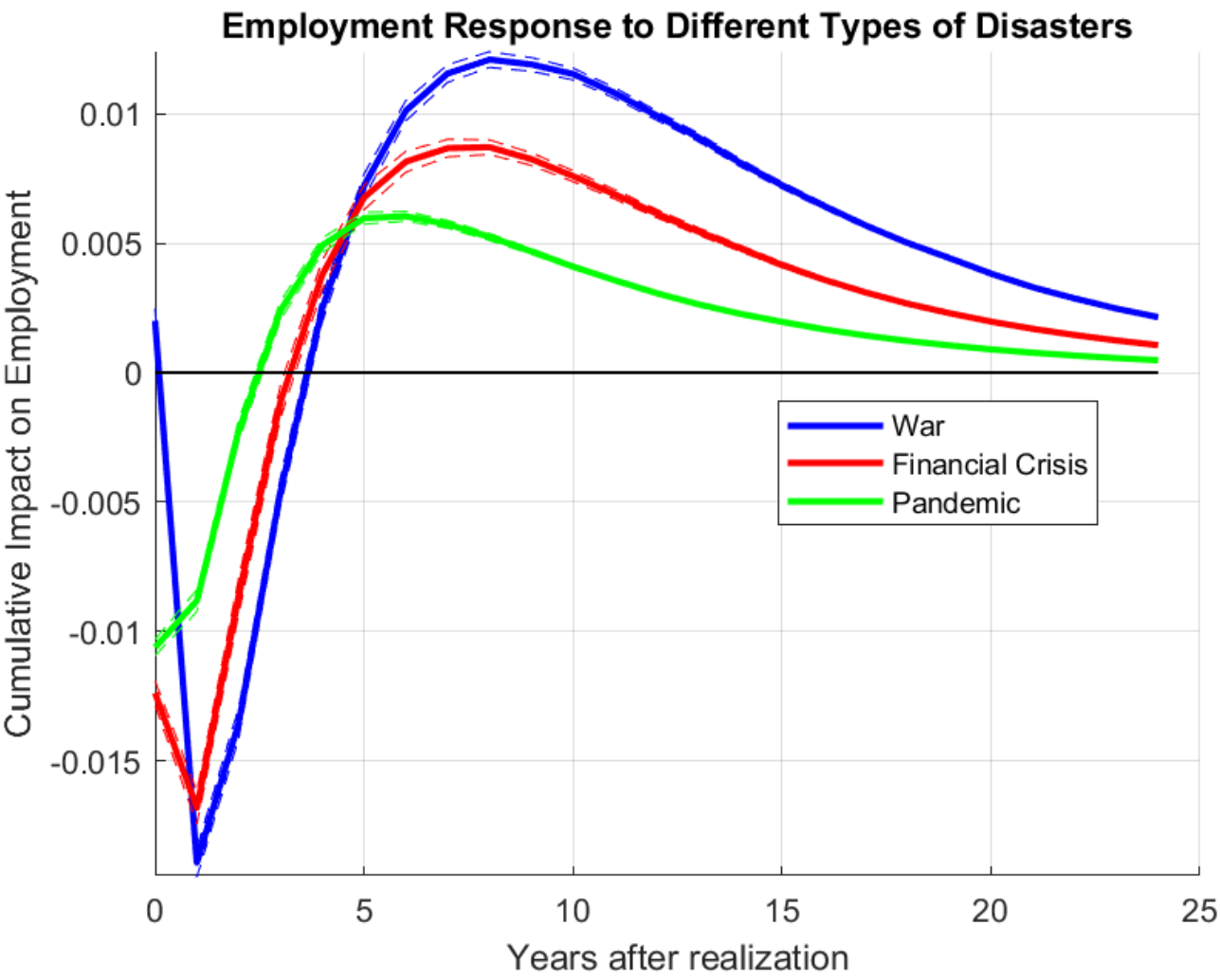


Figure 3.9: IRF of various disaster type over Employment

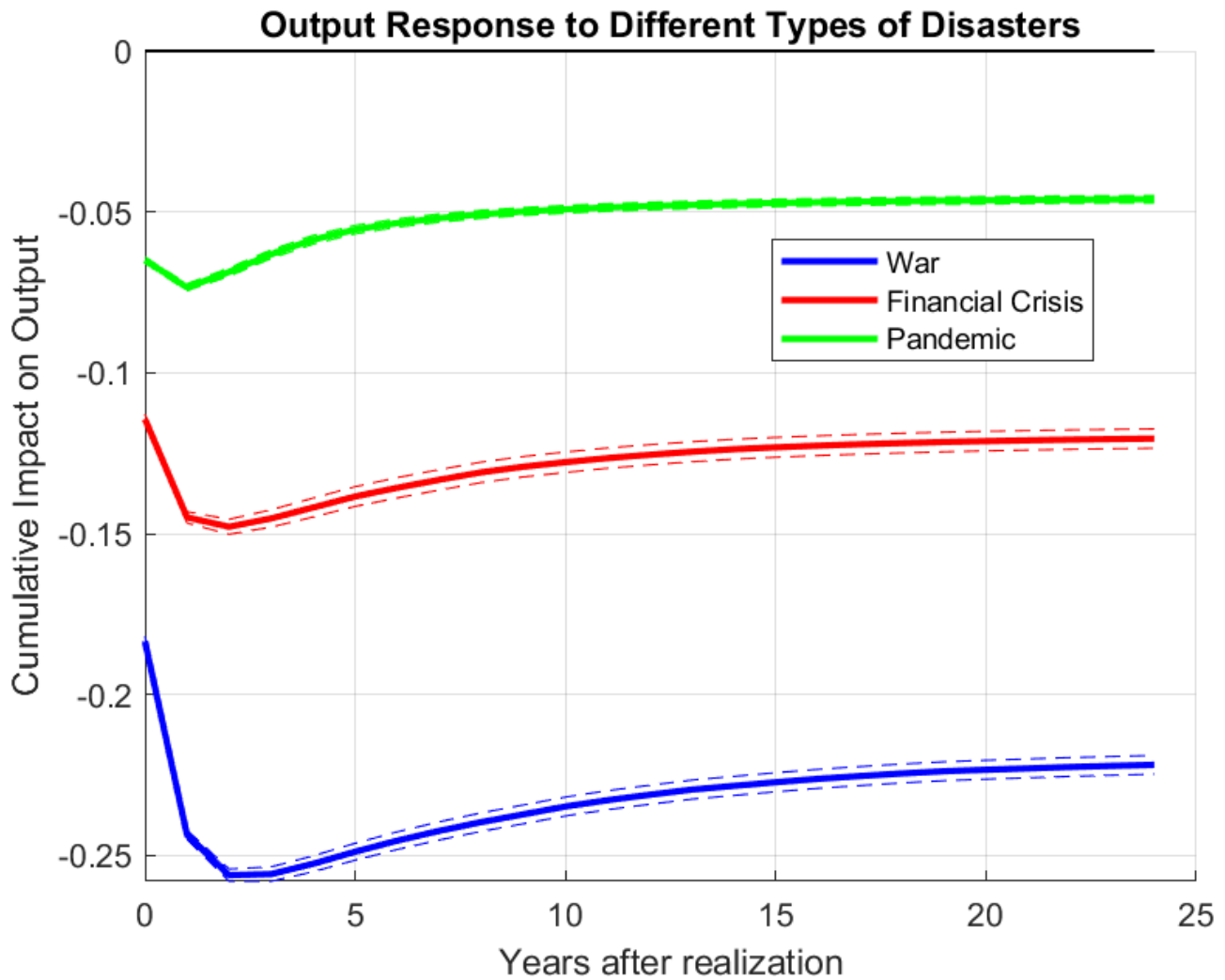


Figure 3.10: IRF of various disaster type over GDP

Output Response

Finally, the IRFs for aggregate output (Figure 3.10) synthesize the broader macroeconomic consequences of different disaster types.

Wars induce the deepest and most prolonged contraction in output (26%), consistent with the destruction of productive capacity, displacement of labor, and erosion of institutional stability. The cumulative output loss remains large even twenty years after the shock, indicating persistent negative effects on potential output.

Financial crises generate substantial output losses as well (15%), though the magnitude is smaller than that of wars. The output gap narrows over time but does not fully close, reflecting the difficulty in re-establishing financial intermediation and restoring investment. This aligns with empirical findings that financial recessions have longer-lasting output effects than normal business cycle downturns (Reinhart and Rogoff, 2014) [66].

Pandemics cause the mildest contraction in output (6%). Although the initial dip is visible, output tends to recover relatively quickly as public health measures are relaxed and normal economic activities resume. Nonetheless, the fact that output does not immediately return to its pre-disaster path suggests that pandemics can still have medium-term scarring effects, especially through changes in productivity and sectoral shifts (Barro, Ursúa, and Weng, 2020) [14].

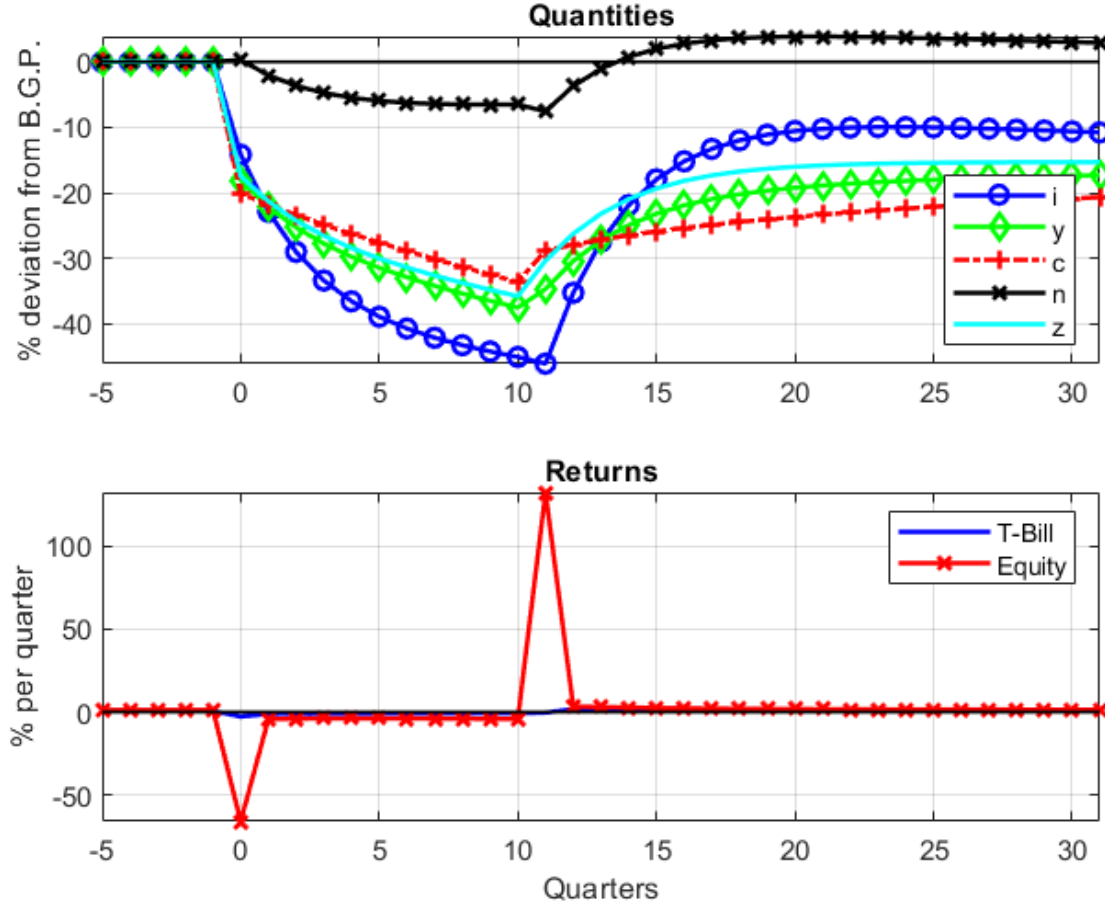


Figure 3.11: Response of Macroeconomic Quantities and Asset Returns to a war realization

In sum, the model highlights that the long-run macroeconomic impact of disasters depends critically on their nature: wars cause destruction that is difficult to reverse, financial crises damage intermediation channels and amplify uncertainty, and pandemics primarily disrupt labor and consumption patterns in a more transitory fashion.

3.6.2 Dynamics and Returns

This chapter systematically analyzes the dynamic macroeconomic and financial consequences triggered by different classes of rare disasters: financial crises, pandemics, and wars. Using the model's simulated impulse response functions (IRFs), I study the joint evolution of quantities and returns following the occurrence of each event. This disaggregated approach allows for a detailed understanding of the specific mechanisms through which each type of disaster propagates through the economy. Each subsection focuses separately on the macro-financial adjustments induced by a given disaster type.

Wars

Wars are modeled as catastrophic events that simultaneously destroy physical capital, impair labor supply, and elevate economic uncertainty. Figure 3.11 presents the impulse responses to a war shock.

The macroeconomic consequences of wars are the most severe among the disaster types considered. Investment collapses by more than 30% from trend within the first few quarters, highlighting the

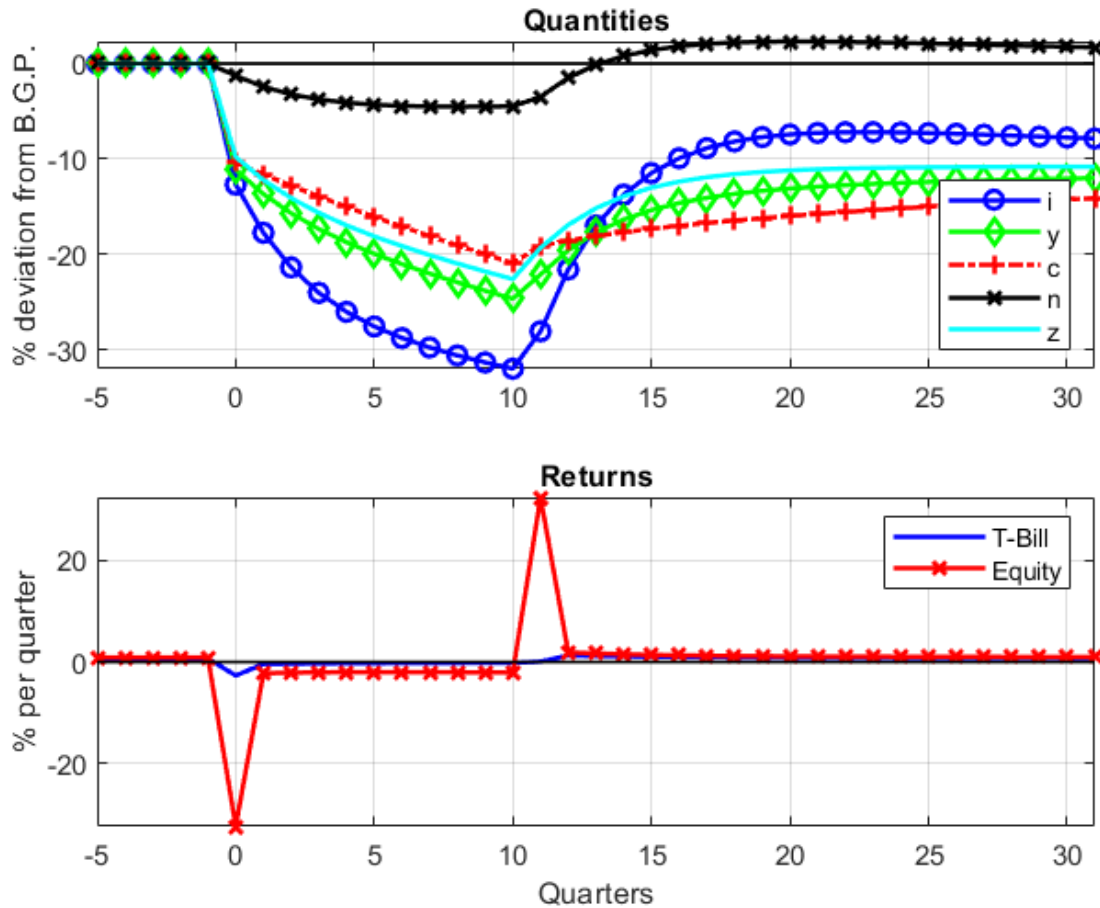


Figure 3.12: Response of Macroeconomic Quantities and Asset Returns to a financial crisis realization

destruction of productive assets and the adverse expectations about future profitability. Output and consumption experience similarly deep contractions, with output falling close to 25% relative to its pre-disaster trajectory. These results are consistent with historical accounts of wartime economies, where mobilization efforts, destruction of infrastructure, and resource misallocation lead to large drops in aggregate activity (Barro and Ursúa, 2009).

Employment initially declines but eventually rebounds sharply as reconstruction efforts commence. The labor market overshoots temporarily, consistent with post-war booms in rebuilding efforts.

From a financial perspective, equity returns undergo a massive negative swing at the onset of the disaster, followed by a dramatic rebound several quarters later. This V-shaped pattern is consistent with extreme repricing of risk at the beginning of the conflict, and the gradual reassessment of growth prospects once uncertainty diminishes (Gourio, 2012).

T-bill returns remain relatively flat, although a slight increase is observed as demand for safe assets rises. However, the dislocation is less pronounced than in the equity market.

Overall, wars exert the deepest and longest, lasting negative effects on macroeconomic aggregates and create extreme volatility in asset prices, reaffirming their status as the most destructive type of disaster in the model.

Financial Crisis

Financial crises are characterized in the model by an abrupt destruction of financial wealth and an increase in borrowing costs. The top panel of Figure 3.12 illustrates the behavior of key macroeconomic quantities following the realization of a financial crisis shock.

Aggregate investment (i), output (y), and consumption (c) all contract sharply on impact, with investment being the most sensitive component. Investment declines by approximately 20% relative to the balanced growth path within a few quarters, reflecting the dramatic deterioration in firms' access to external finance. This pattern is consistent with empirical evidence from post-crisis periods, where deleveraging and credit rationing severely dampen capital expenditures (Dell'Ariccia, Detragiache, and Rajan, 2008) [29].

Consumption and output also experience significant but less dramatic declines. The contraction in consumption mirrors the destruction of household wealth and precautionary saving behavior in response to elevated uncertainty (Mian and Sufi, 2014) [60]. Output declines as aggregate demand falls and production adjusts accordingly.

Interestingly, employment (n) displays a more muted reaction relative to investment, suggesting that financial crises disproportionately affect capital-intensive sectors.

The bottom panel depicts returns: equity returns exhibit a sharp negative spike at the crisis onset, followed by a substantial positive rebound after several quarters. The T-bill rate remains relatively stable, reflecting a flight-to-safety phenomenon where short-term government securities are in high demand (Krishnamurthy and Vissing-Jorgensen, 2012).

Overall, the model captures the key stylized facts associated with financial crises: a deep and persistent contraction in investment and output, a substantial increase in risk premia, and a temporary dislocation in asset markets.

Pandemics

Pandemics introduce disruptions to labor supply and consumer confidence, but do not involve direct destruction of capital or financial infrastructure. The dynamics following a pandemic shock are plotted in Figure 3.13.

Compared to financial crises, the macroeconomic impact of pandemics is more moderate. Investment, output, and consumption decline on impact but to a significantly lesser extent. Investment shows a mild contraction, reflecting firms' caution in undertaking new projects amid temporary shut-downs and health-related uncertainty. However, the speed of recovery is faster: by approximately 15 quarters after the shock, macroeconomic quantities are converging back toward their pre-disaster trends.

This pattern mirrors historical evidence from past pandemics, such as the 1918 influenza and COVID-19 episodes, where economic activity, although severely disrupted in the short run, tends to recover relatively swiftly once public health conditions stabilize (Jordà, Singh, and Taylor, 2022).

Employment dynamics are less favorable compared to consumption and output. The IRF suggests that after an initial rebound, employment does not fully return to its previous trend, consistent with the idea that pandemics may induce structural shifts in labor markets, such as increased automation or reallocation across sectors.

In financial markets, equity returns display a negative jump at the time of the shock, reflecting

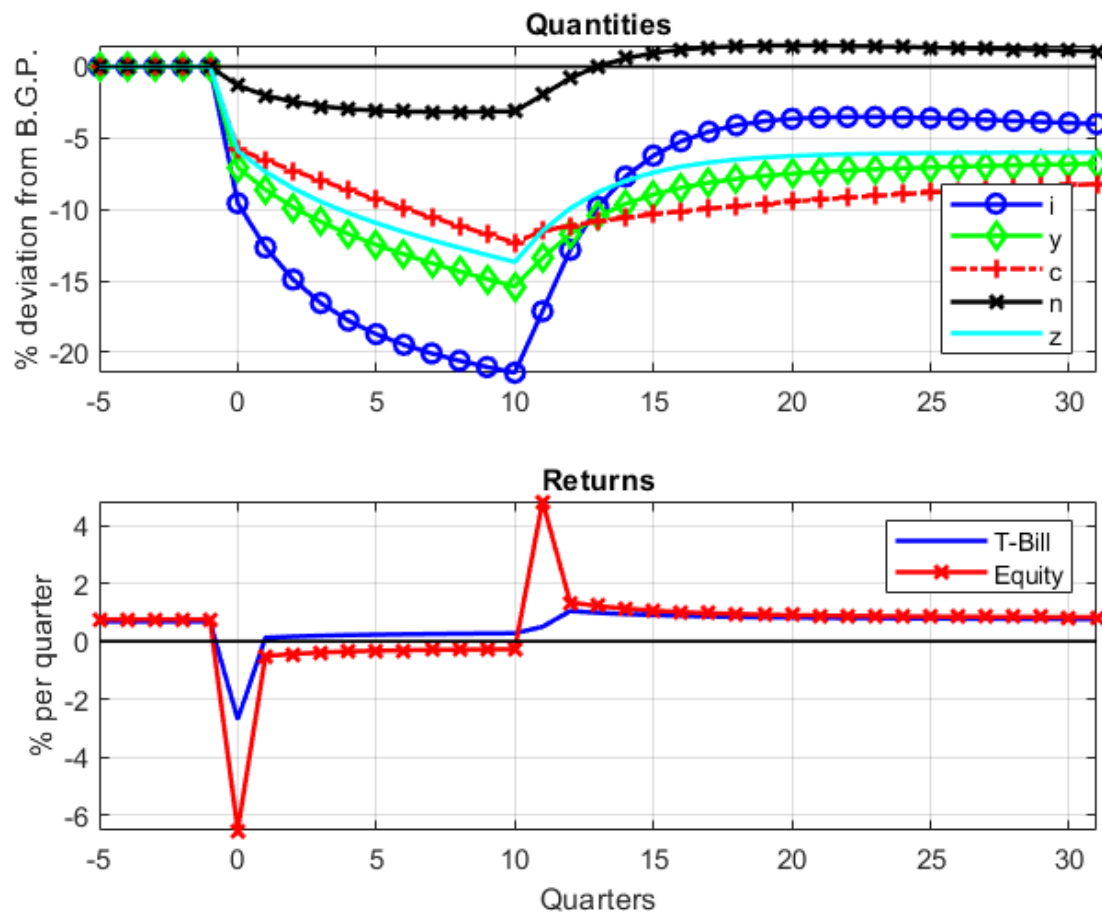


Figure 3.13: Response of Macroeconomic Quantities and Asset Returns to a pandemic realization

increased uncertainty. However, unlike in financial crises, the magnitude of the shock to returns is smaller, and the recovery is faster. T-bill returns remain virtually unchanged, suggesting that pandemic-related risk is less systematically priced into safe assets compared to financial risk.

Thus, the model captures the main features of pandemic recessions: moderate real effects, partial but incomplete labor market recovery, and relatively swift financial stabilization.

3.6.3 Moments of Quantities and Returns

In this section, I analyze the ability of the model to replicate the first and second moments of key macroeconomic aggregates and asset returns following different types of disaster events: wars, financial crises, and pandemics. By separately evaluating the volatility and comovements of output, consumption, investment, and employment, alongside risk-free rates, equity returns, and excess returns, I assess the degree of realism of the simulated economies under each disaster scenario. Table

Table 3.8: Business Cycle Statistics by Disaster for Output, Consumption, Investment, and Employment

	$\sigma(Y)$	$\sigma(C)$	$\sigma(I)$	$\sigma(N)$	$\rho_{C,Y}$	$\rho_{I,Y}$	$\rho_{N,Y}$
1 War	0.91 (0.05)	0.53 (0.03)	1.68 (0.09)	0.29 (0.02)	0.98 (0.01)	0.99 (0.00)	0.96 (0.01)
2 Financial Crisis	0.90 (0.04)	0.53 (0.03)	1.67 (0.09)	0.28 (0.02)	0.98 (0.01)	0.99 (0.00)	0.97 (0.01)
3 Pandemic	0.90 (0.05)	0.53 (0.03)	1.66 (0.09)	0.27 (0.01)	0.99 (0.00)	1.00 (0.00)	0.99 (0.01)

Notes: All series are in growth rates. Standard errors in parentheses. Data 1947:I - 2023:IV.

Table 3.9: Financial Statistics by Disaster: Risk-Free Rate, Equity Return, and Excess Return

	$E(R_f)$	$E(R_b)$	$E(R_e - R_b)$	$\sigma(R_f)$	$\sigma(R_b)$	$\sigma(R_e - R_b)$
1 War	0.51 (0.11)	0.54 (0.09)	0.79 (0.18)	0.41 (0.23)	0.33 (0.19)	3.76 (1.07)
2 Financial Crisis	0.64 (0.04)	0.66 (0.04)	0.21 (0.08)	0.14 (0.07)	0.11 (0.04)	1.46 (0.23)
3 Pandemic	0.67 (0.03)	0.68 (0.03)	0.07 (0.08)	0.06 (0.01)	0.06 (0.01)	1.11 (0.07)

Notes: Mean and standard deviation of the risk-free rate, equity return, and equity excess return. Standard errors in parentheses. Data 1947:I - 2023:IV.

[3.8](#) summarizes the standard deviations and contemporaneous correlations of output (Y), consumption (C), investment (I), and employment (N) across the three types of disasters. Standard errors are reported in parentheses.

Across all disaster types, the model captures some key stylized facts of macroeconomic volatility.

First, investment exhibits the highest volatility among all quantities, consistent with empirical observations that investment is the most procyclical and volatile component of GDP (Greenwood, Hercowitz, and Krusell, 2000) [\[39\]](#). Specifically:

- In the case of wars, the standard deviation of investment reaches 1.68, indicating large swings in capital expenditures, likely due to the destruction of the capital stock and the uncertainty about future growth prospects;
- Financial crises lead to slightly lower investment volatility (1.67), reflecting disruptions in financial intermediation and credit rationing effects;
- Pandemics exhibit the smallest investment volatility (1.66), consistent with the notion that these events primarily affect labor markets and consumption rather than physical capital accumulation.

Second, output and consumption volatility decrease progressively from wars to pandemics. For instance, output volatility is 0.91 following wars, 0.90 in financial crises, and 0.90 during pandemics, while consumption volatility is markedly lower at around 0.53 in all three cases. This reflects the different nature of shocks: wars and crises induce broader disruptions, while pandemics' effects are more contained.

Third, employment displays relatively low volatility compared to other aggregates, particularly in financial crises and pandemics (0.28 and 0.27, respectively). This muted response is consistent with empirical evidence that labor markets adjust more sluggishly, due to frictions such as search and matching constraints (Mortensen and Pissarides, 1994) [62].

Contemporaneous correlations between output and other variables are extremely high in all scenarios:

- The correlation between output and consumption exceeds 0.98 across all disaster types;
- The correlation between output and investment approaches 1.00, reflecting the tight comovement between these two aggregates;
- The correlation between output and employment is above 0.96 in all cases.

These results underscore that despite heterogeneity in volatility levels, the underlying cyclical comovements of macro variables remain robust across different types of disasters.

The second set of moments concerns asset pricing statistics, described in Table 3.9: the average and standard deviation of the risk-free rate (R_f), equity return (R_b), and equity excess return ($R_e - R_b$).

The model successfully reproduces some important qualitative features observed in financial markets during and after disaster events.

First, the mean risk-free rate varies substantially across disaster types:

- After wars, the mean risk-free return is relatively low at 0.51 percent per quarter, reflecting high precautionary savings and low demand for risky assets (Barro, 2006);
- In financial crises, the risk-free rate rises moderately to 0.64 percent;
- Following pandemics, it increases further to 0.67 percent, suggesting that pandemic shocks, being perceived as less catastrophic, induce less precautionary saving and therefore higher real interest rates.

Second, the equity premium (excess return of equities over the risk-free rate) differs dramatically:

- After wars, the equity premium is exceptionally large at 0.79 percent per quarter, consistent with the heightened perceived disaster risk priced into equity markets;
- After financial crises, the equity premium shrinks to 0.21 percent, reflecting partial restabilization of risk perceptions;
- Following pandemics, the equity premium becomes negligible at 0.07 percent, in line with the limited increase in macroeconomic uncertainty.

This hierarchy of risk premia echoes empirical evidence that major wars are associated with persistent increases in risk aversion and equity risk premia, while pandemics have more transitory effects on asset prices (Gourio, 2012; Barro et al., 2020).

Third, regarding return volatilities:

- The standard deviation of the equity excess return is very high after wars (3.76 percent), moderate after financial crises (1.46 percent), and lowest after pandemics (1.11 percent);
- Risk-free rate volatility declines across scenarios, from 0.41 (wars) to 0.06 (pandemics), reflecting the stabilization of monetary conditions as disaster severity decreases.

Overall, the model captures the fact that larger and more destructive disasters induce greater financial volatility and higher compensation for risk.

The analysis of first and second moments shows that the model matches many broad stylized facts about macroeconomic and financial dynamics following disasters. However, some limitations remain.

- Investment volatility is relatively high across all scenarios, potentially overstating the responsiveness of firms to rare disaster shocks;
- Risk-free rates appear somewhat elevated in the case of pandemics compared to historical evidence suggesting a more moderate rise in safe asset yields during health crises (Jordà, Singh, and Taylor, 2022);
- The model abstracts from inflation dynamics and government interventions, which might reduce some of the observed volatilities in actual data.

Nonetheless, the calibration successfully distinguishes between the macroeconomic and financial consequences of different disaster types, offering a promising framework to study risk, business cycles, and asset prices in environments subject to rare but catastrophic shocks.

3.7 Policy Implications of Different Rare Disasters

The empirical analysis of the distinct macroeconomic impacts resulting from rare disasters: wars, financial crises, and pandemics, offers profound insights for policy formulation. Based on the calibrated DSGE model presented, we can observe significant heterogeneity across disaster types, necessitating targeted and nuanced policy interventions to mitigate adverse effects effectively, instead of treating rare disaster as an aggregate homogeneous phenomenon.

This section will discuss the most effective types of policy for each type of disaster, based on the empirical results of the model and the theoretical implications of disasters. The various peculiarities

will then be analyzed, emphasizing the differences in order to justify an ad hoc treatment of impacts for each type.

3.7.1 Wars: Strengthening Economic Resilience through Structural Preparedness

Empirical results consistently show that wars entail severe, lasting damages characterized by pronounced physical capital destruction and deep, sustained productivity losses. Specifically, our calibrated parameters indicate substantial permanent productivity shocks coupled with elevated volatility ($\mu_\theta = -0.0075$, $\sigma_\theta = 0.0107$) and significant transitory disruptions ($\mu_\phi = -0.0692$).

Policy effectiveness in war scenarios hinges critically on preventive and structural strategies rather than purely responsive macroeconomic stimulus. Effective measures include strategic investment in robust infrastructure, diversification of critical supply chains, and maintaining adequate physical and strategic reserves. These policies mitigate capital destruction and enhance long-term recovery. Conversely, standard monetary easing and fiscal stimuli demonstrate limited effectiveness due to their inability to directly address underlying capital and productivity losses.

This view is consistent with the findings of Barro (2009), who emphasizes the outsized welfare costs of disaster risk and highlights the importance of preventive structural measures in mitigating long-term damages. Similarly, Gabaix (2012) introduces asset resilience, reinforcing the necessity for structural robustness to maintain asset values in the face of catastrophic shocks.

3.7.2 Financial Crises: Active Stabilization Policies and Regulatory Frameworks

Financial crises predominantly manifest through severe liquidity constraints and transient yet substantial productivity downturns ($\mu_\theta = -0.0053$, $\mu_\phi = -0.0441$). These results highlight their intrinsically financial nature, driven by credit crunches, asset price collapses, and confidence shocks.

In such contexts, active macroeconomic stabilization policies prove particularly effective. Our simulations underline the critical role of liquidity provisions by central banks, financial regulation enhancement, and targeted fiscal interventions designed to support demand and maintain employment. Financial market stabilization, bank recapitalization, and prudential regulation significantly reduce volatility and accelerate economic recovery. Conversely, policies narrowly focused on structural productivity enhancement without financial stabilization measures fail to achieve immediate crisis mitigation.

The conclusions align closely with Gourio (2012), who highlights the importance of countercyclical risk premia and liquidity stabilization measures during financial crises. Furthermore, Farhi and Gabaix (2016) underscore that addressing liquidity and credit disruptions directly enhances the effectiveness of policy measures during financial crises, supporting our recommendation of robust regulatory frameworks.

3.7.3 Pandemics: Balancing Immediate Fiscal Support with Public Health Investments

Pandemics, uniquely characterized by high transitory disruptions but relatively lower permanent shocks ($\mu_\theta = -0.0030$, $\mu_\phi = -0.0199$), require a dual policy approach combining immediate economic support with substantial public health investments.

The empirical results support aggressive, short-term fiscal measures, including direct transfers and temporary unemployment subsidies, as highly effective in cushioning immediate economic shocks. Moreover, significant investment in healthcare infrastructure, early-warning systems, and vaccine development yields exceptionally high returns by rapidly restoring consumer and investor confidence. Standard monetary policy easing alone is insufficient in pandemic scenarios, where recovery is intrinsically linked to public health outcomes rather than purely economic confidence.

This recommendation finds support in recent literature by Cantelmo (2022), who emphasizes the necessity for integrated health and economic policies, demonstrating how robust public health systems significantly reduce economic disruption. Wachter (2013) also contributes to this argument by showing how proactive investments and preparedness strategies reduce uncertainty and volatility, thus fostering quicker recoveries.

3.7.4 Comparative Analysis and Justification of Policy Differentiation

The differential policy effectiveness across these disaster types emerges naturally from their intrinsic characteristics captured by our calibrated model. Wars produce extensive and enduring capital destruction, rendering immediate economic stimuli less effective compared to structural preparedness. Financial crises, however, with their shorter-term liquidity-driven disruptions, respond strongly to rapid monetary and fiscal interventions aimed at restoring market functioning. Pandemics, due to their predominantly transitory nature linked directly to health outcomes, necessitate rapid fiscal support paired with long-term public health infrastructure investments.

The calibrated DSGE framework thus justifies a differentiated policy approach tailored to disaster-specific characteristics. Policymakers should internalize these differences, focusing on building robust structural preparedness for war risks, proactive financial market regulations for financial crises, and comprehensive public health infrastructure and rapid fiscal responses for pandemics.

In conclusion, the explicit acknowledgment and incorporation of disaster-specific dynamics into macroeconomic models significantly enhance policy effectiveness. Such nuanced understanding is indispensable in fostering economic systems that are not merely resilient but actively antifragile, thriving through informed anticipation and targeted preparedness. As emphasized by Taleb (2007), economies must aim not merely at survival but at improvement from disruptions, incorporating antifragility into their structural and policy frameworks.

Chapter 4

Robustness and Extensions

4.1 Comovement and Consumption Response

An important robustness consideration concerns the immediate response of macroeconomic aggregates to an increase in disaster risk. In the benchmark model, a rise in the probability of a disaster results in a contemporaneous decline in investment, output, and employment, while consumption initially rises. This seemingly counterintuitive outcome stems from the intrinsic equivalence between shocks to disaster risk and preference shocks affecting the intertemporal Euler equation. As highlighted by Barro and King (1984) [11], when an economy experiences a pure preference shock, the labor demand schedule remains unchanged, thus precluding a positive instantaneous comovement between consumption and employment.

In the presence of a pure preference shock, the marginal cost increases, leading to a temporary rise in the real wage without an immediate contraction in employment. This lack of contemporaneous comovement between consumption and employment is not unique to the disaster risk framework but is shared by a broad class of models where preference or risk shocks dominate business cycle dynamics (Smets and Wouters, 2003; King and Rebelo, 1999) [69] [52]. Nevertheless, the model successfully replicates the medium-run comovement observed in empirical studies: following a rise in disaster risk, consumption, investment, and output decline persistently and jointly.

To improve the model's contemporaneous comovement properties, recent extensions have introduced complementarities between consumption and hours worked. Following Hall (2011) [41], preferences are modified to include a complementarity term between consumption C_t and labor supply N_t , resulting in the following preferences:

$$V_t = \frac{C_t^{1-\sigma}}{1-\sigma} - \chi C_t^{1-\sigma} N_t^{1+\phi} - \alpha \frac{N_t^{1+\phi}}{1+\phi} + \beta E_t \left(V_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}}$$

The middle term, featuring the interaction between consumption and labor, mechanically forces employment and consumption to move more synchronously. Various microfoundations can justify this structure, ranging from household production models (Aguiar and Hurst, 2005) [2] to hand-to-mouth behavior in heterogeneous agent economies.

Furthermore, to capture countercyclical movements in markups, a reduced form is assumed where the marginal utility cost parameter χ depends inversely on detrended output y_t , i.e., $\chi = \chi(y_t)$ with

$\chi'(y_t) < 0$. Consequently, the labor demand condition is modified to:

$$(1 - \alpha) \left(\frac{K_t}{z_t N_t} \right)^\alpha \frac{1}{\chi(y_t)} = W_t$$

This specification implies that in booms (high y_t), markups shrink, wages rise, and labor demand is relatively higher, reinforcing the procyclicality of employment and consumption.

Incorporating such features would bring the model's short-run predictions closer to empirical evidence, particularly during large economic shocks. Additionally, financial frictions (Kiyotaki and Moore, 1997) [53] and nominal rigidities (Christiano, et al., 2005) [25] could further amplify and synchronize the response of macroeconomic aggregates.

Finally, the nature of the disaster: war, financial crisis, or pandemic, affects the extent and dynamics of comovement. Wars typically involve physical destruction of capital and dislocation of labor markets, while pandemics predominantly impact labor supply and consumer behavior, possibly yielding different short-run comovement structures (Kalemi et al., 2020) [48]. Introducing active policy responses, such as fiscal stimulus or monetary accommodation, would mitigate the negative co-movements and could even generate positive contemporaneous responses, depending on the design and timing of interventions.

4.2 Modeling Disasters

Another critical dimension of robustness relates to the specification of disasters themselves. In the benchmark model, disasters entail simultaneous shocks to both the permanent and transitory components of productivity, as well as to the capital stock. This structure is informed by empirical studies (Nakamura et. al, 2013) [63] showing that major disasters tend to depress both the productive capacity and the efficient allocation of resources over both short and long horizons.

Alternative specifications are feasible and carry important implications for macroeconomic and financial outcomes. Modeling disasters as pure permanent shocks to productivity, in the spirit of Barro (2006), would emphasize long-term output losses and lower rates of capital accumulation. Conversely, representing disasters purely as capital destruction events (e.g., due to wars or natural disasters) would focus attention on immediate reductions in the capital stock, with potentially faster recoveries as new investment rebuilds lost infrastructure (Cerra and Saxena, 2008).

The specific nature of the disaster affects both the amplitude and the persistence of macroeconomic and asset price responses. In particular:

- Wars, with substantial capital destruction and labor dislocation, would generate deep and prolonged recessions, elevated risk premia, and sharp declines in asset valuations;
- Financial crises, primarily impairing financial intermediation, would generate large investment contractions but potentially milder long-run productivity effects, depending on the severity of credit frictions;
- Pandemics, affecting labor supply and consumption patterns, might produce shallower output drops but more sectorally heterogeneous impacts, with less pronounced capital stock destruction.

Moreover, the inclusion of explicit policy reactions—such as monetary easing, fiscal stimulus, or government guarantees, would considerably alter the model's predictions. For instance, if fiscal

authorities implement countercyclical spending programs in response to pandemics, the consumption decline could be much smaller, and risk premia might not rise as sharply. In contrast, in the absence of effective interventions during financial crises, the amplification mechanisms could lead to deeper and more persistent recessions (Reinhart and Rogoff, 2009) [67].

Finally, it is worth noting that disaster specifications assuming endogenous responses: for example, where agents adjust their behavior based on perceived changes in disaster risk (e.g., increasing precautionary savings or repricing assets more aggressively), could further magnify the feedback loops between disaster shocks and macro-financial outcomes (Gabaix, 2012).

In conclusion, while the baseline model's disaster structure is sufficiently rich to capture key empirical patterns, exploring alternative specifications and integrating policy responses would broaden the model's applicability and shed light on important asymmetries across different types of rare economic disasters.

4.3 Sensitivity Analysis

This section evaluates the robustness of the model by exploring how variations in key structural parameters influence the business cycle moments and asset pricing implications. Tables 4.1 and 4.2 report the sensitivity analysis for a range of alternative parameter values, compared to the benchmark calibration and the empirical data.

Table 4.1: Sensitivity Analysis: Business Cycle Statistics

	$\sigma(Y)$	$\sigma(C)$	$\sigma(I)$	$\sigma(N)$	$\rho_{C,Y}$	$\rho_{I,Y}$	$\rho_{N,Y}$
1 Data	1.12 (0.14)	0.91 (0.23)	2.36 (0.15)	1.29 (0.29)	0.69 (0.10)	0.61 (0.05)	0.81 (0.05)
2 Benchmark	0.94 (0.05)	0.61 (0.06)	2.27 (0.34)	0.49 (0.11)	0.67 (0.16)	0.91 (0.03)	0.78 (0.05)
3 Sample with disasters	0.94 (0.05)	0.61 (0.06)	2.27 (0.34)	0.49 (0.11)	0.67 (0.16)	0.91 (0.03)	0.78 (0.05)
4 $1/\hat{\psi} = 1.5$	0.91 (0.05)	0.59 (0.04)	1.93 (0.20)	0.38 (0.06)	0.82 (0.09)	0.93 (0.03)	0.80 (0.06)
5 $\gamma = 1/\hat{\psi} = 0.5$	0.91 (0.05)	0.54 (0.03)	1.76 (0.11)	0.31 (0.03)	0.94 (0.04)	0.98 (0.01)	0.91 (0.04)
6 $\hat{\psi} = \gamma = 2$	0.82 (0.04)	0.63 (0.03)	1.32 (0.07)	0.17 (0.02)	0.98 (0.02)	0.97 (0.02)	0.85 (0.08)
7 $\rho_p = 0.8$	0.93 (0.05)	0.60 (0.05)	2.15 (0.25)	0.45 (0.08)	0.72 (0.12)	0.92 (0.03)	0.79 (0.05)
8 $\sigma_p = 1.7$	0.93 (0.05)	0.58 (0.04)	2.04 (0.20)	0.42 (0.06)	0.78 (0.09)	0.93 (0.02)	0.81 (0.04)

Notes: All series are in growth rate. Standard errors in parentheses.

Table 4.1 presents the standard deviations and correlations of key macroeconomic variables. In the data, GDP, consumption, investment, and employment display standard deviations of 1.12, 0.91, 2.36, and 1.29 percent, respectively, with relatively high correlations between consumption and output ($\rho_{C,Y} = 0.69$), investment and output ($\rho_{I,Y} = 0.61$), and employment and output ($\rho_{N,Y} = 0.81$).

Table 4.2: Sensitivity Analysis: Financial Statistics

	$E(r_f)$	$E(r_m - r_f)$	$\sigma(r_f)$	$\sigma(r_m - r_f)$
1 Data	0.09 (0.05)	2.09 (0.46)	0.84 (0.05)	8.13 (0.38)
2 Benchmark	0.35 (0.21)	1.76 (0.32)	0.80 (0.43)	6.20 (1.43)
3 Sample with disasters	0.35 (0.21)	1.76 (0.32)	0.80 (0.43)	6.20 (1.43)
4 $1/\hat{\psi} = 1.5$	0.38 (0.22)	1.78 (0.31)	0.82 (0.42)	6.40 (1.46)
5 $\gamma = 1/\hat{\psi} = 0.5$	0.62 (0.08)	0.29 (0.12)	0.29 (0.18)	2.16 (0.63)
6 $\hat{\psi} = \gamma = 2$	0.85 (0.11)	0.54 (0.15)	0.36 (0.22)	2.69 (0.80)
7 $\rho_p = 0.8$	0.34 (0.18)	1.80 (0.25)	0.96 (0.39)	6.52 (1.50)
8 $\sigma_p = 1.7$	0.25 (0.19)	1.80 (0.25)	0.65 (0.25)	4.78 (0.80)

Notes: Mean and standard deviation of the risk-free rate and equity excess returns. Standard errors in parentheses.

The benchmark model reproduces the volatility of output reasonably well ($\sigma(Y) = 0.94$), although it slightly underestimates the volatility of consumption and employment, and matches closely the volatility of investment. Correlations are also broadly consistent, albeit somewhat higher than observed, particularly for $\rho_{I,Y}$ and $\rho_{N,Y}$.

Varying risk aversion and intertemporal elasticity of substitution parameters reveals predictable patterns. Lowering the intertemporal elasticity of substitution ($1/\hat{\psi} = 1.5$) slightly reduces output volatility but maintains strong comovement between quantities. Conversely, increasing risk aversion ($\gamma = 1/\hat{\psi} = 0.5$) substantially increases comovement, with correlations exceeding 0.9 for all pairs, suggesting that heightened risk sensitivity promotes synchronization among macro variables.

In contrast, imposing a high elasticity of intertemporal substitution ($\hat{\psi} = \gamma = 2$) results in a noticeable drop in the volatility of all variables, especially employment ($\sigma(N) = 0.17$), while maintaining very high comovement between output and other aggregates. This configuration reflects an economy with smoother consumption-savings choices and dampened business cycle fluctuations, in line with standard DSGE insights (Hall, 1988) [40].

Adjusting the persistence of the disaster probability process ($\rho_p = 0.8$) or increasing the volatility of disaster risk ($\sigma_p = 1.7$) generates variations that largely preserve the benchmark properties, although $\sigma(I)$ and $\sigma(N)$ are marginally affected, indicating the limited direct impact of these parameters on real fluctuations under the model calibration.

Turning to asset pricing implications, Table 4.2 documents how model moments match empirical regularities. In the data, the mean risk-free rate is 0.09 percent per quarter, while the equity premium averages 2.09 percent, with corresponding standard deviations of 0.84 percent and 8.13 percent, respectively.

The benchmark model slightly overpredicts the mean risk-free rate (0.35 percent) but matches

well the equity premium (1.76 percent) and its volatility (6.20 percent). Sample variations including disasters do not significantly alter these moments, supporting the robustness of the baseline asset pricing implications.

Sensitivity to preference parameters shows sharper effects. Lowering $1/\hat{\psi}$ to 1.5 has minimal impact, while increasing both $\hat{\psi}$ and γ to 2 substantially boosts the mean risk-free rate (0.85 percent) and reduces the equity premium to 0.54 percent, consistent with intuition: higher willingness to substitute intertemporally mitigates precautionary savings demand, dampening excess returns (Campbell and Viceira, 2002).

Interestingly, increasing the volatility of disaster risk ($\sigma_p = 1.7$) sustains a high equity premium (1.80 percent) despite a lower risk-free rate (0.25 percent), aligning with the mechanism proposed by rare disaster models (Barro, 2006), where disaster risk shocks drive a wedge between safe and risky returns.

Overall, the model proves capable of replicating key moments under a range of plausible alternative calibrations, reinforcing the core mechanism: time-varying disaster risk generates simultaneously realistic business cycle fluctuations and asset pricing moments.

Conclusions

Having fully and comprehensively presented the empirical and theoretical results of the present study, it is possible to outline its conclusions, in which the fundamental contributions of the present study are stated, along with answers of the research questions, limitations, and insights for further research.

First, the introduction of a differentiated treatment of disaster risk depending on the type of disaster by calibrating the DSGE model to empirical data on Wars, Financial Crises, and Pandemics made it possible to understand differences in the impact and dynamics of disasters on macroeconomic variables and asset prices. In this way, the heterogeneity that was consequentially found was used to frame a set of efficient policies to be able to respond most effectively and to mitigate the effects of each type of disaster.

In addition, the study's key contribution of incorporating the peculiarities of individual event types rather than treating rare disaster risk as a single undifferentiated entity, can be seen as a novelty in the scientific literature related to the reference topic, thus representing a step in the direction suggested by the limitations of the reference papers, such as Gourio (2012).

Moreover, by aggregating these differences in the benchmark model, it was possible to obtain results consistent with the empirical data, improving the fit of the model on macroeconomic variables and consequently on asset prices, while preserving the dynamics of impact of productivity shocks caused by rare disasters.

The empirical consistency of the relationships between macroeconomic quantities and asset prices is guaranteed by the fact that risk premiums are endogenously counter-cyclical, influencing investments in a mechanism almost never incorporated by previous models.

The data shown, together with the results on the second moments of macroeconomic variables and asset prices, imply that not only the events of disasters, but also the fluctuations in their risk directly affect business cycles, Confirming the intuitions of previous literature, but improving its specificity and adherence to the diversity of risks of each type of disaster.

The model construction typology has proved useful to be easily implemented with new assumptions and features, as shown in the section on robustness and extensions, this is a key attribute for incorporating into the future elements that may represent a further step forward in the study of this type of phenomena. In particular, the opportunity to model different policy equations for each type of disaster makes the model suitable for quantitatively simulating their effects; the same applies to private choices. Both are important features in order to make the system better suited to respond to disaster risk while preserving welfare.

Appendix A

Disaster Dynamics

A.1 Disaster dynamics for other calibrations

This section investigates the sensitivity of model implications to alternative assumptions regarding the specification of disaster dynamics. The goal is to understand how key business cycle statistics and asset pricing moments change when removing certain components of the benchmark formulation, specifically: the transitory productivity shock, and the doubling of the initial productivity drop upon disaster realization. These alternative calibrations are evaluated against the baseline, using the same parametrization for permanent productivity shocks, ensuring comparability of long-run behavior.

Table [A.1](#) reports standard deviations and correlations of key macroeconomic aggregates, while Table [A.2](#) displays mean returns and volatilities of risk-free and risky assets. The benchmark model offers a relatively balanced match between data and simulated statistics: it delivers a standard deviation of output of 0.94, with investment volatility at 2.27, and realistic consumption-output correlation ($\rho = 0.67$). Financially, it features a sizable equity premium (1.76%) with reasonable return volatility (6.20%).

Removing the transitory component of the shock amplifies all real volatilities, with investment becoming highly volatile ($\sigma(I) = 3.65$), but weakens the co-movement between consumption and output ($\rho = 0.10$). This suggests that without the temporary disruption, agents internalize the permanent shift in fundamentals, leading to a stronger precautionary response that decouples consumption from the business cycle. Interestingly, the equity premium increases slightly (1.90%) but at the cost of decreased macro coherence.

On the other hand, the specification without the doubling, which keeps risk aversion constant over the disaster event, delivers a more muted response in investment ($\sigma(I) = 2.79$) and preserves moderate correlation between output and consumption ($\rho = 0.45$). The equity premium rises to 2.25%, driven by the absence of countercyclical shifts in marginal utility. However, the model loses some macro discipline, with consumption volatility too high ($\sigma(C) = 0.70$) and inconsistent with observed consumption smoothing behavior in post-disaster recoveries (Barro, 2009).

Figures [3.1](#), [A.1](#), and [A.2](#) compare the model-generated and empirical impulse response functions (IRFs) of consumption after a disaster shock across the three calibrations.

In the benchmark model (Figure [3.1](#)), the consumption response exhibits a sharp initial contraction, consistent with disaster realizations, followed by a slow and incomplete recovery over the subsequent decades. The model tracks the empirical path closely, capturing both the magnitude and

Table A.1: Alternative Calibrations: Business Cycle Statistics

	$\sigma(Y)$	$\sigma(C)$	$\sigma(I)$	$\sigma(N)$	$\rho_{C,Y}$	$\rho_{I,Y}$	$\rho_{N,Y}$
1 Data	1.12 (0.14)	0.91 (0.23)	2.36 (0.15)	1.29 (0.29)	0.69 (0.10)	0.61 (0.05)	0.81 (0.05)
2 Benchmark	0.94 (0.05)	0.61 (0.06)	2.27 (0.34)	0.49 (0.11)	0.67 (0.16)	0.91 (0.03)	0.78 (0.05)
3 No ψ Doubling	0.99 (0.07)	0.70 (0.09)	2.79 (0.55)	0.65 (0.16)	0.45 (0.22)	0.88 (0.03)	0.75 (0.04)
4 No Transitory Shock	0.99 (0.09)	0.79 (0.13)	3.65 (0.83)	0.87 (0.20)	0.10 (0.24)	0.86 (0.02)	0.76 (0.04)

Notes: Standard deviations and correlations for output, consumption, investment, and employment under alternative calibrations. All series are in growth rates. Standard errors in parentheses.

Table A.2: Alternative Calibrations: Financial Statistics

	$E(R_f)$	$E(R_e - R_f)$	$\sigma(R_f)$	$\sigma(R_e - R_f)$	$\sigma(R_e)$	$\sigma(R_b)$
1 Data	0.09 (0.05)	2.09 (0.46)	0.84 (0.05)	8.13 (0.38)	— —	— —
2 Benchmark	0.35 (0.21)	1.76 (0.32)	0.80 (0.43)	6.20 (1.43)	0.60 —	0.44 —
3 No ψ Doubling	0.40 (0.14)	2.25 (0.22)	0.54 (0.23)	5.51 (0.80)	0.42 —	0.46 —
4 No Transitory Shock	0.42 (0.12)	1.90 (0.30)	0.49 (0.25)	6.91 (1.61)	0.35 —	0.48 —

Notes: Means and standard deviations for risk-free rates, excess returns, and bond returns across calibrations. Standard errors in parentheses.

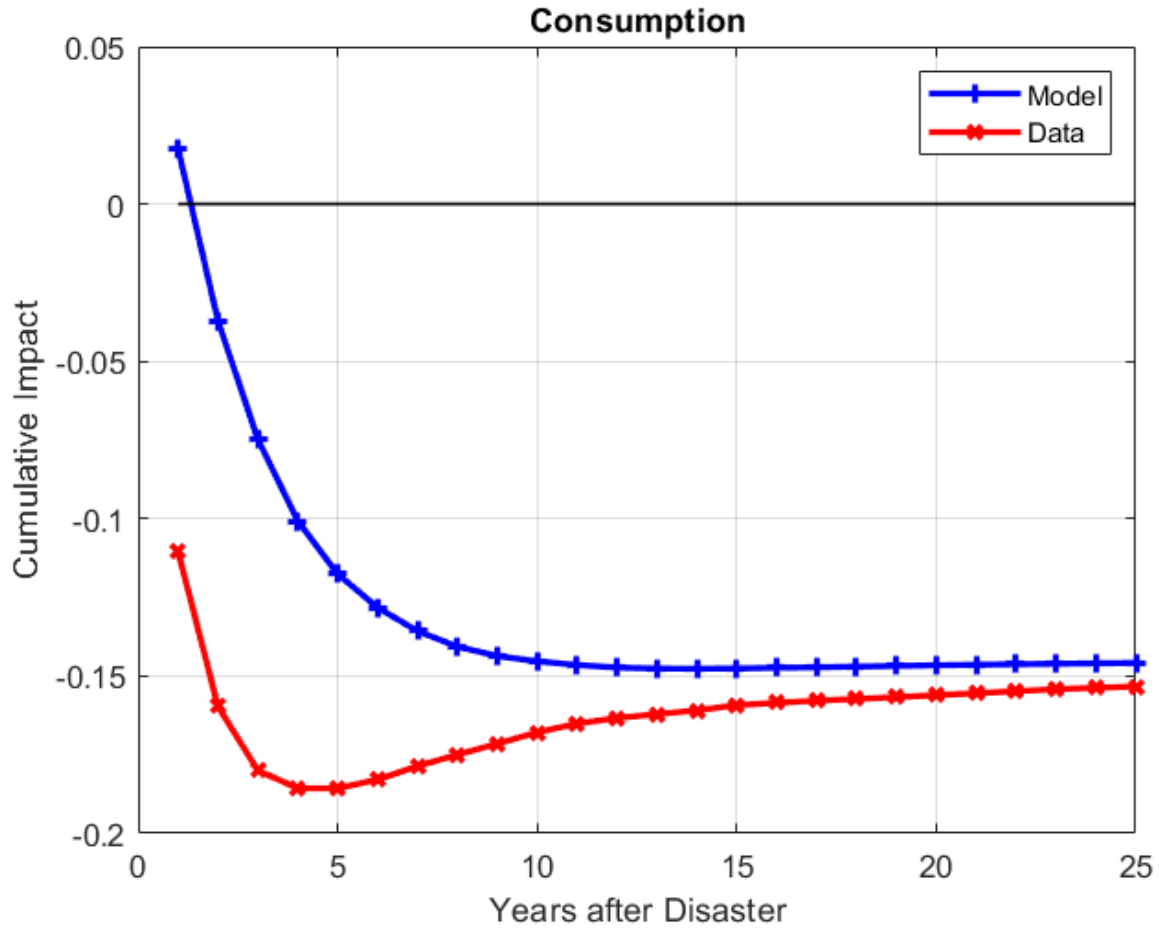


Figure A.1: Response of consumption to a disaster realization, in the data and in the model without transitory productivity shocks.

the hump-shaped adjustment phase. The consumption decline peaks around -20% , with persistent deviation from trend, in line with the findings of Nakamura et al. (2013).

Removing the transitory shock (Figure A.1) introduces a distinct misalignment. The model now predicts a significantly milder consumption drop (initially positive), followed by a monotonic decline. This pattern is inconsistent with empirical IRFs, which typically exhibit a quick negative jump reflecting precautionary adjustments. The absence of a short-run component prevents the model from capturing the rapid behavioral shifts seen after historical disasters.

In contrast, the model without doubling (Figure A.2) exhibits sluggish response dynamics. The consumption drop is overly smoothed and persistent, failing to replicate the rapid trough seen in the data. This suggests that constant risk aversion attenuates the precautionary saving motive, flattening the marginal utility adjustments that are key to explaining high asset returns and swift consumption drops in response to rare events.

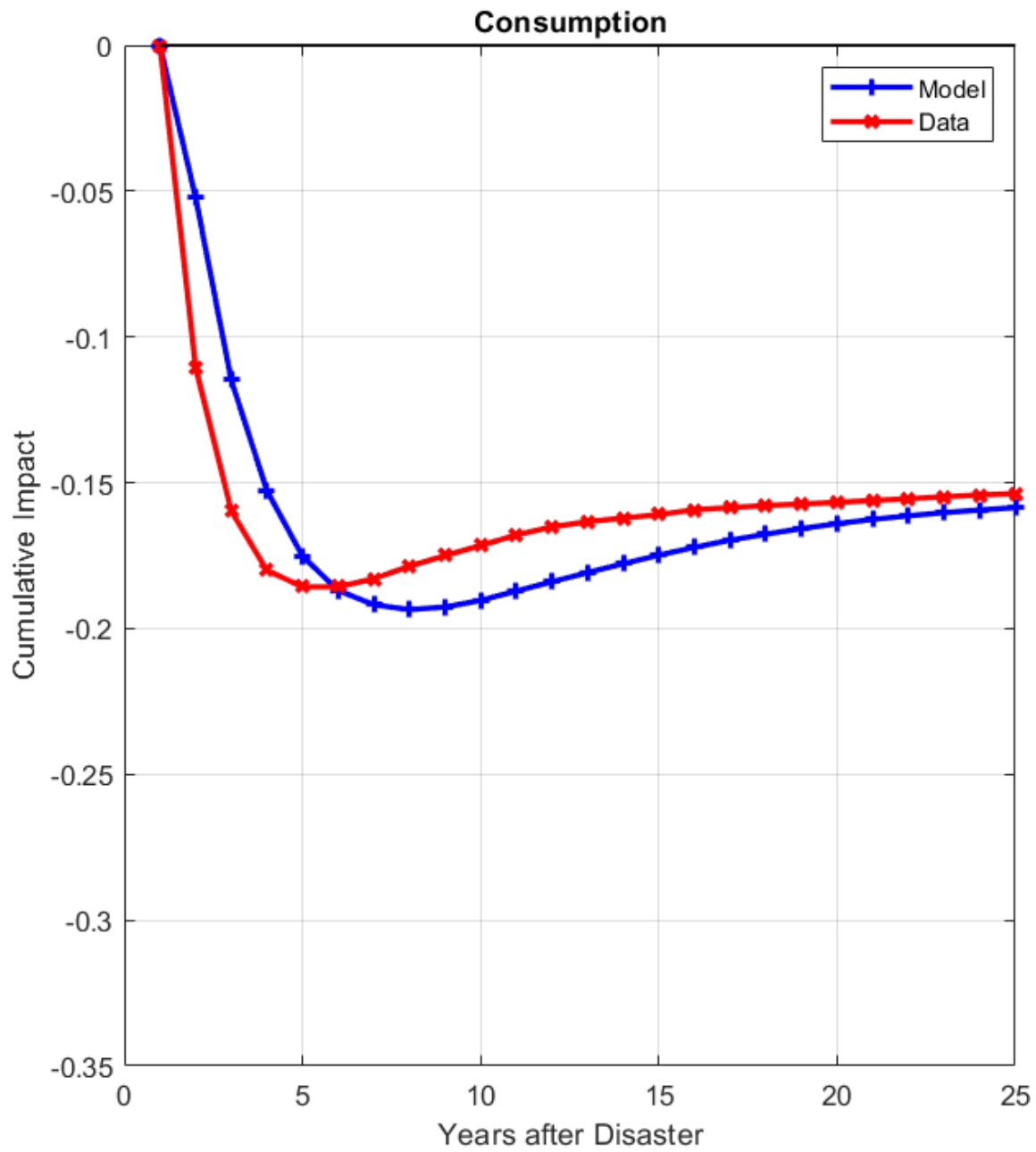


Figure A.2: Response of consumption to a disaster realization, in the data and in the model without a twice larger productivity shock on impact.

Appendix B

Computational Method and Data

B.1 Computational Method

In this section is explained the computational methods that leads to the results of this thesis.

The model is solved using projection methods because of the large state space [6]. Equilibrium is characterized through the recursive formulation of the two policy functions, consumption $c(k, p, z_r, x)$, employment $N(k, p, z_r, x)$ and the value function $g(k, p, z_r, x)$; resulting in three first-order conditions:

$$(1 - \alpha)z_r^{1-\alpha} \left(\frac{k}{N(k, p, z_r, x)} \right)^\alpha = \frac{vc(k, p, z_r, x)}{1 - N(k, p, z_r, x)},$$

$$\mathbb{E} \left(M(k, p, z_r, x; p', \varepsilon', \theta', \varphi', x') R^K(k, p, z_r, x; p', \varepsilon', \theta', \varphi', x') \right) = 1,$$

where $\mathbb{E}$ indicates an expectation over the five shocks: $\mathbb{E}_{p', \varepsilon', \theta', \phi', x'}$, and:

$$\begin{aligned} M(k, p, z_r, x; p', \varepsilon', \theta', \varphi', x') &= \beta \left(e^{\mu + \varepsilon' + \theta' x'} \right)^{-\gamma} \\ &\times \left(\frac{c(k', p', z_r', x')}{c(k, p, z_r, x)} \right)^{-\psi} \\ &\times \left(\frac{1 - N(k', p', z_r', x')}{1 - N(k, p, z_r, x)} \right)^{v(1-\psi)} \\ &\times \frac{g(k', p', z_r', x')^{\frac{\psi-1}{1-\psi}}}{\mathbb{E} \left[\left(e^{\mu + \varepsilon' + \theta' x'} \right)^{(1-\psi)} g(k', p', z_r', x')^{\frac{\psi-1}{1-\psi}} \right]}, \end{aligned}$$

$$\begin{aligned} g(k, p, z_r, x) &= c(k, p, z_r, x)^{1-\psi} (1 - N(k, p, z_r, x))^{v(1-\psi)} \\ &+ \beta e^{\mu(1-\psi)} \left(\mathbb{E}_{\varepsilon', x', \theta'} \left[e^{\varepsilon' + x' \theta'} (1 - \gamma) g(k', p', z_r', x')^{\frac{1-\gamma}{1-\psi}} \right] \right)^{\frac{1-\psi}{1-\gamma}}, \end{aligned}$$

$$\begin{aligned} R_K(k, p, z_r, x; p', \varepsilon', \theta', \varphi', x') &= e^{x' \varepsilon'} \varphi' \left(\frac{i(k, p, z_r, x)}{k} \right) \times \dots \\ &\dots \left[1 - \delta + \phi \left(\frac{i(k', p', z_r', x')}{k'} \right) + \alpha \frac{y(k', p', z_r', x')}{k'} \left(\frac{i(k', p', z_r', x')}{k'} \right) \right], \end{aligned}$$

where k' is derived from the law of motion:

$$k' = k'(k, p, z_r, x; p', \varepsilon', x', \theta', \varphi') = \frac{e^{x'\theta'} ((1 - \delta)k + i(k, p, z_r, x))}{e^{\mu + \varepsilon' + x'\theta'}} = \frac{((1 - \delta)k + i(k, p, z_r, x))}{e^{\mu + \varepsilon'}},$$

and

$$\log z'_r = \log z_r + x'(\varphi' - \theta'),$$

with output and investment in the form:

$$\begin{aligned} y(k, p, z_r, x) &= k^\alpha (z_r N(k, p, z_r, x))^{1-\alpha}, \\ i(k, p, z_r, x) &= y(k, p, z_r, x) - c(k, p, z_r, x), \end{aligned}$$

as well as the law of motion for discrete variables (x and p). Also the 3 functions $c(k, p, z_r, x)$, $N(k, p, z_r, x)$ and $g(k, p, z_r, x)$ is expressed as a tensor product of Chebychev polynomials:

$$c(k, p, z_r, x) = \sum_{i=1}^{N_k} \sum_{j=1}^{N_z} \alpha_{i,j,p,x} T_i(k) T_j(z_r),$$

where $T_i()$ denotes the i -th Chebyshev polynomial of the first kind, adjusted to have a domain $[\underline{k}, \bar{k}]$ for k and $[1-x, 1+x]$ for z_r , with coefficients $\alpha_{i,j,p,x}$ that has to be determined. Thus a two-dimensional Chebycev polynomial can be seen as an approximation of each discrete value of p and x , $c(., p, ., x)$.

The 3 first order conditions are evaluated at the Nodes of Chebychev polinomial for each value of probability and disaster state in order to find the coefficients for c , N and g . This leads to a square system of $3N_k N_z \times 2N_p$ equations, that can be solved using a quasi-Newton algorithm.

In order to deal easily with convergence, the strategy was to start with small values for N_k ; N_z ; N_p , same for risk aversion parameter, and progressively increase these parameters, using as initial guess the previous solution. This allows to solve the model for at least $N_c = 7$, $N_z = 4$ and $N_p = 7$. Expanding the number of points beyond this does not significantly alter the solution, the specific choiche was $N_c = 5$, $N_z = 3$ and $N_p = 6$.

Once the policy functions are found, asset prices are readily calculated by the expression of stochastic discount factor and the expectations over all the shocks. More precisely, we can calculate the investment return using

$$R_{t+1}^K = e^{x_{t+1}\xi_{t+1}} \phi' \left(\frac{I_t}{K_t} \right) \left(\frac{1 - \delta + \phi \left(\frac{I_{t+1}}{K_{t+1}} \right)}{\phi' \left(\frac{I_{t+1}}{K_{t+1}} \right)} + \alpha \frac{Y_{t+1}}{K_{t+1}} - \frac{I_{t+1}}{K_{t+1}} \right),$$

and long-term bond prices are calculated by iterating on the standard recursion (approximating them as function of states with Chebycev polynomials). Hence the levered equity return can be constructed.

To conclude, VIX is calculated using the formula of the main text; for the sake of simplicity, the equity return used in this formulation is calculated assuming that firms adjusting their leverage to keep it constant each period. Approximation accuracy is guaranteed by the very strong correlation between this equity returns and the benchmark model equity return.

B.2 Data Sources

The moments of [3.6](#) and [3.7](#) are calculated using standard US data sources, for the sample 1947q1-2023q4. Consumption is nondurable plus services, investment is nonresidential fixed investment, and output is GDP, all from the NIPA Table 1.1.3. Hours is nonfarm business hours from the BLS productivity program (through FRED: HOABNS). The return data is from Ken French's webpage: monthly benchmark factors, aggregated to quarterly frequency, and deflated by the CPI (CPIAUCSL through FRED)). TFP is computed as output divided by labor to the power $2/3$ and capital to the power $1/3$. Capital is from the fixed asset tables, and is linearly interpolated within the year. To be consistent with Bloom (2009), volatility is derived on the 1963q1-2023q4 sample. Every computation and plot was programmed in MATLAB

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