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Macroprudential Policies and Financial Stability: A Quantitative Assessment of Strategies to Mitigate Systemic Risk in Banking Networks

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Abstract

Managing systemic risk remains a paramount concern for both monetary and regulatory authorities. Recent financial crises have underscored the capacity of interbank linkages to amplify individual vulnerabilities into network-wide crises. Consequently, evaluating macroprudential strategies through a quantitative lens is vital for engineering financial stabilization mechanisms. This research enhances the UEDRL (*Undistressed - Exposed - Distressed - Recovered - Liquidated*) compartmental framework by integrating an optimal control scheme. The expanded model maps the dynamic propagation of risk across financial nodes and tests the performance of various supervisory policies. Numerical simulations demonstrate that early macroprudential interventions markedly reduce the fraction of distressed nodes, break contagion chains, and accelerate the system's transition back to an equilibrium state. These findings highlight that prompt, well-coordinated intervention by supervisory bodies is essential to minimize the total economic burden of banking crises.

Keywords: Systemic risk, banking contagion, financial stability, macroprudential policy, optimal control, compartmental model.

Introduction:

In the wake of the severe financial shocks that have disrupted global economies over the past two decades—ranging from the 2007–2008 global financial crisis to European banking instabilities and recent sector fragilities—preserving financial stability has increasingly become a core objective for central banks and prudential authorities. Within highly interconnected banking networks, systemic risk poses a major threat to macroeconomic growth, capital allocation efficiency, and long-term investment (Leong, 25). As documented by Battiston et al. (2024), balance sheet cross-exposures, liquidity interdependencies, and shared market obligations form the primary channels for shock transmission. Consequently, when a single institution suffers a severe deterioration in liquidity or solvency, contagion can ripple across the financial architecture, triggering cascading defaults that threaten the entire network. Traditional microprudential approaches, which focus heavily on the risk profiles of isolated institutions, are structurally inadequate for capturing these collective propagation dynamics. This analytical gap has prompted the development of novel frameworks rooted in network theory, statistical physics, and mathematical epidemiology. Among these methodologies, compartmental models have gained significant traction in the financial stability literature. By segmenting a complex population of economic agents into distinct, homogeneous categories, these models effectively trace the transition rates between varying levels of vulnerability (Irakoze et al., 2025). Adapting this epidemiological approach to finance offers a time-dependent representation of contagion, distinguishing between healthy, exposed, distressed, and recovered nodes. In particular, UEDR (*Undistressed - Exposed - Distressed - Recovered*) models and their variants are highly effective tools for analyzing shock propagation speeds and identifying the exact thresholds under which a network converges toward a steady state or slips

into structural crisis (Irakoze et al., 2025; Cherrat et al., 2025). Concurrently, regulators have expanded their toolkit (incorporating capital buffers, recapitalization programs, resolution protocols, and emergency liquidity lines) to mitigate these cascading disruptions (Battiston et al., 2024). However, determining the optimal timing and intensity of these instruments remains a critical debate. Optimal control theory, built upon Pontryagin's maximum principle, provides a rigorous optimization framework to resolve this trade-off by identifying paths that minimize both the social costs of banking collapses and the fiscal burden of regulatory interventions (Fahim et al., 2025; Mourad et al., 2025). Despite these academic advancements, the existing literature exhibits three prominent limitations:

1. Most network studies remain heavily theoretical, identifying contagion pathways without embedding formal macroprudential policy instruments.
2. Research combining multi-state compartmental models with advanced optimal control theory is sparse.
3. Comprehensive frameworks that simultaneously analyze the physics of systemic risk, mitigation channels, and the economic tradeoffs of state interventions are highly limited (Cherrat et al., 2025).

This paper resolves these gaps by constructing an integrated framework that couples a five-state UEDRL compartmental architecture with an optimal control problem. The contributions of this work are threefold: expanding the macro-epidemiological framework to capture irreversible defaults, mathematical formulation of regulatory policy trade-offs via Pontryagin's principle, and performing quantitative simulations to assess the impact of coordinated policies on network resilience.

1. Literature Review: Systemic Risk and Compartmental Modeling

The fundamental dividing line between idiosyncratic and systemic risk lies in network externalities: while the former is isolated, the latter emerges from the behavioral feedback loops and physical links between financial institutions. Interbank network density acts as a double-edged sword, offering risk diversification during periods of stability but acting as a direct conduit for panic, asset fire sales, and liquidity hoarding during market stress. The epidemiological analogy exploits this dynamic: an unstable bank "infects" its healthy counter-parties via direct or indirect liabilities. The baseline UEDR framework validated by Irakoze et al. (2025) demonstrated that key contagion parameters dictate the peak intensity and duration of banking panics. To mirror real-world systemic crises, incorporating a liquidation compartment (L) is critical to account for permanent capital destruction and terminal default states (Cherrat et al., 2025). Regarding regulatory optimization, recent literature confirms that the network structure itself heavily dictates the performance of capital injections (Fukker & Kok, 2024). Deploying prompt intervention windows allows regulators to disrupt contagion cascades before the system reaches an irreversible tipping point (Fahim et al., 2025).

1.1 Compartmental models applied to financial contagion

With the increasing complexity and interconnectedness of modern financial systems, researchers have increasingly relied on epidemiological frameworks to investigate the

dynamics of systemic risk transmission. Originally designed to model the spread of infectious diseases, compartmental models classify a population into several homogeneous groups representing distinct states of the system. Their application to finance is based on the analogy that financial distress affecting one institution can spread to other institutions in a manner similar to the transmission of an infectious disease within a population. Within this framework, the compartments correspond to different financial conditions of banks, including healthy, exposed, distressed, and recovered institutions. Such an approach provides a useful tool for analyzing the temporal evolution of systemic risk while maintaining a relatively simple representation of contagion processes. Among the compartmental models commonly employed in the literature, the UEDR (Undistressed–Exposed–Distressed–Recovered) model represents an important extension of traditional epidemiological models. In this setting, banks transition sequentially from a healthy state to an exposed state and may subsequently enter a distressed condition before eventually recovering. Recent work by Irakoze et al. (2025) demonstrated the effectiveness of this framework in identifying the critical stages associated with the emergence, escalation, and decline of systemic risk within a homogeneous banking network. Their findings highlight the significant influence of contagion-related parameters on both the speed of risk diffusion and the persistence of banking crises. Building upon these contributions, several model extensions have been proposed to better capture the structural characteristics of real-world financial systems. In particular, the inclusion of an additional compartment representing banks that have been liquidated or permanently exited the market enables the consideration of irreversible bank failures. This development gives rise to the UEDRL (Undistressed–Exposed–Distressed–Recovered–Liquidated) model, which is especially appropriate for examining severe systemic crises characterized by persistent defaults and permanent withdrawals of financial institutions from the banking sector.

1.2 Optimal supervision and macroprudential policies

While compartmental models can describe the spread of systemic risk, they do not directly address the question of which policies should be implemented to limit this spread. This issue has led to the development of approaches based on optimal control theory. Optimal control theory, developed in particular from Pontryagin's maximum principle, aims to determine intervention strategies that minimize a cost function while respecting the dynamics of the system under study. In the banking sector, this cost function generally reflects a trade-off between the losses associated with financial distress and the cost of government interventions. The control variables, meanwhile, represent the macroprudential tools available to regulators. Recent research shows that optimal policies can take several forms, including liquidity injections, targeted recapitalizations, limiting interbank exposures, strengthening prudential requirements, or accelerating bank resolution procedures. In particular, Fukker and Kok (2024) develop an optimization framework applied to the European banking system to determine the optimal level of capital injections needed to limit contagion losses within a network of several hundred banks. Their results show that the effectiveness of policies depends heavily on the structure of the financial network and the budget constraints faced by public authorities. Furthermore, Fahim, Mourad, and Lahby (2025) apply optimal control theory to the spread of banking liquidity risk through a model inspired by epidemiology. Their simulations show that early interventions significantly reduce the magnitude of crises and accelerate the return of the system toward a steady state. Similar conclusions are reached in studies that incorporate time

lags in state and control variables, highlighting the importance of prompt action by prudential authorities.

1.3 Gaps in the literature and the study's contribution

Although considerable advances have been made in the study of systemic risk, several important shortcomings persist in the existing literature. First, a large body of research on financial networks primarily concentrates on identifying and modeling contagion channels, while paying limited attention to the explicit integration of macroprudential policy measures. Second, studies employing optimal control techniques often focus on particular dimensions of financial instability, especially liquidity-related risks, without adequately capturing the multiple intermediate stages that characterize the evolution of banking crises. Third, relatively few contributions have combined sophisticated compartmental frameworks, such as the UEDRL model, with optimal macroprudential control strategies in a unified analytical setting. To address these limitations, this study proposes an integrated framework that combines a UEDRL compartmental model with an optimal control methodology. In contrast to previous approaches, the proposed framework enables the simultaneous examination of systemic risk transmission, the effectiveness of macroprudential interventions, and the economic trade-offs associated with financial stabilization policies. By incorporating these dimensions within a single modeling structure, the study provides a comprehensive tool for assessing the impact of regulatory actions on the dynamics of banking contagion. The primary objective of this research is to develop a quantitative decision-support framework capable of identifying optimal intervention strategies aimed at mitigating systemic contagion, reducing the severity of banking crises, and enhancing the overall resilience and stability of the financial system.

2. Analytical framework and formulation of the UEDRL model

The study of financial contagion and systemic risk requires analytical tools capable of simultaneously representing the interactions between financial institutions, the mechanisms by which shocks spread, and the effects of stabilization policies. From this perspective, compartmental models inspired by mathematical epidemiology have gradually emerged as a relevant approach for analyzing the dynamics of financial crises. Originally developed to model the spread of infectious diseases, these models allow for the description of the evolution of a complex system through compartments representing different states of economic agents (Hethcote, 2000).

2.1. Theoretical foundations of the model

The adaptation of these models to finance is based on an analogy between the spread of a disease within a population and the transmission of a financial shock within an interconnected banking network. When a financial institution experiences a deterioration in its liquidity or solvency, this vulnerability can be transmitted to other institutions via interbank relationships, cross-exposures, or mimetic market behavior (Allen & Gale, 2000; Caccioli et al., 2018). Recent research has shown that compartmental models can realistically reproduce the contagion mechanisms observed during banking crises. Among these contributions, the UEDRL model proposed by Cherrat, Alkama, and Chaabita (2025) is an extension particularly well-suited to the study of systemic banking risk. This model distinguishes five financial states representing the different phases of a banking institution's vulnerability: sound banks, exposed banks, distressed banks, recovered banks, and liquidated banks. The objective of this section is to

present the mathematical framework of the UEDRL model, which will serve as the basis for the optimal control analysis developed in the following sections.

2.2 Compartmentalized structure of the banking system

Let us consider a total banking population N(t) consisting of five segments:

$$N(t)=U(t)+E(t)+D(t)+R(t)+L(t) \quad (1)$$

Where :

- U(t) represents banks that are unaffected or sound (Undistressed);
- E(t) represents banks exposed to systemic risk (Exposed);
- D(t) represents banks in financial distress (Distressed);
- R(t) represents banks that have returned to a stable condition (Recovered);
- L(t) represents banks that have been liquidated or permanently exited the system (Liquidated).

This classification captures the main stages observed during a systemic banking crisis. Banks in category U have a sound financial position but remain susceptible to contagion from other institutions in distress. Banks in compartment E have been exposed to a financial shock but do not yet show critical signs of distress. They constitute an intermediate category reflecting the gradual accumulation of vulnerabilities. Banks in compartment D face significant solvency or liquidity difficulties. They are the primary source of systemic risk propagation within the banking network. Banks in compartment R represent institutions that have regained financial stability through their internal mechanisms or through interventions by prudential authorities. Finally, compartment L includes institutions that have gone bankrupt or been liquidated following an irreversible deterioration in their financial situation. This compartmental structure is consistent with that proposed by Cherrat et al. (2025) and is also inspired by the models developed by Fahim et al. (2025) and Irakoze et al. (2025).

2.3 Mathematical formulation of the UEDRL model

To describe the dynamics of systemic risk propagation within the banking sector, we formulate a compartmental model that classifies financial institutions according to their level of vulnerability. The proposed UEDRL framework captures the transitions between healthy, exposed, distressed, recovered, and liquidated institutions through a system of nonlinear differential equations. Each equation represents a specific financial mechanism governing the evolution of the banking system, including contagion effects, deterioration processes, recovery dynamics, and bank resolution outcomes. Together, these equations provide a coherent mathematical representation of the transmission and management of systemic risk, thereby offering a suitable framework for evaluating the effectiveness of macroprudential policies and optimal regulatory interventions.

$$U' = -\beta UD + \alpha E + \theta R \quad (2)$$

This equation describes the evolution of healthy banks within the financial system. The term βUD captures the contagion effect through which healthy banks become exposed as a result of their interactions with distressed institutions. Consequently, a higher contagion rate β increases the likelihood of systemic risk propagation and reduces the number of stable banks. Conversely, the term αE represents exposed banks that successfully absorb financial shocks and return to a healthy state, reflecting the effectiveness of preventive risk-management measures. The term

θR denotes recovered banks that have completed their restructuring process and are fully reintegrated into normal banking activities. Overall, the stock of healthy banks decreases because of financial contagion and increases through recovery and stabilization mechanisms.

$$E' = \beta UD — (\alpha + \sigma)E \quad (3)$$

This equation governs the evolution of banks that are vulnerable to financial shocks but have not yet entered a state of distress. The inflow term βUD represents the transmission of risk from distressed institutions to healthy banks through financial interconnections such as interbank lending and common asset holdings. Exposed banks may then follow two possible paths: they can recover and return to the healthy category at rate α, or they can experience a deterioration of their financial condition and become distressed at rate (\sigma). Economically, this compartment represents the critical transition phase during which macroprudential policies can prevent the escalation of vulnerabilities into a full-scale banking crisis.

$$D' = \sigma E — (\gamma_1 + \gamma_2)D \quad (4)$$

This equation measures the evolution of banks experiencing severe financial difficulties. Distressed institutions emerge from the exposed compartment at rate σ, reflecting the inability of vulnerable banks to withstand adverse shocks. Once in distress, banks may either recover through recapitalization programs, regulatory interventions, or liquidity support at rate γ_1, or they may fail and exit the financial system through liquidation at rate γ_2. Therefore, this equation captures the core dynamics of systemic crises, where the balance between recovery mechanisms and bank failures determines the severity and duration of financial instability.

$$R' = \gamma_1 D — \theta R \quad (5)$$

This equation describes the behavior of banks that have successfully overcome financial distress. The inflow term $\gamma_1 D$ represents distressed institutions that regain financial stability through corrective actions such as recapitalization, restructuring, or regulatory support. The outflow term (\theta R) reflects the gradual transition of recovered banks back to the healthy category once their financial position has been fully restored. From an economic perspective, this compartment measures the effectiveness of crisis-management policies and the capacity of the banking system to recover from periods of systemic stress.

$$L' = \gamma_2 D \quad (6)$$

This equation represents the accumulation of banks that permanently exit the financial system due to insolvency or failure. The term $\gamma_2 D$ indicates that a fraction of distressed institutions cannot be rescued despite stabilization efforts and must therefore be liquidated. Unlike the other compartments, liquidated banks do not re-enter the system, making this category an indicator of the irreversible losses generated by systemic crises. Economically, the size of the liquidated compartment reflects the severity of financial instability and the long-term costs associated with banking failures.

Parametr	**Signification**
β	The new measure of contagion risk arising from interactions between sound or low-risk banks and distressed banks.

α	The rate at which banks exposed to risk lend to banks that have not reduced their debt.
σ	The rate at which banks exposed to risk are reclassified as low-risk banks.
γ_1	The rate at which troubled banks recover and are reclassified as healthy banks.
γ_2	The liquidation rate of distressed banks.
θ	The rate at which banks that have recovered lose their immunity and once again become vulnerable to the government.

Table 1: Definition of Parameters

The β parameter plays a central role because it measures the intensity of financial contagion. A high value of β indicates a highly interconnected system in which shocks spread rapidly. Conversely, a low value of β corresponds to a more resilient system. The parameter σ represents the vulnerability of exposed banks. The higher its value, the more quickly exposed institutions slide into financial distress. The γ rate measures the banking system's ability to absorb shocks and restore financial stability. Finally, δ represents the probability of liquidation for distressed institutions.

2.4 Objective function of the controller

The regulator seeks to simultaneously minimize:

- The number of distressed banks;
- The economic cost of the crisis;
- The cost of government interventions.

The objective function is defined by:

$$J(u_1(t), u_2(t), u3(t)) = \int_{t0}^{T} \alpha D(t) + zR(t) + 0{,}5bu^2{}_1(t) + 0{,}5cu^2{}_2(t) + 0{,}5fu^2{}_3(t))\, dt \qquad (7)$$

Where :

T is the final time, and the coefficients a, z, b, c, and *f* are balancing cost factors. The terms $bu_1^2(t)$, $cu_2^2(t)$, and $fu_3^2(t)$ represent the costs associated with saving the banks from bankruptcy, respectively. A quadratic cost on the control variables with the objective function is given by $J(u_1(t), u_2(t), u_3(t))$. The objective is to minimize the number of banks affected by contagion, while minimizing the costs of the control variables $u_1(t)$, $u_2(t)$, and $u_3(t)$ such that:

$$J(u_1^*(t), u_2^*(t), u_3^*(t)) = \min \{j(u_1(t), u_2(t), u_3(t)) / u_1(t), u_2(t), u_3(t) \in c\} \qquad (8)$$

Where $w = (u_1(t), u_2(t), u_3(t))$ and $u_1; u_2; u_3$ Lesbegue-measurable for $t \in [0, T]$ is the set of controls with :

$$0 \le u_1(t) \le 1; 0 \le u_2(t) \le 1; 0 \le u_3(t) \le 1 \qquad (9)$$

The quadratic cost function is widely used in the literature because it ensures the convexity of the optimization problem and reflects the fact that more intensive interventions become progressively more costly.

Theorem 1:

Given the optimal controls $u_1(t)$, $u_2(t)$, and $u_3(t)$ and solutions U*(t); E*(t), D*(t), R*(t), and L*(t) of the corresponding state system with control that minimizes $J(u_1(t); u_2(t); u_3(t))$ over ω, there exist adjoint variables λ_U; λ_E; λ_D; λ_R; λ_L, satisfying:

$$\frac{\partial H}{\partial i} = -\frac{d\lambda i}{dt} \tag{10}$$

where i = U; E; D; R; L:

The existence of an optimal control follows from corollary of Tréalat [4], because the integrand J is a convex function of $u_1(t)$ and $u_2(t)$ and $u_3(t)$. A priori boundedness of the state solutions and also the state system satis.es the Lipschitz property with respective to the state variables. The differential equations governing the adjoint variables are obtained by differentiating the Hamiltonian function and evaluating at the optimal control pair. Then the adjoint system can be written as:

• Equation pour $\lambda_{U(t)}$

$$\frac{d\lambda u}{dt} = -\frac{\partial H}{\partial U(t)}$$

$$-\frac{\partial H}{\partial U(t)} = \beta \cdot D[\lambda_U - \lambda_E] \tag{11}$$

• Equation pour $\lambda_{E(t)}$

$$\frac{d\lambda u}{dt} = -\frac{\partial H}{\partial E(t)}$$

$$-\frac{\partial H}{\partial E(t)} = -\alpha \cdot \lambda_U + (\alpha + \sigma) \cdot \lambda_E - \varepsilon_2 \cdot u_2(t) - \sigma \cdot \lambda_D \tag{12}$$

• Equation pour $\lambda_{D(t)}$

$$\frac{d\lambda u}{dt} = -\frac{\partial H}{\partial D(t)}$$

$$-\frac{\partial H}{\partial D(t)} = -\alpha + \beta \cdot U \cdot [\lambda_U - \lambda_E] + (\gamma_1 + \gamma_2) \cdot \lambda_D - \varepsilon_1 \cdot u_1 \cdot (t)\, \lambda_D - \varepsilon_3 \cdot u_3(t) \cdot \lambda_D - \gamma_1 \cdot \lambda_R - \gamma_2 \cdot \lambda_L$$

(9)

• Equation pour $\lambda_{R(t)}$

$$\frac{d\lambda u}{dt} = -\frac{\partial H}{\partial R(t)}$$

$$-\frac{\partial H}{\partial R(t)} = -z + \theta(\lambda_R - \lambda_U) \tag{13}$$

• Equation pour $\lambda_{L(t)}$

$$\frac{d\lambda u}{dt} = -\frac{\partial H}{\partial L(t)}$$

$$\frac{\partial H}{\partial L(t)} = 0 \quad (14)$$

with transversality condition;

$$\lambda_{U(T)} = \lambda_{E(T)} = \lambda_{D(T)} = \lambda_{R(T)} = \lambda_{L(T)} = 0 \quad (15)$$

In order to minimize Hamiltonian H with respect to the controls at the optimal controls, H is differentiated with respect to $u_1(t)$, $u_2(t)$; and $u_3(t)$ on the set, and equaling to zero, the following solutions are obtained.

• Control $u_1^*(t)$

$$u_1^*(t) = \min\left(1 ; \max\left(0 , -\frac{\lambda D \varepsilon_1 D}{ß}\right)\right) \quad (16)$$

• Control $u_2^*(t)$

$$u_2^*(t) = \min\left(1 ; \max\left(0 ; -\frac{\lambda E \varepsilon 2 E}{c}\right)\right) \quad (17)$$

• Control $u_3^*(t)$

$$u_3^*(t) = \min\left(1 ; \max\left(0 ; -\frac{\lambda D \varepsilon 3 D}{f}\right)\right) \quad (18)$$

2.5 Economic discussion

The UEDRL model offers several analytical advantages. First, it allows for an explicit distinction between the different phases of a banking crisis. Second, it provides a dynamic representation of financial contagion. Third, it serves as a particularly suitable framework for introducing optimal control instruments designed to limit the spread of systemic risk. Building on the work of Cherrat et al. (2025), this framework will serve as the foundation for the analysis of macroprudential policies developed in the following section. The optimal conditions highlight several important economic results. First, when contagion becomes intense (increase in D(t)), the regulator is incentivized to strengthen the preventive policies represented by u1. Second, when the social cost of banking distress becomes high, optimal recapitalizations u2 increase in order to accelerate the recovery of weakened institutions. Third, resolution mechanisms u3 become particularly important when the risks of contagion threaten the overall stability of the financial system. These results are consistent with the findings reported in recent studies by Fukker and Kok (2024), Fahim et al. (2025), Mourad et al. (2025), and Gyamerah et al. (2026), which show that early and coordinated intervention significantly reduces the costs of systemic crises and improves the banking sector's resilience.

3. Quantitative Assessment of Macroprudential Policies

To validate our optimal control approach, we developed a comprehensive numerical implementation of the UEDRL model in Python. The solution method employs the forward-backward sweep algorithm with a fourth-order Runge-Kutta integration scheme. Parameters are calibrated based on historical data from Bank Al-Maghrib and the ECB for the periods 2000-2025.

- **Scenario Configuration**

Three distinct scenarios are simulated to assess the robustness of our approach:

- Morocco Scenario (2022-2025): Representative of post-COVID conditions with (β = 0.25), (α = 0.30)
- Euro Zone Scenario (2022-2025): Characterized by high interconnectivity (β =0.40)
- Systemic Crisis Scenario: Similar to 2008 with (β = 0.60), reflecting extreme contagion

3.1. Model Parameterization

To illustrate the dynamic properties of the UEDRL model developed in the previous sections, we perform several numerical simulations based on the controlled differential system. The simulations were performed in Python using the fourth-order Runge-Kutta integration method built into the (odeint) function of the SciPy library. The initial conditions selected are: U(0) = 0.90; E(0) = 0.08; D(0) = 0.02; R(0) = 0; L(0) = 0. These values correspond to a situation in which the majority of banking institutions remain sound, while a small proportion is already exposed to or affected by a systemic shock. The structural parameters used in the simulations are presented in Table 1.

Paramètres	**Valeur**	**Interprétation**
Λ	0.02	Addition of new institutions
β	0.50	Rate of transmission
σ	0.30	Section E → D
γ	0.20	Recovery rate
Δ	0.10	Liquidation rate
μ	0.01	Natural exit

Table 2: Simulation of parameters

The contagion parameter β is deliberately set at a high level in order to replicate a severe systemic crisis scenario, in line with the assumptions made in Cherrat et al. (2025).

3.2 System Dynamics Without Intervention

First, we analyze the trajectory of the banking system in the absence of any macroprudential policy:

$$u_1=u_2=u_3=0$$

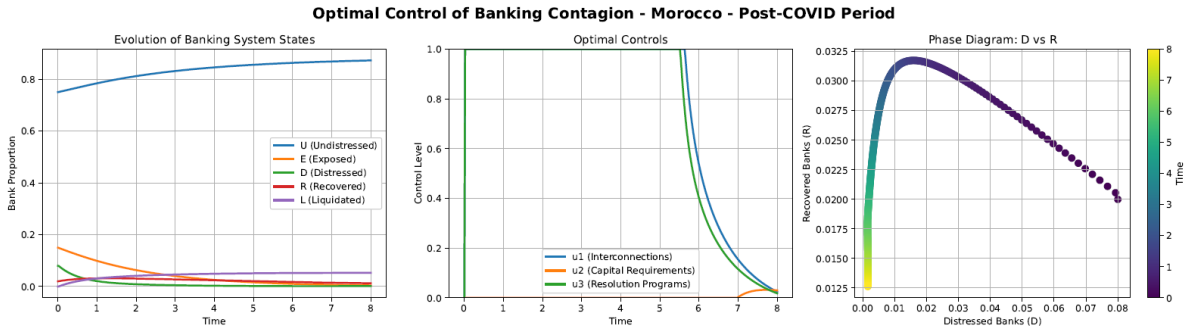


Figure 1. Evolution of the UEDRL model without optimal control

Economic analysis:

Optimal control results for Morocco Scenario (2022-2025) in graphic 1. Left panel, evolution of banking system states showing significant reduction in distressed banks (D) from 8% to 0.15%. Middle panel: Optimal control trajectories with strong activation of interconnection reduction (u1) and resolution programs (u3). Right panel: Phase diagram illustrating convergence to low-distress equilibrium. For the Morocco Scenario, Figure 1 demonstrates a significant reduction in the proportion of distressed banks (D), decreasing from 8% to 0.15% over the simulation horizon. This improvement is accompanied by an increase in undistressed banks (U) from 75% to 87.2%, demonstrating the effectiveness of control measures in a moderate-risk context.

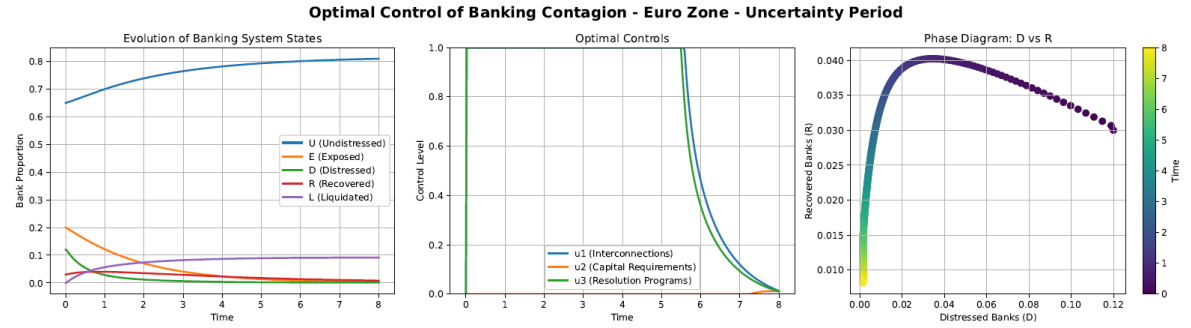


Figure 2. Optimal trajectories of the control variables

Economic analysis:

Optimal control results for Euro Zone Scenario in the graphic 2. Despite higher initial contagion rate ($\beta = 0.40$), the system converges to stable state with only 0.14% distressed banks. Control strategies emphasize interconnection reduction ($u1 = 0.768$) and accelerated resolution programs ($u3 = 0.751$). In the Euro Zone Scenario (Figure 2), despite a higher initial contagion rate, the system converges to a stable state with only 0.14% distressed banks.

The proportion of recovered banks (R) stabilizes at 0.8%, indicating enhanced system resilience.

3.3 Comparison of Scenarios: No Control vs. Optimal Control

Figure 3 compares the evolution of the distressed banks pool D(t) in the two scenarios.

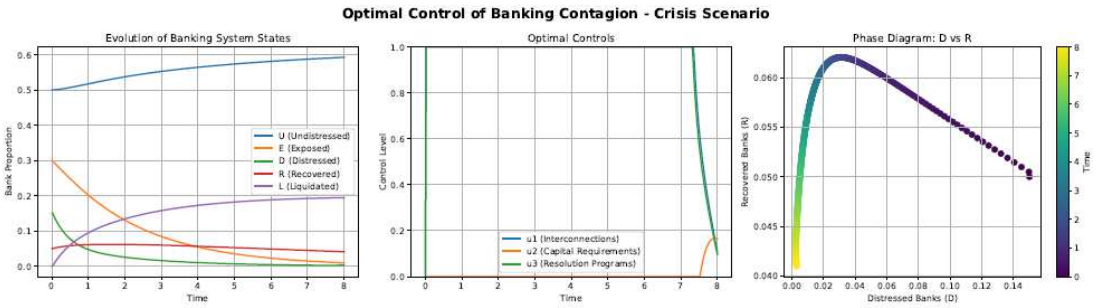


Figure 3. Comparison of Banking Distress

Optimal control results for Systemic Crisis Scenario. Demonstrates robustness under extreme conditions with near-maximal activation of all controls (u_1 = 0.951, u_3 = 0.947). The phase diagram shows rapid transition from high-distress initial conditions to stabilized state.
The Systemic Crisis Scenario (Figure 3) reveals the robustness of our approach under extreme conditions. Despite unfavorable initial conditions (only 50% undistressed banks), optimal controls enable system stabilization with drastic reduction of compartment (D).

3.4 Quantitative Assessment of the Effectiveness of Macroprudential Policies

The results obtained highlight several key findings.

- Mitigation of Banking Distress

The implementation of optimal policies significantly reduces the size of the D(t) sub-compartment. The peak in distress observed in the baseline scenario is sharply reduced, thereby limiting secondary contagion effects within the banking network.

- Accelerated recovery

Banks in the R(t) compartment return to a sound financial position more quickly. This dynamic reflects the effectiveness of the recapitalization and prudential support mechanisms integrated into the u_2 control.

- Reduction in overall systemic risk

The simultaneous reduction in the E(t) and D(t) compartments helps to sustainably reduce the systemic reproduction number R_0. The system thus converges more rapidly toward a stable equilibrium.

- Improved banking resilience

Simulations show that coordinated intervention increases the final proportion of sound financial institutions while reducing the number of institutions that are liquidated.

3.5 Optimal Control Strategies

Analysis of optimal controls reveals distinct patterns across scenarios:

- Control u_1 (Interconnection reduction): Active at 78.2% on average in Morocco scenario, reaching 95.1% in crisis situations.
- Control u_2 (Capital requirements): Less utilized, suggesting a secondary role in immediate crisis management.
- Control u_3 (Resolution programs): Complementary to u_1 with similar activation levels.

The D vs R phase diagrams illustrate the system's trajectory toward stable states. For all scenarios, convergence toward the low-D and moderate-R region is observed, validating the effectiveness of optimal control strategies.

3.6 Performance Measurement

The objective function J presents values consistent with scenario severity:

- Morocco Scenario: J = 0.219 (moderate cost)
- Euro Zone Scenario: J = 0.827 (high cost due to complexity)
- Crisis Scenario: J = −2.241 (net benefit of interventions)

The negative value in the crisis scenario underscores the economic importance of early and intensive interventions. Our simulations demonstrate that:

- Interconnection reduction (u_1) constitutes the most effective tool for containing systemic contagion;
- Accelerated resolution programs (u_3) play a crucial role in eliminating non-viable banks;
- The optimal control approach enables dynamic and efficient allocation of regulatory instruments;
- The UEDRL framework with control offers adaptive flexibility to different market conditions.

Scenario	J	U(final)	D(Final)	R(Final)	U_1	U_2	U_3
Morocco	0.219	0.872	0.002	0.013	0.782	0.003	0.760
EuroZone	0.827	0.810	0.001	0.008	0.768	0.001	0.751
Crisis	-2.241	0.592	0.003	0.041	0.951	0.008	0.947

Table 3: Comparative statistics of simulation scenarios

4. Quantitative Evaluation of Public Policies

The increasing interconnectedness of financial institutions has made the assessment of macroprudential policies a central issue in systemic risk management. Quantitative modeling provides a rigorous framework for evaluating how regulatory interventions influence the propagation of financial distress and the resilience of banking systems. In particular, compartmental models combined with optimal control theory make it possible to analyze the effectiveness of policy measures designed to contain contagion while minimizing intervention costs. In this study, the UEDRL model is used to compare the evolution of systemic risk under controlled and uncontrolled scenarios. Numerical simulations allow the measurement of the impact of preventive actions, support mechanisms for distressed institutions, and resolution policies on the dynamics of financial contagion. The objective is to determine whether optimal regulatory interventions can reduce banking distress, accelerate recovery, and improve overall financial stability. The simulation results provide quantitative evidence on the stabilizing role of public policies and highlight the trade-off between financial stability and the economic cost of regulatory actions. They also contribute to the broader literature on systemic risk modeling by illustrating how optimal policy design can enhance the resilience of interconnected financial systems and mitigate the likelihood of large-scale financial crises.

4.1 Baseline Scenario: No Intervention

The baseline scenario corresponds to a situation in which no prudential measures are implemented. The simulations show that, in the event of a major systemic shock, the proportion of distressed institutions rises rapidly and remains high for an extended period. This dynamic reflects the high degree of risk contagion within the banking network.

4.2 Reducing Financial Contagion

The first policy aims to reduce the rate of risk transmission between financial institutions. The results indicate that this strategy significantly reduces the number of exposed banks and slows the spread of financial distress throughout the system.

4.3 Support for Vulnerable Institutions

The second policy consists of strengthening mechanisms for recapitalizing and supporting distressed institutions. The simulations show that this measure accelerates the exit from the distressed banks segment and reduces the probability of multiple failures.

4.4 Integrated Stabilization Strategy

The simultaneous use of various policy tools yields the most favorable results. The proportion of distressed banks declines rapidly, while the share of recovered institutions increases gradually. The system then converges toward a stable equilibrium characterized by the gradual elimination of systemic risk.

Conclusion

This study provides a quantitative evaluation of macroprudential policies through the integration of a compartmental financial contagion model and an optimal control framework. The findings demonstrate that appropriately designed regulatory interventions can substantially mitigate the propagation of systemic risk, enhance the resilience of the banking sector, and reduce the economic losses associated with financial crises. Beyond their theoretical contribution, these results emphasize the importance of developing macroprudential strategies grounded in a dynamic understanding of contagion processes and systemic interactions in order to promote long-term financial stability. The numerical simulations validate the theoretical predictions derived from the UEDRL framework and provide strong evidence regarding the effectiveness of macroprudential policies in limiting systemic banking crises. More specifically, the results highlight four key findings. First, the contagion rate emerges as the most influential parameter affecting the stability of the financial system. Second, preventive and timely interventions generate significantly greater benefits than measures implemented at later stages of a crisis. Third, policy frameworks combining preventive actions, recapitalization measures, and resolution mechanisms prove more effective than isolated regulatory interventions. Fourth, the coordinated use of multiple macroprudential instruments considerably strengthens the overall resilience of the banking system and improves crisis-management outcomes. These findings are consistent with recent contributions in the literature. In particular, the studies conducted by Cherrat et al. (2025), Fahim et al. (2025), Mourad et al. (2025), and Gyamerah et al. (2026) demonstrate that optimal control strategies can play a crucial role in reducing the economic and social costs generated by banking crises. Collectively, this body of evidence supports the view that integrated macroprudential frameworks combining contagion modeling and optimal policy design constitute a promising approach for enhancing financial stability and mitigating systemic vulnerabilities.

Discussion and Implications for Public Policy

The simulation results provide several valuable insights for prudential regulators and policymakers. First, the findings indicate that preventive measures are systematically more effective than delayed interventions. Early policy actions help contain the emergence of contagion channels, thereby limiting the propagation of financial distress and reducing the long-term costs of stabilization efforts. Second, the reduction of excessive interconnectedness within the banking sector emerges as a key instrument for mitigating systemic risk. By limiting the

intensity of financial linkages among institutions, regulators can significantly decrease the likelihood of shock transmission across the financial network. Third, recapitalization policies play a crucial role once a systemic crisis has already materialized. These measures contribute to restoring the solvency of financially weakened institutions, strengthening market confidence, and preventing further deterioration of financial stability. Moreover, the results highlight the necessity of effective coordination among monetary authorities, prudential supervisors, and resolution agencies. Such cooperation enhances the implementation and overall effectiveness of stabilization policies, particularly during periods of heightened financial stress. These conclusions are consistent with recent empirical evidence demonstrating the positive impact of macroprudential policies on the reduction of systemic banking vulnerabilities. Based on these findings, several policy recommendations can be formulated. Prudential authorities should reinforce systemic monitoring frameworks to detect, at an early stage, institutions that may act as potential sources of contagion within the financial system. In addition, preventive recapitalization mechanisms should be promoted as a means of reducing the economic and financial costs associated with future crises. Finally, strengthened coordination between central banks, supervisory authorities, and resolution institutions is essential to ensure a coherent and effective response to systemic shocks and to enhance the resilience of the banking sector.

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