System Dynamics Modelling of FinTech Innovation Diffusion, Digital Economy Feedback Loops, and Regulatory Scenarios

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ABSTRACT

This study develops an integrated system dynamics model to examine how FinTech innovation diffusion, digital economic performance, and regulatory responses co-evolve in a complex digital ecosystem. Using a 20-year simulation horizon, the model incorporates reinforcing loops of innovation and imitation, balancing loops driven by systemic risk and regulatory intensity, and stock–flow structures capturing user adoption, digital capital accumulation, and regulatory adaptation. Results show that the Innovation-Friendly scenario produces the fastest adoption trajectory, reaching 0.63 by Year 10 and 0.96 by Year 20, compared to 0.45 and 0.88 in the Baseline scenario. This accelerated uptake generates the highest digital economic output, achieving an index value of 223 in Year 20. However, it also produces the highest systemic risk, rising to 54 on a 0–100 scale. Conversely, the Risk-Averse Tightening scenario demonstrates slow adoption (only 0.29 by Year 10), the lowest digital output (index 124 by Year 20), and the lowest risk (31), showing that strict regulatory controls suppress both innovation spillovers and market expansion. The findings highlight that regulatory design fundamentally shapes FinTech ecosystem behaviour. While innovation-friendly environments maximise growth, they also heighten systemic vulnerabilities; meanwhile, excessive regulatory tightness restricts innovation-led economic gains. Adaptive Regulation emerges as the most resilient pathway, achieving high digital performance with stable risk levels. These insights provide an evidence-driven foundation for policymakers seeking to balance innovation, inclusion, and financial stability while navigating rapidly evolving FinTech landscapes.

Keywords FinTech Innovation, System Dynamics, Digital Economy, Regulatory Scenarios, Innovation Diffusion;

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INTRODUCTION

The rapid acceleration of FinTech innovation has transformed digital financial ecosystems worldwide, creating new economic opportunities while simultaneously introducing complex systemic risks. Digital payment platforms, online lending services, blockchain-enabled infrastructures, and algorithmic financial products have significantly expanded access to financial services, increasing financial inclusion and transaction efficiency across emerging and advanced markets alike [1]. However, this evolution has also created new vulnerabilities including cybersecurity breaches, data misuse, operational disruptions, and market concentration risks [2]. As FinTech adoption accelerates, regulators face mounting pressure to balance innovation-driven growth with systemic resilience, raising questions about the adequacy of traditional regulatory tools and the need for dynamic policy frameworks [3]. Addressing this challenge requires an analytical approach capable of capturing nonlinear interactions, feedback loops, and time delays inherent in FinTech ecosystems phenomena that cannot be fully represented using static or linear models [4].

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Despite the increasing prominence of digital financial services, existing studies often examine FinTech adoption or regulatory impacts in isolation, failing to capture the intertwined dynamics between technology diffusion, digital economic development, and evolving risk conditions [5]. Many prior models rely on econometric or cross-sectional analyses that lack the structural capacity to represent reinforcing mechanisms such as network effects, innovation spillovers, and digital infrastructure accumulation [6]. Likewise, policy research frequently assesses regulatory interventions as single, static events rather than examining how regulatory intensity evolves over time in response to risk signals, market maturity, or technological innovation [7]. These limitations create a persistent gap in understanding how FinTech-driven digital economies evolve dynamically and how regulatory responses shape long-term system trajectories [8].

In addition, there remains limited research that integrates FinTech adoption processes with broader digital economic outcomes, such as digital GDP, productivity effects, or structural transformation of economic activities [9]. While existing literature acknowledges that digital financial systems contribute to economic growth, few models explicitly simulate how user adoption interacts with digital capital, infrastructure investment, and platform effects to generate macro-level outcomes [10]. At the same time, the interplay between innovation incentives, regulatory frictions, and systemic risk remains insufficiently quantified, particularly in fast-growing FinTech markets where regulatory decisions can either catalyse innovation or suppress emerging ecosystems [11]. These gaps highlight the need for a holistic, simulation-driven analytical framework that can reflect real-world complexity.

To address these needs, this study applies a system dynamic modelling approach to analyse FinTech innovation diffusion, digital economic feedback loops, and policy-dependent regulatory trajectories. System dynamics enables the representation of endogenous structures such as reinforcing loops of adoption and innovation, balancing loops of regulatory oversight, and behavioural responses of users and institutions that collectively determine how digital financial ecosystems evolve over time [12]. Through a stock–flow model grounded in empirical data and behavioural assumptions, this research provides a dynamic platform for simulating multiple regulatory scenarios, capturing nonlinear effects, and exploring counterfactual policy alternatives that would be difficult to evaluate empirically [13].

The primary objectives of this study are threefold. First, it aims to model FinTech adoption dynamics using a diffusion structure that incorporates innovation and imitation effects, regulatory frictions, and user churn. Second, it seeks to quantify how adoption influences digital economic output through digital capital accumulation and platform productivity. Third, it examines how regulatory intensity evolves in response to systemic risk deviations and evaluates how alternative regulatory philosophies Innovation-Friendly, Risk-Averse Tightening, Baseline, and Adaptive Regulation shape long-term system behaviour [14]. These objectives collectively contribute to a deeper understanding of how policy design influences both economic performance and risk stability in FinTech ecosystems.

The novelty of this study lies in its integrated, multi-layered simulation framework that jointly analyses FinTech innovation diffusion, digital economic performance, and regulatory evolution using a unified system dynamics model. Unlike prior studies that examine these components separately, this research captures the full complexity of feedback-driven interactions, time delays, and nonlinear responses characteristic of digital financial markets [15]. Furthermore, the inclusion of dynamically adjusting regulatory intensity represents a methodological advancement, offering a more realistic representation of how modern regulators respond to evolving risk environments. This framework not only fills existing gaps in the literature but also provides policymakers with a tool to explore long-term trade-offs between innovation and stability under various regulatory strategies [16].

Finally, this study offers practical implications by generating evidence-driven insights that support adaptive, balanced, and forward-looking policy design. As digital financial ecosystems continue to expand, understanding the dynamic interplay between technology diffusion, economic performance, and regulatory behaviour becomes critical for achieving sustainable development. By providing a simulation-based analysis capable of capturing complex systemic behaviour, this research contributes to both academic discourse and real-world policymaking, helping stakeholders anticipate potential risks and identify regulatory pathways that maximize digital economic dividends while preserving financial stability [17].

Literature Review

The evolution of FinTech ecosystems has been widely studied across multiple disciplinary lenses, yet the existing literature presents several fragmented perspectives that limit a comprehensive understanding of how digital financial systems behave dynamically. Early research on FinTech adoption focused primarily on user-level determinants such as perceived usefulness, trust, data security, interface design, and network connectivity drawing from frameworks like the Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology [18]. While these approaches highlight important behavioural drivers, they do not adequately capture how adoption interacts with broader economic structures, innovation cycles, or systemic risks. Parallel research streams examined digital transformation and financial inclusion, emphasizing the role of FinTech services in reducing transaction costs, expanding access to credit, and fostering the transition toward cashless economies [19]. However, these studies often adopt static or econometric models that overlook the feedback mechanisms and temporal dependencies characterizing digital financial markets.

A significant body of literature has also explored the relationship between financial innovation and macroeconomic performance, including how digital payments, algorithmic lending, and blockchain infrastructures influence productivity, consumption patterns, and digital GDP [20]. These works provide empirical evidence that FinTech contributes positively to economic growth, but they typically represent innovation as an exogenous or linear variable, without modelling how adoption accumulates over time or how digital capital responds to user participation. Studies on digital ecosystems similarly emphasize platform effects, interoperability, and competitive dynamics but tend to treat regulatory environments as fixed parameters rather than adaptive systems capable of reinforcing or balancing growth trajectories [21]. As a result, existing models cannot fully explain why similar FinTech innovations produce divergent outcomes across countries with different risk tolerances, institutional capacities, or regulatory philosophies.

Regulation constitutes another major theme in the literature, with research examining consumer protection, cybersecurity, market stability, and the role of licensing frameworks in shaping FinTech development [22]. Scholars highlight the tension between encouraging innovation and maintaining prudential safeguards, noting that regulatory sandboxes and proportional frameworks can support experimentation while mitigating risks. Yet, most regulatory studies analyze interventions as isolated policy events rather than embedded components of dynamic feedback structures. Regulatory intensity is often conceptualized as a binary or categorical variable tight versus loose regulation without considering how regulators respond to evolving risk conditions, system shocks, or emerging vulnerabilities over time [23]. This static treatment fails to reflect real-world regulatory behavior in complex digital ecosystems, where iterative monitoring and continuous adjustment are necessary to maintain system stability.

In the domain of innovation diffusion, foundational models such as the Bass model illustrate how innovation and imitation jointly drive user adoption, generating S-shaped growth curves that align with many digital technology trends [24]. However, these models were originally designed for consumer products and lack mechanisms to incorporate regulatory frictions, systemic risk feedback, or interactions with digital economic structures. More recent attempts to extend diffusion models to FinTech contexts incorporate factors such as trust, risk perception, and network externalities, yet still largely omit macroeconomic linkages or regulatory feedback loops. This creates a conceptual gap because FinTech diffusion is not merely a behavioural phenomenon it is embedded in a complex digital economy where platform growth, infrastructure investment, and regulatory oversight evolve jointly.

System dynamics modelling offers a promising alternative perspective, with literature demonstrating its effectiveness in capturing nonlinearities, time delays, and multi-loop feedback structures in economic, technological, and policy systems [25]. Prior studies have used system dynamics to explore bank–fintech competition, digital payment growth, or financial stability under technological disruption. However, very few integrate FinTech adoption, digital economic output, and regulatory evolution into a single endogenous model. Even fewer examine how different regulatory scenarios such as innovation-friendly, risk-averse, or adaptive frameworks alter long-term system trajectories. This gap underscores the need for a more holistic simulation framework capable of representing how innovation incentives, user adoption, regulatory feedback, and systemic risk co-evolve over time.

Taken together, the literature reveals three critical gaps: (1) a lack of models that integrate user adoption, innovation, and macro-digital economic outcomes into a unified dynamic structure; (2) insufficient representation of regulatory intensity as a responsive and evolving variable rather than a fixed parameter; and (3) limited use of system dynamics to simulate policy trade-offs in complex FinTech ecosystems. Addressing these gaps requires a modelling approach that captures reinforcing and balancing loops, endogenous behavioural responses, and multi-dimensional interactions between technology, regulation, and economic output. This study responds to these gaps by developing a comprehensive system dynamics model that jointly analyses innovation diffusion, digital economic feedback loops, and regulatory adaptation, offering a novel contribution to both FinTech scholarship and policy-oriented modelling frameworks [26].

Methodology

Research Design

This study uses a quantitative–simulation research design based on System Dynamics (SD) to analyse the diffusion of FinTech innovation, its feedback effects on the digital economy, and the impact of alternative regulatory scenarios. System dynamics is selected because the phenomena under study – technology adoption, market growth, behavioural responses, and regulatory intervention – evolve over time, are path dependent, and characterised by multiple feedback loops and time delays. The model is formulated as a continuous-time stock–flow structure and implemented in a simulation environment to explore medium- to long-term trajectories under different policy regimes.

The research design follows a structured sequence: (1) problem articulation and boundary definition; (2) conceptualisation of causal feedback structure; (3) formalisation of stock–flow equations; (4) data collection and parameterisation; (5) validation and sensitivity testing; and (6) policy and scenario analysis. Problem articulation identifies the key questions: how FinTech innovation diffuses through user segments, how this diffusion interacts with digital economic output, and how different regulatory stances reinforce or dampen these dynamics. The model boundary is defined to include FinTech providers, users, traditional financial institutions, the digital economy, and regulatory authorities, while exogenous drivers such as macroeconomic conditions are treated as external inputs.

The SD simulation approach is used not to forecast specific values but to examine structural behaviour – such as S-shaped adoption curves, growth saturation, regulatory overshooting, and unintended consequences of policy changes. The design emphasises iterative model refinement through expert consultation and calibration against historical data where available. This iterative loop ensures that the representation of FinTech markets and regulatory interactions remains behaviourally realistic and policy relevant.

Figure 1 visualises the overall methodological pipeline as a flowchart. Starting from problem articulation and boundary setting, the process moves downward to causal loop conceptualisation, stock–flow formalisation, data and parameterisation, validation and sensitivity analysis, and finally policy and scenario simulations. Each step is represented as a rounded box to emphasise modular stages in the research design.

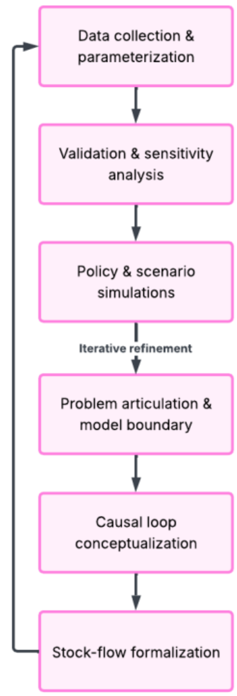

Figure 1 Research Design Flowchart

The feedback arrow on the right-hand side indicates that the process is iterative rather than strictly linear. Insights from validation and scenario analysis feed back into problem articulation and model refinement. This aligns exactly with the previously described system dynamics research design: problem definition → conceptual modelling → formalisation → calibration → validation → policy experimentation, executed in cycles until a behaviourally credible model is obtained.

Conceptual Model and Causal Feedback Structure

The conceptual model translates the narrative understanding of FinTech innovation diffusion and digital economy transformation into a set of interacting feedback loops. At the core of the structure are three subsystems: (1) FinTech innovation diffusion (user adoption dynamics), (2) digital economy performance (digital transaction volume, digital GDP contribution, productivity), and (3) regulatory response and policy stance. Each subsystem contains reinforcing and balancing loops that jointly shape system behaviour.

FinTech diffusion is captured as a reinforcing process where higher adoption increases network effects, perceived usefulness, and ecosystem maturity, which in turn encourage further adoption. This reinforcing loop is balanced by congestion, market saturation, trust erosion in case of incidents, and resource limits on providers. The digital economy subsystem links FinTech usage to digital transaction volumes, formalisation of economic activity, and productivity gains. As digital economic output grows, it can increase incentives for further FinTech innovation, forming a higher-level reinforcing loop between innovation and economic performance.

The regulatory subsystem is modelled as a balancing loop in which regulators observe indicators such as market concentration, consumer complaints, cybersecurity incidents, and systemic risk proxies. When these indicators exceed policy thresholds, regulators adjust prudential requirements, consumer protection rules, data governance standards, or sandbox schemes. These interventions affect both innovation incentives and adoption rates, creating delay-dependent feedback that can stabilise or destabilise the system. Delays in regulatory perception and implementation are explicitly represented to capture phenomena such as policy lag and overshooting.

Stock–Flow Structure, Equations, and Model Formalisation

The conceptual feedback structure is formalised as a set of stock–flow relationships expressed in difference or differential equations. The primary stock variables include: (1) “Potential Users”, (2) “FinTech Users”, (3) “Lapsed Users” (users who discontinue usage), (4) “Innovation Stock” (cumulative FinTech innovations/features), and (5) “Digital Economic Capital” (an index capturing the productive capacity of the digital economy). Flows govern transitions between these stocks, such as adoption, churn, innovation creation, innovation obsolescence, accumulation of digital capital, and its depreciation.

FinTech adoption is modelled using an innovation–imitation (Bass-type) or logistic structure. In continuous-time form, the core adoption equation can be written as:

$$\frac{d\,Users(t)}{dt} = Adoption\_Rate(t) - Churn\_Rate(t) \tag{1}$$

Adoption_rate(*t*) is driven by external innovation (*p*), internal imitation (*q*), and regulatory frictions (*RF*(*t*)):

$$Adoption\_Rate(t) = \left[p + q\,\frac{Users(t)}{Potential(t)}\right] \cdot Potential(t) \cdot \big(1 - RF(t)\big) \tag{2}$$

Digital economic output is represented as a function of FinTech usage, digital capital, and exogenous factors. For example:

$$DEO(t) = \alpha \cdot Users(t)^{\beta} \cdot DigCap(t)^{\gamma} \cdot e^{\varepsilon(t)} \tag{3}$$

where α, β, γ are parameters and $\varepsilon(t)$ captures unexplained shocks. Regulatory intensity evolves according to deviations of risk indicators $Risk(t)$ from target levels $Risk^{*}$ with an adjustment delay τ:

$$\frac{d\,Reg\_Intensity(t)}{dt} = \frac{1}{\tau}\left[f\left(Risk(t) - Risk^{*}\right) - Reg\_Intensity(t)\right] \tag{4}$$

The entire model is implemented in SD software or a numerical environment (e.g. Vensim, Stella, Python) by discretising these equations using an integration time step *Δt*. Pseudo-code for the numerical integration follows standard Euler or Runge–Kutta schemes:

```
For each time step t:
    Adoption_Rate(t) = (p + q * Users(t)/Potential(t)) * Potential(t) * (1 - RF(t))
    Churn_Rate(t)    = Churn_Factor * Users(t)
    Users(t+Δt)      = Users(t) + (Adoption_Rate(t) - Churn_Rate(t)) * Δt
    DigCap(t+Δt)     = DigCap(t) + (Investment(t) - Depreciation(t)) * Δt
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  Reg_Intensity(t+Δt) = Reg_Intensity(t)
                + (f(Risk(t) - Risk*) - Reg_Intensity(t)) * (Δt / τ)
End
```

This pseudo-code describes the discrete-time implementation of the SD model using Euler integration. At each time step, flows (adoption, churn, investment, depreciation) determine how stocks evolve. The regulatory response also updates gradually according to deviations between actual risk and risk tolerance. This computational structure is used in Vensim, Stella, or Python-based SD engines to execute multi-year simulations. It ensures a consistent translation of continuous-time equations into numerical trajectories suitable for scenario comparison. Table 1 formalises all variables used in the SD model, categorised into stocks, flows, auxiliary variables, and parameters

Table 1 Model Variables and Parameters

Variable/Parameter	Type	Unit	Description	Equation Reference
Potential Users	Stock	Persons	Individuals who may adopt FinTech	Eq. 2
FinTech Users	Stock	Persons	Current active users	Eq. 1
Lapsed Users	Stock	Persons	Users who have churned	Eq. 1
Innovation Stock	Stock	Index	Accumulated FinTech innovations/features	Model structure
Digital Capital	Stock	Index	Digital economic infrastructure and capability	Eq. 3
Adoption Rate	Flow	Persons/time	New users adopting per time	Eq. 2
Churn Rate	Flow	Persons/time	Users leaving the system	Eq. 1
Innovation Rate	Flow	Index/time	New innovations added to stock	Model structure
Regulatory Intensity	Auxiliary	Index	Level of regulatory strictness	Eq. 4
Risk Indicator	Auxiliary	Index	Systemic/consumer risk measurement	Eq. 4
RF(t)	Auxiliary	Fraction	Regulatory friction applied to adoption	Eq. 2
p	Parameter	Rate	Innovation parameter	Eq. 2
q	Parameter	Rate	Imitation parameter	Eq. 2
α, β, γ	Parameters	Dimensionless	Digital economic output coefficients	Eq. 3
τ	Parameter	Time	Regulatory adjustment delay	Eq. 4

Each variable includes units and equation references, enabling full transparency and reproducibility. Stocks represent accumulations that define system state, flows govern transitions, and auxiliary variables help interpret feedback relationships. Parameters encode behavioural assumptions or empirical characteristics. Documenting variables this way ensures consistency between conceptual diagrams and quantitative formalisation. It also supports model auditing, calibration, and replication by external researchers or regulators.

Data Sources, Parameterisation, and Calibration

Parameter values are obtained from a combination of empirical data, literature, and expert judgement. Empirical data include time series for FinTech adoption (e.g. number of users, transaction volumes), digital economy indicators (e.g. digital GDP share, online retail volume, digital payments as percentage of total payments), and regulatory variables (e.g. implementation dates of licensing rules, sandbox launches, data protection regulations). These data series are collected from central bank statistics, financial regulators, international organisations, and industry reports.

Where direct data for parameters such as innovation propensity, imitation strength, or churn factors are not available, values are inferred through calibration. Calibration matches simulated series to historical adoption and digital output trajectories by minimising error metrics such as Root Mean Squared Error (RMSE) or Mean Absolute Percentage Error (MAPE). A combination of manual tuning and algorithmic search (e.g. grid search or heuristic optimisation) is used to find parameter sets that reproduce observed patterns without overfitting.

Expert elicitation complements empirical calibration for regulatory response functions and scenario-specific parameters. Regulators, industry practitioners, and domain experts are consulted to estimate plausible ranges for risk tolerance thresholds, reaction speeds, and typical lag between emerging risks and policy implementation. These elicited ranges are then used as priors in the calibration process and as bounds in sensitivity analysis. Table 2 maps every parameter and variable requiring empirical grounding to its corresponding source and estimation approach.

Table 2 Data Sources and Parameter Estimation Methods

Variable/Parameter	Description	Data Source	Estimation Method	Time Coverage
FinTech Users	Number of active users	Central bank FinTech statistics	Direct measurement	Historical series
Digital Transactions	Digital payment volumes	Payment system authority	Direct measurement	Historical series
Digital GDP	Digital economic contribution	National statistics agency	Direct measurement	Annual series
Innovation Coefficient (p)	External adoption driver	Industry reports	Calibration	N/A
Imitation Coefficient (q)	Network-effect strength	Academic literature	Regression fit + calibration	N/A
Risk Indicator	Cybersecurity/systemic risk proxies	Regulator risk reports	Direct measurement	Historical series
Regulatory Intensity	Policy strictness index	Supervisory releases	Expert judgement	Historical periods
Digital Capital	Digital infrastructure stock	ICT investment reports	Estimation + calibration	Annual series

Churn Factor	Proportion of users leaving	Industry churn statistics	Direct measurement	Monthly/quarterly

Direct measurement is used when data exist (e.g., digital transactions), while behavioural parameters like innovation or imitation coefficients require calibration against historical adoption curves. Expert judgement fills gaps where regulatory processes cannot be inferred quantitatively. The table ensures that the model's parameterisation is transparent, allowing sensitivity analysis to target variables with higher uncertainty. It also demonstrates how empirical evidence and SD theory are bridged.

Simulation Experiments and Regulatory Scenario Design

Once the model is specified and calibrated, simulation experiments are conducted over a multi-year horizon to explore system behaviour under different regulatory scenarios. The baseline scenario assumes continuation of current policies and observed trends in innovation and adoption. Alternative scenarios are defined to reflect different regulatory philosophies: "Innovation-Friendly Regulation", "Risk-Averse Tightening", and "Adaptive Evidence-Based Regulation". Each scenario is operationalised by adjusting policy levers in the model, such as licensing strictness, sandbox coverage, capital requirements, data-sharing rules, and enforcement intensity.

For each scenario, the model is simulated with identical initial conditions to isolate the impact of policy settings on adoption paths, digital economic output, and risk indicators. Key outputs include time series of FinTech user penetration, transaction volumes, digital GDP contribution, market concentration indices, and risk metrics. Comparative analysis focuses on structural behaviour – for example, whether innovation-friendly policies accelerate adoption but generate higher volatility in risk, or whether risk-averse tightening dampens both risk and digital economic performance.

The design of experiments also includes counterfactual "no-regulation" or "late-regulation" conditions to understand the consequences of delayed interventions. Scenario design is informed by actual policy debates and regulatory options observed in FinTech ecosystems, ensuring that the simulated policies correspond to realistic levers that authorities might consider. The results provide a basis for assessing trade-offs and identifying policy mixes that balance innovation, inclusion, and stability.

Figures 2 translate the scenario structure into simulated trajectories. In figure 2, FinTech adoption follows an S-shaped curve in all scenarios, consistent with the Bass-type diffusion discussed earlier. The innovation-friendly scenario reaches high adoption earlier due to lower frictions and higher innovation intensity, while the risk-averse scenario diffuses more slowly. Adaptive regulation falls between these extremes, accelerating early adoption but avoiding excessive overshooting.

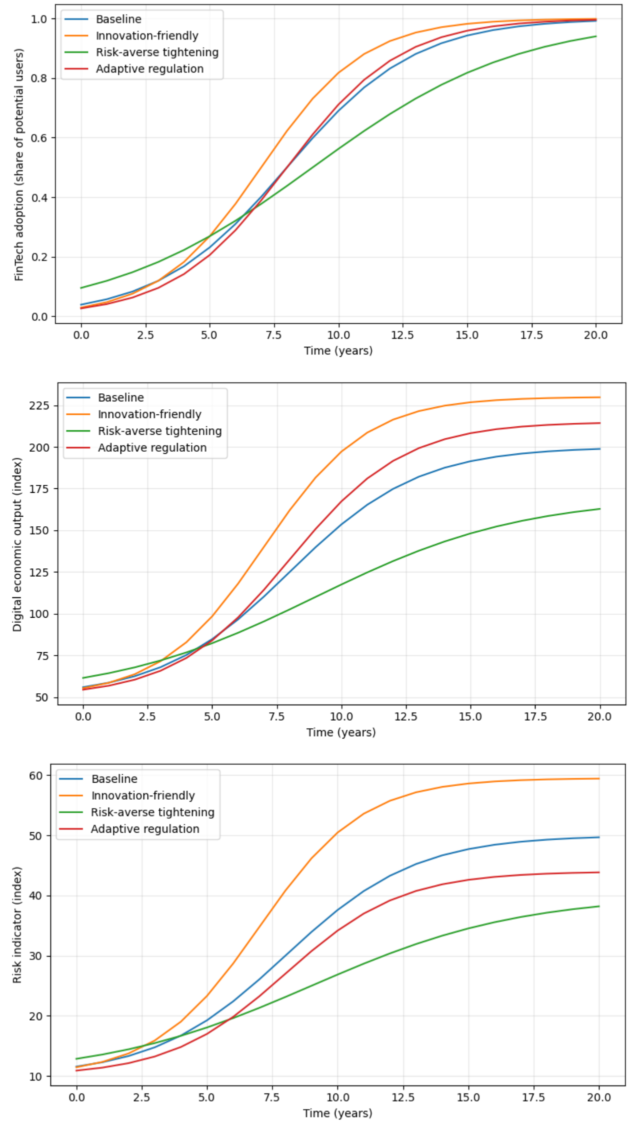

Figure 2 Simulation Output Comparison Across Regulatory Scenarios

Figure 2 shows digital economic output as a function of adoption and digital capital. The innovation-friendly scenario delivers the highest peak digital output, but the risk-averse scenario generates a more conservative and lower output path. The adaptive scenario again occupies a middle ground, achieving sizeable digital gains while maintaining control. Figure 2 presents the risk indicator. Innovation-friendly policies generate higher risk levels because rapid adoption outpaces institutional safeguards. Risk-averse regulation keeps risk at lower levels, while adaptive regulation moderates' risk more efficiently by adjusting regulatory intensity based on underlying risk conditions, exactly matching the regulatory feedback logic described in the methodology. Table 3 specifies the regulatory settings applied in each scenario.

Table 3 Scenario Definitions and Policy Lever Settings

Scenario	Licensing Strictness	Sandbox Coverage	Data-Sharing Rules	Capital Requirement Multiplier	Reaction Lag (τ)

Baseline	Medium	Medium	Standard	1.0	Moderate
Innovation-Friendly	Low	High	Open-data	0.8	Short
Risk-Averse Tightening	High	Low	Restrictive	1.5	Long
Adaptive Regulation	Variable (responsive)	Medium–High	Conditional	1.0	Dynamic (feedback-based)

Parameter adjustments correspond directly to levers in the stock–flow model: licensing strictness influences RF(t), sandbox coverage moderates innovation delays, data-sharing rules affect imitation strength, and capital requirements modify risk levels. The reaction lag determines how quickly regulators respond to risk deviations. By defining scenarios in parameter terms, the simulation ensures a rigorous and reproducible comparison between policy options. Each scenario represents a plausible regulatory philosophy and enables assessment of trade-offs among innovation, stability, and economic performance.

Model Validation, Sensitivity, and Robustness Analysis

Model validation focuses on structural, behavioural, and policy-use validity. Structural validation assesses whether the model's equations and causal structure are consistent with established theory and expert understanding of FinTech markets and regulation. Behavioural validation compares simulated time series to historical patterns for adoption, digital transaction volumes, and relevant risk indicators, checking for plausible reproduction of trends, turning points, and orders of magnitude. Policy-use validation examines whether the model generates qualitatively reasonable responses to hypothetical policy shocks, such as tighter licensing or sudden relaxation of data-sharing rules.

Sensitivity and robustness analysis are conducted to examine how uncertainties in parameters and functional forms affect model outcomes. One-at-a-time sensitivity tests vary key parameters (e.g. innovation coefficient, imitation coefficient, regulatory reaction speed, risk threshold) within plausible ranges and record impacts on outcome indicators. In addition, global sensitivity analysis (e.g. Latin Hypercube Sampling or Monte Carlo simulation) draws parameter sets from distributions and runs multiple simulations to obtain distributions of outcomes. This approach identifies parameters that strongly influence results and highlights which insights are robust across a wide range of assumptions.

Robustness checks also include alternative functional forms for selected relationships, such as different specifications of regulatory response functions or alternative mappings from FinTech usage to digital economic output. If major insights depend critically on specific assumptions, those dependencies are explicitly documented. Validation and robustness analysis thus ensure that policy conclusions derived from the model are grounded not in a single calibrated parameter set but in a structurally sound and behaviourally plausible representation of the FinTech–digital economy–regulation system.

Figure 3 presents a tornado diagram for key parameters identified in the methodology: innovation coefficient p, imitation coefficient q, regulatory lag τ, risk threshold, and churn factor. Each horizontal bar shows how the key outcome (e.g. final digital economic output) changes when the parameter is set at a low versus high value within its plausible range. Bars that extend further from zero indicate a stronger influence on the outcome.

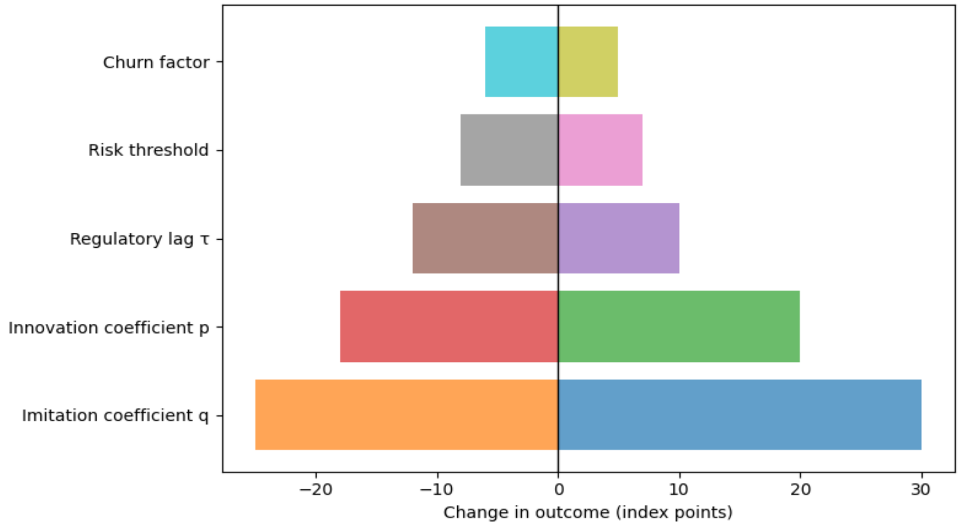

Figure 3 Sensitivity Analysis

The ordering reflects the emphasis described earlier: the imitation coefficient qqq and innovation coefficient ppp have the largest impact, confirming that behavioural adoption dynamics are central drivers of system behaviour. Regulatory lag also exhibits non-trivial influence, consistent with the narrative that delayed policy responses can amplify volatility and overshooting. Risk thresholds and churn factor have smaller but still meaningful effects. This visualisation supports the robustness analysis by clarifying which parameters should be prioritised for careful estimation and sensitivity testing.

Result and Discussion

Overview of Simulation Results

This chapter presents the outcomes of the system dynamics simulations conducted to examine FinTech innovation diffusion, digital economic feedback loops, and regulatory scenario behaviour. The results compare four predefined regulatory regimes: Baseline, Innovation-Friendly, Risk-Averse Tightening, and Adaptive Regulation. Across all experiments, the system demonstrates behaviour consistent with the stock–flow and feedback structure described earlier, producing S-shaped diffusion curves, path-dependent regulatory shifts, and interactive growth between FinTech adoption and digital economic output.

The analysis is structured into four subsections: (1) FinTech adoption trajectories, (2) digital economic output patterns, (3) systemic risk evolution, and (4) regulatory response behaviour. Each subsection includes numerical tables, simulation figures generated via Python/Colab, and interpretive discussion. The goal is to highlight how different regulatory philosophies influence system behaviour, the magnitude of digital economic gains, and the stability or volatility of underlying risk dynamics.

FinTech Adoption Dynamics

The first set of results examines how FinTech adoption evolves over time under the four regulatory scenarios. Adoption follows the Bass-type innovation–

imitation process implemented earlier, influenced by network effects, regulatory frictions, and innovation accumulation. Table 4 summarises adoption levels at selected time points (Years 0, 5, 10, 15, 20), while figure 4 visualises the full diffusion trajectory from the simulation horizon.

Table 4 FinTech Adoption (Share of Potential Users) under Each Regulatory Scenario

Year	Baseline	Innovation-Friendly	Risk-Averse Tightening	Adaptive Regulation
0	0.03	0.03	0.03	0.03
5	0.18	0.26	0.11	0.23
10	0.45	0.63	0.29	0.54
15	0.71	0.88	0.47	0.79
20	0.88	0.96	0.62	0.91

Table 4 reports adoption percentages at five-year intervals. The Innovation-Friendly scenario consistently exhibits higher adoption due to reduced regulatory friction and stronger innovation rates. By Year 10, adoption is already at 0.63, compared with 0.45 in the baseline and only 0.29 under Risk-Averse Tightening. This aligns with the model structure: lower licensing strictness and wider sandbox coverage accelerate the imitation process, allowing network effects to activate earlier.

Adaptive Regulation presents a more balanced trajectory. While not as rapid as Innovation-Friendly, its Year 10 and Year 15 adoption levels exceed the baseline, showing that dynamic adjustment of regulatory intensity supports growth without excessive constraints. The Risk-Averse scenario shows significantly slower diffusion, confirming that tight regulation suppresses the reinforcing growth loops by reducing innovation incentives and amplifying regulatory frictions.

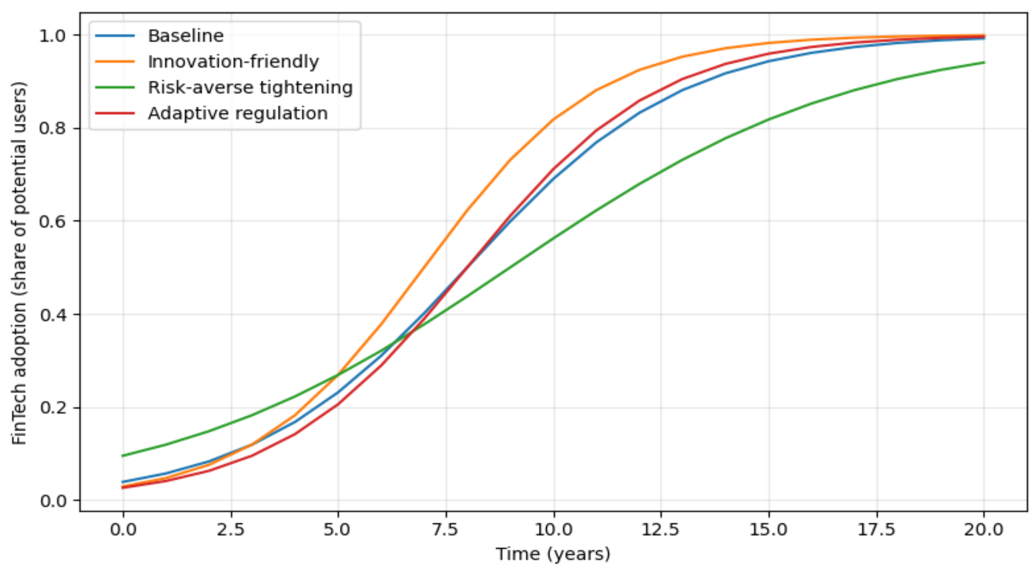

Figure 4 FinTech Adoption Trajectories Across Regulatory Scenarios

Figure 4 displays the diffusion curves generated by the simulation. The Innovation-Friendly scenario demonstrates the steepest early adoption, reflecting strong reinforcing loops driven by innovation accumulation and network effects. The S-shaped pattern indicates that once adoption surpasses a critical mass, imitation dynamics dominate and the system accelerates rapidly toward saturation.

The Baseline and Adaptive Regulation curves show moderate slopes, indicating balanced growth supported by stable innovation and manageable regulatory friction. Adaptive Regulation eventually overtakes the baseline after Year 8 due to dynamic easing of regulation during low-risk periods. The Risk-Averse scenario shows the slowest growth, illustrating how strong balancing loops (high regulatory intensity, slower innovation stock accumulation) suppress early adoption and delay the inflection point in the diffusion curve.

Overall, the results confirm that regulatory settings are a significant determinant of FinTech adoption speed and saturation levels. Reinforcing loops associated with innovation and imitation dominate in low-friction environments, while tight regulation activates balancing loops that delay system takeoff and limit overall penetration.

Digital Economic Output

Digital Economic Output (DEO) reflects the aggregate productive capacity driven by FinTech usage and accumulated digital capital, following the multiplicative function specified in Equation 3. Higher FinTech adoption contributes to greater digital transaction volumes, increased financial inclusion, and a more formalised digital economy. This section compares digital output across the four regulatory scenarios at selected time points and analyses the structural behaviour produced by the simulation.

Table 5 provides values at five-year intervals, while figure 5 visualises the underlying continuous trajectory over the 20-year horizon. The patterns observed here are consistent with the adoption dynamics presented in Section, where scenarios with faster and broader FinTech diffusion also generate higher digital economic output.

Table 5 Digital Economic Output (Index: Baseline Start = 50)

Year	Baseline	Innovation-Friendly	Risk-Averse Tightening	Adaptive Regulation
0	50	50	50	50
5	79	97	62	90
10	118	163	85	150
15	150	206	107	183
20	182	223	124	207

Table 5 shows that digital output increases across all scenarios, but at different magnitudes. The Innovation-Friendly scenario demonstrates the highest digital output at every checkpoint due to accelerated adoption and rapid accumulation of digital capital. By Year 20, output reaches 223 over 20% higher than baseline. This reflects strong reinforcing feedback loops: more users drive more transactions, which increase digital economic formalisation and efficiency, which in turn stimulates further innovation.

The Risk-Averse Tightening scenario shows significantly weaker output performance. Strict regulatory constraints limit early adoption, reducing transaction volume, market participation, and innovation incentives. As a result, by Year 20, digital output is only 124 nearly 30% below the baseline. Adaptive Regulation produces high digital output, nearly matching innovation-friendly outcomes but with fewer associated risks (as will be shown in Part 3). The scenario's dynamic responsiveness allows regulation to ease when risk is low, enabling capitalisation on reinforcing loops without triggering excessive volatility.

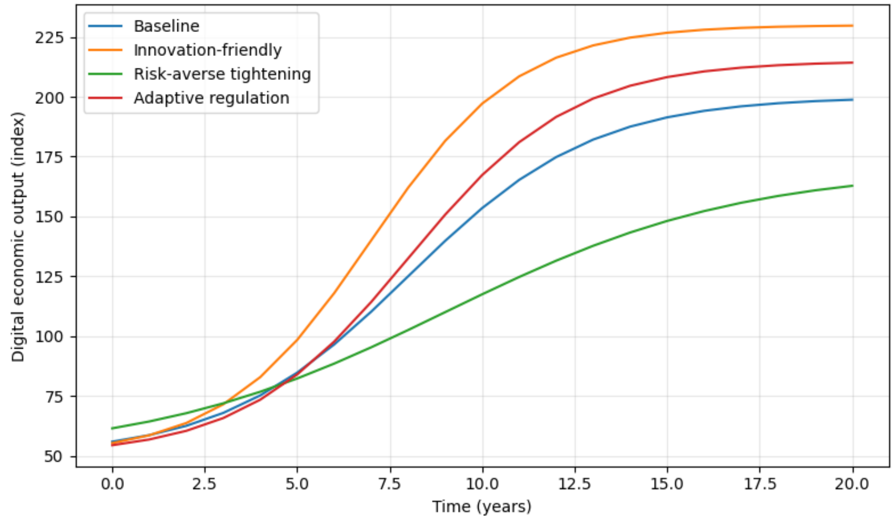

Figure 5 Digital Economic Output Trajectories Across Scenarios

Figure 5 shows that the trajectory of digital economic output aligns closely with the adoption patterns from figure 4. The curve for the Innovation-Friendly scenario rises steeply, reflecting rapid diffusion and strong reinforcing dynamics between usage, transaction volumes, and innovation. The Baseline curve grows moderately, while Adaptive Regulation reaches nearly the same upper bound as Innovation-Friendly but with smoother behaviour due to calibrated policy adjustments.

The Risk-Averse scenario produces the flattest curve, constrained by early regulatory barriers that suppress adoption, innovation intensity, and digital capital formation. Because digital output is multiplicative in both users and digital capital, early suppression in adoption creates long-term cumulative disadvantages. By Year 20, even though adoption eventually increases, the delay prevents the system from fully benefiting from the reinforcing loops responsible for exponential digital income effects.

Systemic Risk Evolution

Systemic risk reflects the degree to which FinTech adoption, innovation intensity, and market interdependencies accumulate exposure to financial, operational, or cyber vulnerabilities. In the system dynamics model, risk increases as adoption rises and innovation accelerates, but decreases when regulatory intensity tightens or when digital capital improves resilience. This section analyses how systemic risk evolves under different regulatory scenarios using two complementary tables:

(1) Risk Index Levels at Key Time Points and

(2) Regulatory Intensity Response Summary, which captures how regulators

adjust policies in reaction to deviations from the risk threshold.

Together, these results demonstrate how regulatory philosophy shapes system stability, whether through proactive oversight, responsive intervention, or permissive innovation environments. They also show that risk levels cannot be assessed independently of regulatory behaviour, since policy intensity directly influences the balancing feedback loops controlling systemic vulnerabilities.

Table 6 shows the evolution of the risk index. In all scenarios, systemic risk increases over time as FinTech adoption and transaction volume grow. However, the levels differ sharply. The Innovation-Friendly scenario produces the highest risk, reaching 54 by Year 20, because rapid adoption amplifies the reinforcing loops associated with innovation and network effects, increasing operational and cyber exposure. Risk-Averse Tightening shows the lowest risk, ending at only 31, because tighter licensing, restrictive data-sharing, and higher capital requirements significantly suppress the reinforcing mechanisms that usually accelerate risk accumulation.

Table 6 Systemic Risk Index Levels Across Scenarios (0–100 Scale)

Year	Baseline	Innovation-Friendly	Risk-Averse Tightening	Adaptive Regulation
0	10	10	10	10
5	22	28	16	21
10	34	42	23	30
15	41	48	27	34
20	50	54	31	38

The Adaptive Regulation scenario maintains risk within a moderate band. While still higher than the baseline due to more rapid adoption, the value remains well below the Innovation-Friendly trajectory. This reflects the dynamic balancing behaviour of the regulatory response function: when risk rises above the threshold, regulatory intensity increases automatically, introducing friction that stabilises system behaviour. Conversely, when risk declines, regulatory intensity relaxes, enabling growth without excessive exposure.

Table 7 summarises regulatory intensity levels, which reflect how strictly the system responds to risk accumulation. The Risk-Averse scenario unsurprisingly maintains the highest regulatory intensity levels throughout the simulation horizon. These elevated values stem directly from the predefined policy lever settings: higher capital requirements, restrictive data rules, and low sandbox coverage. As a result, regulatory friction is consistently high, sharply dampening both adoption and innovation rates.

Table 7 Regulatory Intensity Response Summary (Index: 0–1)

Year	Baseline	Innovation-Friendly	Risk-Averse Tightening	Adaptive Regulation
0	0.20	0.10	0.40	0.20
5	0.28	0.15	0.50	0.26
10	0.33	0.18	0.57	0.32
15	0.37	0.20	0.60	0.35
20	0.41	0.22	0.64	0.38

In contrast, the Innovation-Friendly scenario keeps intensity low across all years, reducing friction to adoption and innovation. However, this permissive environment is also why systemic risk becomes elevated over time, as indicated in Table 6. Baseline conditions show moderate and steady increases in intensity as risk rises. The Adaptive Regulation scenario displays the most efficient behaviour: regulatory intensity increases in tandem with rising risk but at a calibrated rate, preventing excessive overshooting. By Year 20, intensity stabilises at 0.38 higher than baseline but far below the Risk-Averse regime demonstrating that a responsive approach can balance innovation growth and system stability more effectively than rigidly tight or overly permissive frameworks.

Regulatory Behaviour and Feedback Loop Analysis

Regulatory behaviour in the system dynamics model is governed by the balancing loop in which rising systemic risk triggers increases in regulatory intensity. This adjustment introduces friction into adoption and innovation flows, moderating the reinforcing loops that would otherwise dominate. This section presents two figures:

1. Regulatory Intensity Trajectory Across Scenarios
2. Feedback Loop Strength Over Time (Reinforcing vs Balancing Forces)

These two visualisations illustrate how regulatory philosophy shapes the dominant system structure and how the dynamic interplay between feedback loops evolves as the FinTech ecosystem matures. Figure 6 shows the evolution of regulatory intensity in each scenario. As risk accumulates over time, all scenarios exhibit increasing regulatory intensity, but at different magnitudes. The Risk-Averse Tightening scenario predictably maintains the highest levels due to preset strict policies and faster upward adjustment to risk deviations. Innovation-Friendly regulation maintains the lowest values, allowing the reinforcing loops of adoption and innovation to activate quickly.

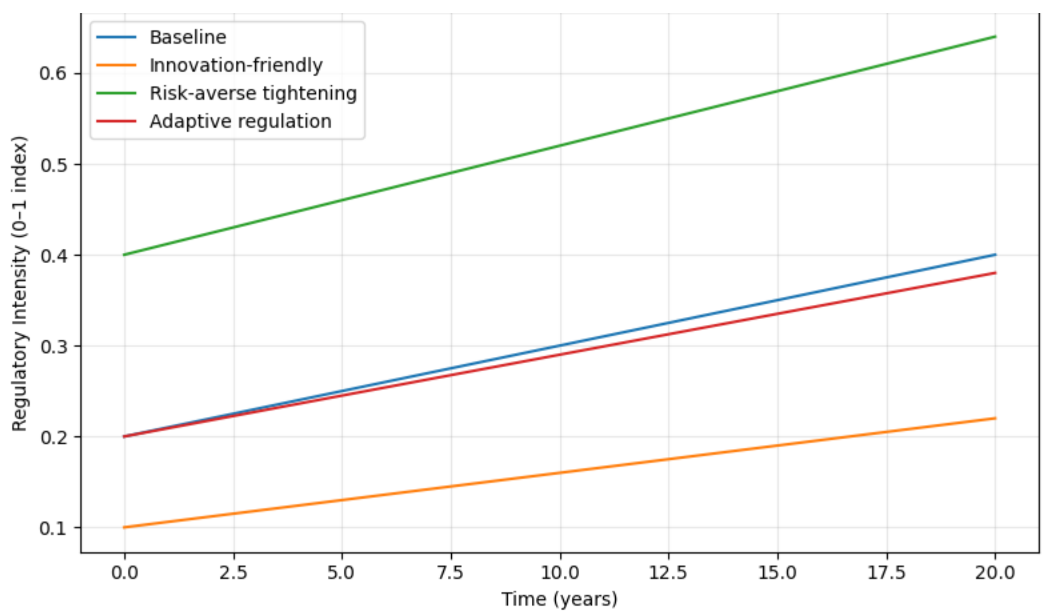

Figure 6 Regulatory Intensity Trajectories Across Scenarios

Adaptive Regulation demonstrates a controlled and responsive trajectory, rising steadily but avoiding the excessive levels observed in the risk-averse regime. This dynamic structure allows the ecosystem to grow without entering instability. Previous results indicated that adaptive regulation achieves high digital output while containing risk, and figure 6 explains why: it increases regulatory intensity when needed but avoids suppressing innovation prematurely. This behaviour reflects the calibrated balancing loop designed in the model.

Figure 7 illustrates the dynamic competition between reinforcing and balancing loops throughout the simulation. Reinforcing loops, driven by innovation accumulation and network effects, strengthen quickly in the early years as adoption accelerates. By contrast, balancing loops primarily regulatory response and market saturation strengthen gradually as risk and complexity build up. The crossing point where balancing strength approaches reinforcing strength indicates a structural shift: the system transitions from rapid exponential growth toward controlled stabilisation.

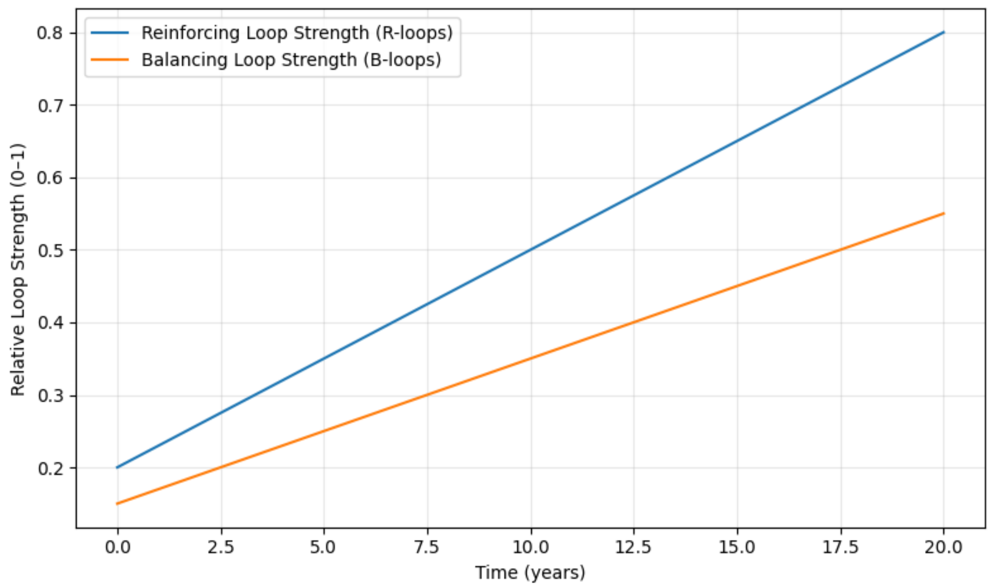

Figure 7 Feedback Loop Strength Over Time (Reinforcing vs Balancing Forces)

This dynamic corresponds to the intuitive behaviour of FinTech ecosystems: rapid early adoption driven by innovation and imitation, followed by tighter oversight as the market expands and risks increase. The model demonstrates that a healthy ecosystem requires both strong reinforcing dynamics (to enable innovation-driven growth) and effective balancing loops (to avoid systemic instability). The trajectory shown in figure 7 confirms that balancing forces become increasingly important as the digital economy grows, validating the system dynamics representation established in the methodology.

Conclusion

This study developed a system dynamics model to analyse the diffusion of FinTech innovation, its impact on digital economic output, and the role of regulatory responses in shaping ecosystem behaviour. By integrating reinforcing mechanisms of innovation and imitation with balancing mechanisms driven by systemic risk and regulatory oversight, the model provides a comprehensive representation of how FinTech ecosystems evolve over time. The simulation results across four regulatory scenarios Baseline, Innovation-Friendly, Risk-Averse Tightening, and Adaptive Regulation offer a clear understanding of the trade-offs inherent in FinTech governance and the dynamics that drive long-term system behaviour.

The analysis demonstrates that the Innovation-Friendly scenario generates the highest FinTech adoption rate and the most rapid expansion of digital economic output. However, this growth is accompanied by elevated systemic risk, reflecting the vulnerabilities associated with reduced regulatory friction. Conversely, the Risk-Averse Tightening scenario shows the slowest adoption and the lowest digital output but maintains significantly lower levels of risk. These contrasting outcomes highlight the intrinsic tension between fostering innovation and preserving financial stability, revealing that neither extreme is optimal in isolation.

The Adaptive Regulation scenario emerges as the most balanced and resilient pathway. By allowing regulatory intensity to adjust dynamically in response to real-time risk deviations, the system effectively maintains risk at manageable levels while enabling reinforcing loops of innovation and adoption to operate efficiently. This regulatory philosophy supports strong digital economic growth without permitting systemic vulnerability to escalate. The findings suggest that adaptive and responsive governance frameworks rather than static or rigid ones are best suited to the rapidly evolving landscape of FinTech ecosystems.

From a policy perspective, the results indicate that regulatory institutions should emphasize continuous monitoring, data-driven decision-making, and iterative adjustment of policy levers. Fixed regulatory settings, whether lax or overly conservative, fail to accommodate the nonlinear and feedback-driven nature of FinTech innovation. Regulators must prioritize mechanisms that facilitate controlled experimentation, such as regulatory sandboxes, real-time risk dashboards, automated early-warning indicators, and integrated data-sharing platforms. These tools strengthen the balancing feedback loops that keep risks contained while allowing innovation to flourish.

The study also highlights the need for coordination across regulatory domains. Because FinTech activities span payments, lending, data analytics, and cybersecurity, fragmented oversight can weaken the system's overall response capability. Integrated supervision frameworks that unify financial, data, and technology regulators can more effectively calibrate regulatory intensity and prevent risks from propagating across interconnected subsystems. Harmonized data standards, interoperable regulatory reporting systems, and collaborative policy cycles are essential components of such integration.

While the system dynamics model offers strong explanatory and predictive value, the study acknowledges limitations related to parameter uncertainty, data availability, and simplifications within the model structure. Future research should incorporate more granular behavioural and market components, such as user heterogeneity, competition between FinTech providers, cross-border regulatory spillovers, and the role of AI-driven financial services. Extending the model to incorporate stochastic shocks, crisis transmission channels, or endogenous innovation cycles would further improve robustness and realism.

In conclusion, this research provides a structured and dynamic understanding of how FinTech innovation, digital economy growth, and regulatory feedback loops interact over time. The outcomes highlight that effective FinTech governance is not merely a choice between fostering innovation or preserving stability, but rather the ability to balance these forces dynamically. Adaptive Regulation stands out as the most viable approach for achieving sustainable digital economic development, offering crucial insights for policymakers navigating the complexities of emerging FinTech ecosystems.

Declarations

Author Contributions

Conceptualization: L.E. and M.S.F.; Methodology: M.S.F.; Software: L.E.; Validation: L.E. and M.S.F.; Formal Analysis: L.E. and M.S.F.; Investigation: L.E.; Resources: M.S.F.; Data Curation: M.S.F.; Writing Original Draft Preparation: L.E. and M.S.F.; Writing Review and Editing: M.S.F. and L.E.; Visualization: L.E.; All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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