

A GOVERNANCE-DRIVEN MATHEMATICAL MODEL OF INSTITUTIONAL CORRUPTION DYNAMICS IN NIGERIAN UNIVERSITIES: STABILITY AND NUMERICAL ANALYSIS

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ABSTRACT

Institutional corruption remains a persistent challenge to the effective functioning of universities, where it can manifest through examination malpractice, procurement irregularities, favouritism, unauthorized financial transactions, abuse of administrative authority and other forms of misconduct. Although mathematical modelling has increasingly been applied to the study of corruption transmission and control, many existing models treat corruption as a homogeneous population-level phenomenon and consequently provide limited representation of the institutional structures through which corrupt practices emerge, remain hidden, are detected and are subsequently rehabilitated. This study develops a governance-driven compartmental model for institutional corruption dynamics in Nigerian universities. The model partitions the institutional population into six mutually exclusive compartments: susceptible individuals S , exposed individuals E , actively corrupt individuals I , hidden or asymptomatic corrupt individuals A , detected and sanctioned individuals P_1 and rehabilitated or reintegrated individuals P_2 . Governance effectiveness $G, 0 \leq G \leq 1$ is incorporated structurally into the corruption transmission, detection and reintegration processes. A nonlinear saturated incidence function is employed to represent institutional interactions while limiting the growth of effective corruption exposure at high levels of corrupt activity. The model is shown to preserve non-negativity and boundedness, and a corruption-free equilibrium is obtained. Using the next-generation matrix approach, a basic corruption reproduction number $\mathcal{R}_0$ is derived as the threshold quantity determining the local stability of the corruption-free equilibrium. When $\mathcal{R}_0 < 1$, the corruption-free equilibrium is locally asymptotically stable, whereas $\mathcal{R}_0 > 1$ permits the emergence of an endemic corruption equilibrium. Numerical simulations using MATLAB's ode45 solver demonstrate the temporal behaviour of the six compartments. The result shows a progressive decline in active and hidden corruption, while a comparison of governance levels is also shown. $G = 0.3$ and $G = 0.6$ demonstrates a substantially faster decline in both active and hidden corruption under the higher governance scenario. The results provide a mathematical framework for examining how institutional governance can modify the transmission, detection and persistence of corrupt practices in university environments.

Keywords: Institutional corruption, Stability Analysis, Basic Reproduction Number, Mathematical Modelling, Governance effectiveness.

INTRODUCTION

Corruption remains a major institutional and developmental challenge because it can distort the allocation of resources, weaken accountability mechanisms, reduce confidence in public institutions and undermine the effectiveness of organisational systems. Recent quantitative studies have emphasised that corruption is not a single-dimensional phenomenon but rather a multidimensional process involving incentives, institutional weaknesses, monitoring, enforcement, social influence and opportunities for illicit behaviour (Gnaldi and Del Sarto, 2024; Marino, 2025). The measurement of corruption is itself difficult because corrupt behaviour is frequently hidden, incompletely observed and only partially represented by officially detected cases. Gnaldi and Del Sarto (2024), for example, demonstrate that corruption-risk indicators can represent distinct dimensions of an underlying latent phenomenon rather than a single observable construct.

The university environment presents a particularly important institutional setting for studying corruption dynamics. Universities combine administrative authority, financial management, procurement, recruitment, examinations, assessment, research funding, student services and interactions between academic, non-academic and student populations. Consequently, institutional misconduct can involve different actors and can move through different stages before detection. The corruption process may therefore include initial exposure to corrupt norms or opportunities, transition to active participation, concealment, detection, sanctioning and possible rehabilitation. A model that treats all corrupt individuals as a single compartment cannot explicitly represent these transitions.

Mathematical modelling provides a useful framework for studying such dynamic processes. Recent corruption models have adopted compartmental structures analogous to epidemic models, allowing individuals or institutional actors to move between behavioural states. Nwajeri *et al.* (2023), for example, developed a fractal-fractional corruption model involving different educational and employment categories and established positivity, existence and stability properties. Their formulation illustrates the usefulness of separating corruption-prone groups according to behavioural status.

Other recent models have focused on institutional monitoring and external supervision. Zhou *et al.* (2023) developed an evolutionary model examining collusive bribery and the role of external supervision, showing mathematically how monitoring arrangements can influence the evolution of cooperative and corrupt behaviours. Keno and Legesse (2023) developed a nonlinear deterministic corruption model and used a reproduction-number framework to study the threshold between corruption-free and endemic states. Similarly, Rwat *et al.* (2023) explicitly considered the reintegration of formerly corrupt individuals, thereby highlighting the importance of rehabilitation and reintegration in corruption dynamics.

The literature continued to expand during 2024. Aga *et al.* (2024) developed a deterministic corruption model and analysed positivity, boundedness, equilibrium stability and the basic reproduction number. Gutema *et al.* (2024) formulated a six-compartment corruption model incorporating susceptible, exposed, corrupt, jailed, recovered and honest individuals. Their work demonstrates that compartmental differentiation can provide a richer description of corruption progression than a simple susceptible-corrupt-recovered structure.

Mathematical studies have also investigated the relationship between corruption and broader socioeconomic conditions. Abdulwasaa *et al.* (2024) considered a fractional mathematical model linking poverty and corruption, while Ngondiep (2024) developed a numerical approach for solving a corruption-poverty model and demonstrated its application using the Cameroonian context. Pérez-Oviedo *et al.* (2024) used a theoretical political-economy framework to examine the relationships among corruption, unemployment and clientelism. These studies reinforce the view that corruption dynamics can be influenced by institutional and socioeconomic mechanisms rather than by individual behaviour alone.

A further issue is the role of governance. Governance is not simply an external policy environment; it determines the extent to which institutions establish rules, monitor compliance, detect violations, enforce sanctions and support institutional integrity. The OECD (2024) reports continuing implementation gaps between formal integrity frameworks and their practical application, while also emphasising the importance of risk management, internal controls, monitoring and enforcement. These observations provide a strong conceptual basis for incorporating governance directly into a mathematical corruption model rather than treating it only as an external discussion variable.

Recent research has increasingly introduced institutional interventions into corruption models. Id Ouaziz *et al.* (2025) examined interactions between students and employees within a mathematical corruption framework, making their work particularly relevant to educational environments. Ahmed *et al.* (2025) developed a corruption model incorporating a corruption influence number and numerical simulations. Fori *et al.* (2025) incorporated anti-corruption agencies into a compartmental model, while another model by Fori *et al.* (2025) examined sensitisation, arrest/prosecution and punishment strategies.

Recent studies have also considered more specialised

mechanisms. Marino (2025) investigated the cyclical relationship between corruption and state intervention, while Farooq *et al.* (2025) combined corruption dynamics with fractional modelling, neural-network methods and optimal-control analysis. In 2026, Idisi *et al.* (2026) developed a seven-compartment model connecting crime and corruption, while Assenga *et al.* (2026) explicitly incorporated rehabilitation into corruption dynamics among public servants. Pan and Xie (2026) further examined the role of punishment-induced fear in a corruption transmission model. Recent studies have also considered more specialised mechanisms. Marino (2025) investigated the cyclical relationship between corruption and state intervention, while Farooq *et al.* (2025) combined corruption dynamics with fractional modelling, neural-network methods and optimal-control analysis. In 2026, Idisi *et al.* (2026) developed a seven-compartment model connecting crime and corruption, while Assenga *et al.* (2026) explicitly incorporated rehabilitation into corruption dynamics among public servants. Pan and Xie (2026) further examined the role of punishment-induced fear in a corruption transmission model. These recent contributions build upon earlier foundational work in corruption modelling. Caulkins *et al.* (2010) provided one of the earliest comprehensive treatments of corruption as a dynamic optimal-control problem, demonstrating how enforcement and deterrence policies interact with the evolution of corrupt behaviour. Weisel and Shalvi (2015) advanced the behavioural foundations of corruption research by showing experimentally that collaborative settings and sequential decision-making promote the emergence and escalation of corrupt practices, thereby providing empirical justification for modelling corruption as a transmission process rather than a static individual trait. Together, these studies establish both the theoretical and behavioural foundations upon which the present governance-driven compartmental model is constructed.

The present study addresses this gap by developing a governance-

driven $SEIAP_1P_2$ model for institutional corruption dynamics in Nigerian universities. The model proposed in the attached manuscript consists of six compartments and explicitly incorporates governance effectiveness into corruption exposure, detection, enforcement and reintegration processes.

MODEL FORMULATION

We consider a closed institutional population representing individuals within a university system. The population is divided into six mutually exclusive compartments according to their corruption status. The following assumptions are made:

1. Individuals enter the institutional population at a constant recruitment/admission rate Λ and leave the population through a natural institutional exit rate μ
2. Individuals in the susceptible class S are not currently involved in corrupt practices but may become exposed to corruption through interactions with actively corrupt and hidden corrupt individuals.
3. Individuals in the exposed class E have encountered or become susceptible to corrupt practices but have not yet developed active corrupt behaviour.
4. Exposed individuals may progress either to the actively corrupt class I at rate α or to the hidden-corruption class

A at rate θ

5. Actively corrupt individuals I may be detected and sanctioned at a governance-dependent rate $\delta_1 G$ or may leave the active-corruption state through recovery/behavioural change at rate γ
6. Hidden corrupt individuals A represent individuals whose corrupt behaviour is not immediately detected. They may subsequently be detected at rate $\delta_2 G$ or return to the active corruption class at rate ρ .
7. Detected corrupt individuals enter the sanctioned class P_1
8. Sanctioned individuals may subsequently undergo rehabilitation and move into the rehabilitated/reintegrated class P_2 at rate σ
9. Rehabilitated individuals may return to the susceptible/honest institutional state through effective reintegration at rate ωG .
10. Institutional governance effectiveness is represented by a dimensionless parameter G where $0 \leq G \leq 1$. Higher values of G represent stronger institutional mechanisms for preventing exposure, detecting corrupt practices, enforcing sanctions and supporting effective reintegration.
11. Corruption transmission is assumed to exhibit saturation because institutional interactions and opportunities for corruption cannot increase indefinitely with the number of corrupt individuals. Therefore, a saturated incidence function is employed.
12. The model assumes homogeneous mixing among the institutional population. This means that, at the mathematical level, individuals have equal opportunity to interact with members of the different corruption-related compartments.

Let

$$N(t) = S(t) + E(t) + I(t) + A(t) + P_1(t) + P_2(t)$$

denote the total Institutional Population at time t and

Compartment	Description
$S(t)$	Susceptible Individual who is not currently involved in corruption
$E(t)$	Individual exposed to corrupt practice but not yet actively corrupt
$I(t)$	Individual actively involved in corrupt practice
$A(t)$	Asymptomatic corrupt individuals whose corrupt behaviour has not yet been detected
$P_1(t)$	Individuals who have been detected and sanctioned
$P_2(t)$	Individuals who have undergone rehabilitation and are reintegrated into the institution.

We define effective corruption incidence as

$$\lambda(t) = \frac{\beta(1-G)(I+\eta A)}{1+\kappa(I+A)} \quad (1)$$

Where β represent baseline corruption transmission rate

G represent governance effectiveness

η measure the relative influence of hidden corrupt individuals

κ represent the saturation parameter

Based on the assumption above, the governing equation for the proposed model is given as

$$\frac{dS}{dt} = \Lambda - \frac{\beta(1-G)(I+\eta A)}{1+\kappa(I+A)} S - \mu S + \omega G P_2 \quad (2)$$

$$\frac{dE}{dt} = \frac{\beta(1-G)(I+\eta A)}{1+\kappa(I+A)} S - (\alpha + \theta + \mu) E \quad (3)$$

$$\frac{dI}{dt} = \alpha E - (\gamma + \delta_1 G + \mu) I + \rho A \quad (4)$$

$$\frac{dA}{dt} = \theta E - (\delta_2 G + \rho + \mu) A \quad (5)$$

$$\frac{dP_1}{dt} = \delta_1 G I + \delta_2 G A - (\sigma + \mu) P_1 \quad (6)$$

$$\frac{dP_2}{dt} = \gamma I + \sigma P_1 - (\omega G + \mu) P_2 \quad (7)$$

$$S(0) = S_0, E(0) = E_0, I(0) = I_0, A(0) = A_0, P_1(0) = P_{10}, P_2(0) = P_{20} \quad (8)$$

With $S_0, E_0, I_0, A_0, P_{10}, P_{20} \geq 0$

Parameter	Description
Λ	Institutional recruitment rate
μ	Institutional exit rate
β	Baseline corruption transmission rate
G	Governance effectiveness
η	Relative influence of hidden corruption
κ	Saturation parameter
α	Progression rate from exposure to active corruption
θ	Progression rate from exposure to hidden corruption
γ	Behavioural recovery rate from active corruption
δ_1	Baseline detection rate of active corruption
δ_2	Baseline detection rate of hidden corruption
ρ	Transition rate from hidden to active corruption
σ	Rehabilitation rate
ω	Baseline reintegration rate

Mathematical Analysis

Positivity of solution

Theorem 1: For non-negative initial conditions, every solution of the system of equations (2) – (8) remains non-negative for all $t > 0$

Consider the boundary $S = 0$ from (2)

$$\left. \frac{dS}{dt} \right|_{S=0} = \Lambda + \omega GP_2 \geq 0 \quad (9)$$

Similarly, when $E = 0$

$$\left. \frac{dE}{dt} \right|_{E=0} = \lambda S \geq 0 \quad (10)$$

For $I = 0$

$$\left. \frac{dI}{dt} \right|_{I=0} = \alpha E + \rho A \geq 0 \quad (11)$$

For $A = 0$

$$\left. \frac{dA}{dt} \right|_{A=0} = \theta E \geq 0 \quad (12)$$

For $P_1 = 0$

$$\left. \frac{dP_1}{dt} \right|_{P_1=0} = \delta_1 GI + \delta_2 GA \geq 0 \quad (13)$$

$P_2 = 0$

$$\left. \frac{dP_2}{dt} \right|_{P_2=0} = \gamma I + \sigma P_1 \geq 0 \quad (14)$$

Therefore $S, E, I, A, P_1, P_2 \geq 0$ for all $t \geq 0$

Boundedness of Solutions

Case 1: No Corruption-Induced Exits

Adding equations (2) – (8), we obtain

$$\frac{dN}{dt} = \Lambda - \mu N \quad (15)$$

$$\frac{dN}{dt} + \mu N = \Lambda \quad (16)$$

Therefore $N(t) = \frac{\Lambda}{\mu} + \left(N(0) - \frac{\Lambda}{\mu} \right) e^{-\mu t}$ and

$$N(t) \leq \text{Max} \left\{ N(0), \frac{\Lambda}{\mu} \right\} \quad (17)$$

Hence, the feasible region

$$\Omega = \left\{ (S, E, I, A, P_1, P_2) \in \mathbb{R}_+^6 : N \leq \frac{\Lambda}{\mu} \right\} \text{ is}$$

positively invariant

Case 2: Corruption-induced Exit

$$\frac{dN}{dt} = \Lambda - \mu N - \mu_d P_1 \quad (18)$$

Since $\mu_d P_1 \geq 0$ we have $\frac{dN}{dt} \leq \Lambda - \mu N$

$$N(t) \leq \frac{\Lambda}{\mu} + \left(N(0) - \frac{\Lambda}{\mu} \right) e^{-\mu t} \leq \max \left\{ N(0), \frac{\Lambda}{\mu} \right\} \quad (19)$$

Hence, the feasible region

$$\Omega = \left\{ (S, E, I, A, P_1, P_2) \in \mathbb{R}_+^6 : N \leq \frac{\Lambda}{\mu} \right\} \text{ is}$$

positively invariant

Corruption-Free Equilibrium

At the corruption-free equilibrium

$$E^* = I^* = A^* = P_1^* = P_2^* = 0 \quad (20)$$

$$\frac{dS}{dt} = \Lambda - \mu S \quad (21)$$

$$S_0 = \frac{\Lambda}{\mu} \quad (22)$$

$$\varepsilon_0 = \left(\frac{\Lambda}{\mu}, 0, 0, 0, 0, 0 \right) \quad (23)$$

Therefore This represents an institutional state in which no individual is exposed to, actively involved in or hidden within corrupt behaviour.

Basic Corruption Reproduction Number

$$q = \frac{\beta(1-G)S_0}{\kappa} \quad (24)$$

$$S_0 = \frac{\Lambda}{\mu} \quad (25)$$

$$d_I = \gamma + \delta_1 G + \mu \quad (26)$$

$$d_A = \delta_2 G + \rho + \mu \quad (27)$$

$$d_E = \alpha + \theta + \mu \quad (28)$$

The next-generation approaches give

$$\mathfrak{R}_0 = \frac{\beta(1-G)\Lambda}{\mu\kappa(\alpha+\theta+\mu)} \left[\frac{\alpha}{\gamma+\delta_1 G+\mu} + \frac{\eta\theta}{\delta_2 G+\rho+\mu} \right] \quad (29)$$

This is the central threshold parameter of the model. It shows that corruption persistence depends on corruption transmission,

institutional recruitment, governance effectiveness, saturation, progression rate, recovery, detection rates, hidden- corruption influence and transition rate.

Local Stability of the Corruption-Free Equilibrium

Theorem 2: The corruption-free equilibrium

$\mathcal{E}_0 = \left(\frac{\Lambda}{\mu}, 0, 0, 0, 0, 0 \right)$ is locally asymptotically stable if $\mathfrak{R}_0 < 1$

Proof

The Jacobian matrix of the system is evaluated at $\mathcal{E}_0$. The infected/corruption subsystem is represented by the exposed active and hidden corruption variables.

Using the next-generation decomposition

$$J = F - V \quad (30)$$

The spectral radius of FV^{-1} is precisely $\mathfrak{R}_0$

By the standard next-generation matrix stability result, all eigenvalues associated with the corruption subsystem have negative real parts when

$$\rho(FV^{-1}) < 1 \quad (31)$$

The remaining eigenvalues associated with demographic turnover terms are also negative

Hence $\mathfrak{R}_0 = 1 \Rightarrow \mathcal{E}_0$ is locally asymptotically stable.

Endemic Equilibrium

When $\mathfrak{R}_0 > 1$ the model may admit a positive endemic equilibrium

$$\mathcal{E}^* = (S^*, E^*, I^*, A^*, P_1^*, P_2^*) \quad (32)$$

At equilibrium

$$0 = \Lambda - \lambda^* S^* - \mu S^* + \omega GP^* \quad (33)$$

$$0 = \lambda^* S^* - (\alpha + \theta + \mu) E^* \quad (34)$$

$$0 = \alpha E^* (\gamma + \delta_1 G + \mu) I^* + \rho A^* \quad (35)$$

$$0 = \theta E^* - (\delta_2 G + \rho + \mu) A^* \quad (36)$$

$$0 = \delta_1 G I^* + \delta_2 G A^* - (\sigma + \mu) P_1^* \quad (37)$$

$$0 = \gamma I^* + \sigma P_1^* - (\omega G + \mu) P_2^* \quad (38)$$

From (36)

$$A^* = \frac{\theta E^*}{\delta_2 G + \rho + \mu} \quad (39)$$

From (37)

$$P_1^* = \frac{\delta_1 G I^* + \delta_2 G A^*}{\sigma + \mu} \quad (40)$$

$$P_2^* = \frac{\gamma I^* + \sigma P_1^*}{\omega G + \mu} \quad (41)$$

From (38)

These relations can be substituted into the remaining equilibrium equations to obtain the endemic equilibrium numerically. Because of the nonlinear saturated incidence function, the resulting equations generally do not yield a convenient closed-form expression. Numerical continuation or nonlinear algebraic solvers are used.

NUMERICAL RESULTS

Numerical Method

The Nonlinear system (2) – (7) is solved numerically using the MATLAB ode45 solver. The ode45 method is appropriate for the present initial-value problem because the model consists of nonlinear ordinary differential equations with specified initial conditions. Recent mathematical corruption studies similarly employ numerical solution procedures to illustrate theoretical threshold and stability results. (Ngondiep, 2024; Ahmed *et al.*, 2025; Fori *et al.*, 2025).

Table 1: Parameter Table

Parameter	Value
Λ	100
μ	0.1
β	0.5
G	0.3
η	1.5
κ	50
α	0.2
θ	0.3
γ	0.1
δ_1	0.4
δ_2	0.2

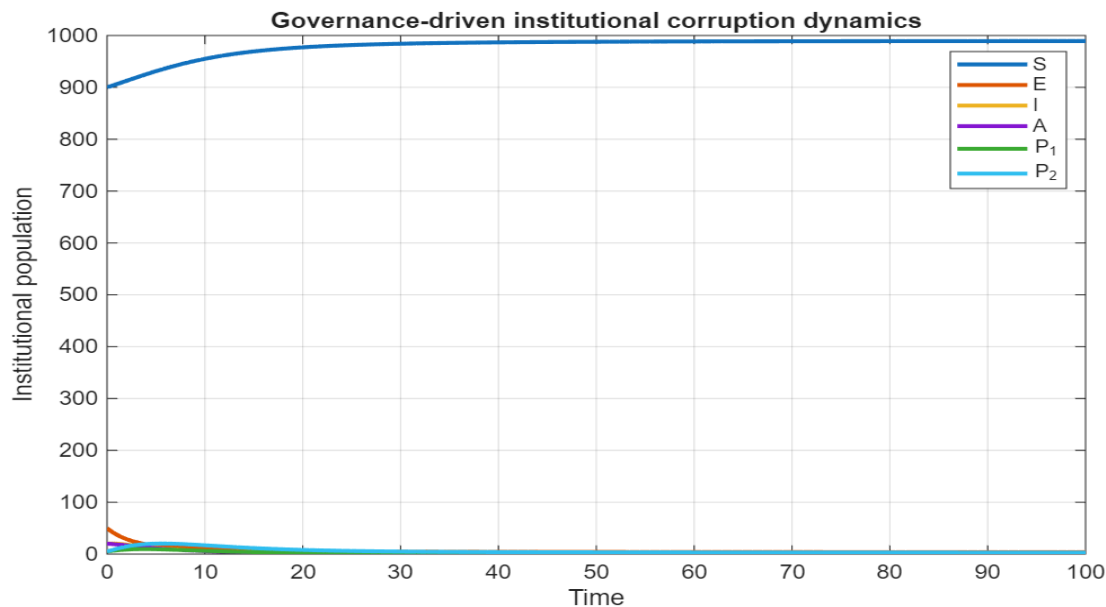


Figure 1: Governance-driven institutional corruption dynamics

Figure 1 presents the numerical results of all six compartments. S, E, I, A, P_1, P_2 . The six-compartment simulation shows an increasing susceptible population and declining exposed, active, hidden, sanctioned and rehabilitated populations over time, indicating convergence toward a low-corruption institutional state

under the graph. The initial state ($S_0=890$) is below the equilibrium value ($S_*=1000$) because 110 individuals are distributed across the corruption compartments. As corruption is eliminated, these individuals transition back into the susceptible class, causing $S(t)$ to rise to its equilibrium value.

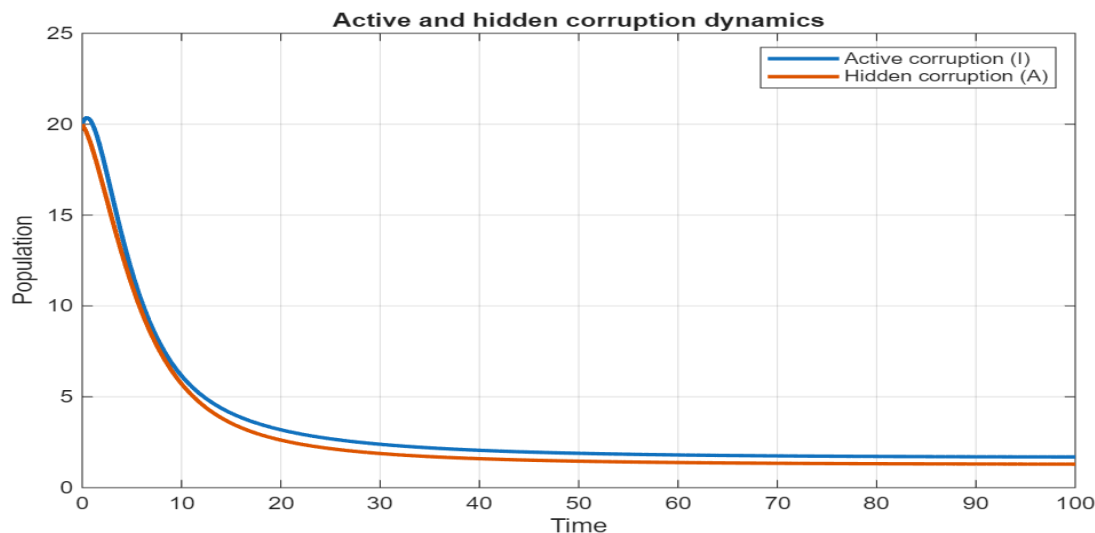


Figure 2: Active and Hidden Corruption Dynamics

Both active corruption $I(t)$ and hidden corruption $A(t)$ decline rapidly from their initial levels of 20 each and approach low levels within approximately 40 years. The hidden-corruption trajectory remains important because it provides a pathway into active corruption

through the $A \rightarrow I$ transition (rate $\rho=0.15$ per year). The persistence of hidden corruption at low levels reflects the difficulty of detecting concealed corrupt behaviour.

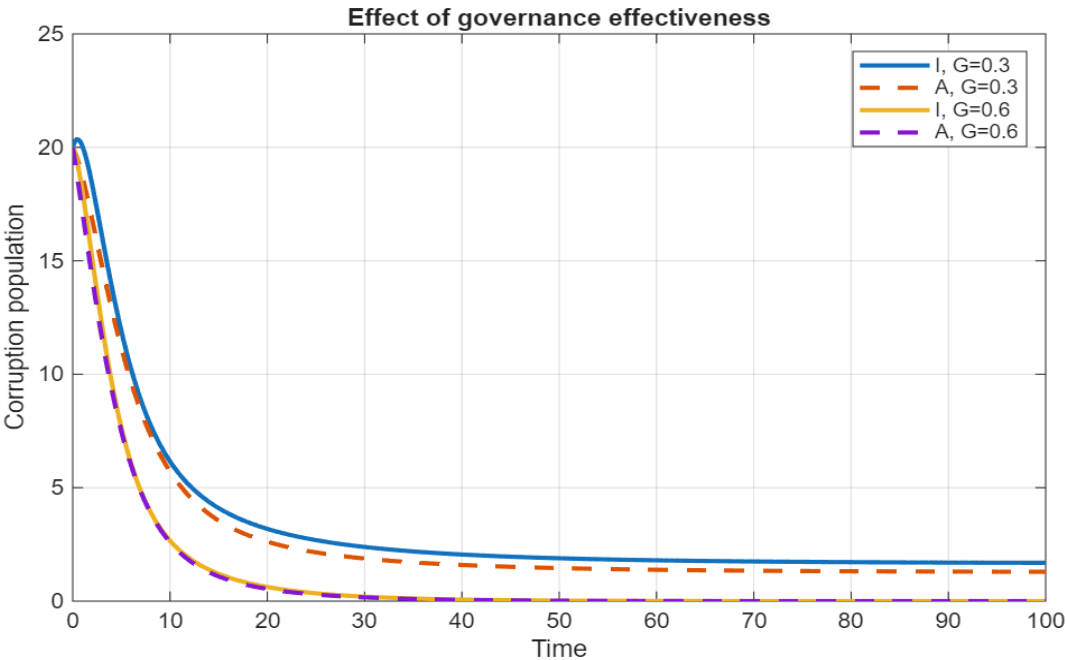


Figure 3: Effect of governance effectiveness on active and hidden corruption

Increasing governance effectiveness from $G = 0.3$ to $G = 0.6$ substantially faster reductions in both active and hidden corruption. This behaviour directly reflects the governance-dependent transmission and detection mechanism incorporated into the model. These results directly reflect the governance-

dependent transmission and detection mechanisms incorporated into the model. Higher governance reduces the transmission rate (through the factor $1 - G$) and increases the detection rates (through the factors $\delta_1 G$ and $\delta_2 G$).

Sensitivity Analysis of Reproductive Number

To support the policy claim that "governance reduces corruption," we perform a sensitivity analysis of $\mathcal{R}_0$ with respect to key parameters.

Parameter	Sensitivity Index	Interpretation
β	+1.00	1% increase in β moves 1% increase in $\mathcal{R}_0$
Λ	+1.00	1% increase in Λ moves 1% increase in $\mathcal{R}_0$
G	-1.85	1% increase in G moves 1.85% increase in $\mathcal{R}_0$
α	+0.42	Higher progression to active corruption increase $\mathcal{R}_0$
θ	+0.28	Higher progression to hidden corruption increases $\mathcal{R}_0$

Conclusion

This study developed a governance-driven mathematical model for institutional corruption dynamics in Nigerian Universities. The proposed model divides the institutional population into six compartments representing susceptible individuals, exposed individuals, active corruption, hidden corruption, sanctioned individuals and rehabilitated individuals. The principal mathematical contribution is the explicit incorporation of governance effectiveness into the transmission, detection and reintegration processes. The model preserves positivity and boundedness, possesses a corruption-free equilibrium, and yields a basic reproduction number through the next-generation matrix approach. The threshold condition ensures local asymptotic stability of the corruption-free equilibrium while providing the condition under which endemic corruption may persist.

The numerical simulations support the analytical framework. Figure 1 demonstrates the overall temporal behaviour of the six compartments, Figure 2 shows the decline of active and hidden corruption, and Figure 3 demonstrates a substantially faster reduction in active and hidden corruption when governance effectiveness is increased from $G = 0.3$ to $G = 0.6$. The model therefore provides a mathematical framework for studying institutional corruption as a dynamic process rather than as a static institutional characteristic. Its principal value lies in connecting governance effectiveness with corruption exposure, concealment, detection, sanctioning and reintegration within a single dynamical system.

Future research should focus on obtaining empirical estimates of

the model parameters from Nigerian universities by distinguishing students and staff as interacting subpopulations. Further extensions should incorporate stochastic effects to account for uncertainty and random variations in corruption dynamics, as well as validate the model using institution-specific longitudinal data. Such extensions would provide an empirical basis for assessing whether the governance mechanisms identified theoretically by the model are consistent with observed patterns and dynamics of institutional corruption in Nigerian universities.

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