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The Impact of Financial Sustainability and Structural Transformation on Investments using QARDL Model Optimized by the Marine Predator Algorithm

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ABSTRACT

The present article explores the asymmetric dynamic effects of fiscal sustainability and structural transformation on the private investment in Iraq over the timeframe (2008-2025) in a QARDL model optimized by Marine Predators Algorithm (MPA). The approach incorporates the use of MPA to improve on the efficiency of best lag choice followed by the estimation of the parameters to overcome non-convexity in the quantile loss function. The findings indicate asymmetric cointegration and a fiscal crowding out in both senses, and in both the structural transformation is revealed as the major source of driving in the low-credit period. The findings indicate that the emerging investments are very susceptible to inflation and parallel exchange rate shocks and therefore require specific monetary interventions. The paper suggests the use of the QARDL-MPA due to the high ability to predict nonlinear time series in economically uncertain settings.

1. Introduction

Complex econometric models are quite difficult to estimate, especially when considering the combination of several statistical models that are intended to accommodate different aspects of economic relationships.

The Quantile Autoregressive Distributed Lag (QARDL) model is a highly developed model; a combination of the benefits of quantile regression and the dynamic ability of ARDL specifications. Although this hybrid method offers superior informational advantages on the asymmetric relationships throughout the conditional distribution of the economic variables, QARDL parameter estimation is still computationally expensive. This is mainly because the quantile objective function is not differentiable and the parameter space is high dimensional in nature common in empirical applications.

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There is a long history of using linear programming and iteration techniques to develop traditional estimation methods of QARDL models. Though theoretically these techniques tend to face convergence problems, in many situations where the underlying optimization problem has multiple local optima or when samples are small compared to the number of parameters, they are highly likely to fail. Such constraints are further compounded in the developing countries where the constraint of data availability requires sparse but parameter intensive specifications to disclose both the short-long term effects on a set of quantiles.

One way of providing a solution to such estimation challenges is the Marine Predators Algorithm (MPA). This metaheuristic algorithm is shown to have an impressive level of skill in solving highly complicated optimization problems by balancing strategic search (exploration, searching new areas) and exploitation (refining promising solutions). The algorithm is based on the foraging behaviour of natural predators in the oceans, namely the switch between the Levy flight behaviour in low-density prey regions and the Brownian motion behaviour in high-density regions. The algorithm is inspired by these natural foraging strategies and the resulting algorithm is converted to mathematical operators that efficiently explore the parameter space of the econometric models.

Iraqi economy is an excellent case study when it comes to this methodology. The 2008-2025 periods are highly volatile due to the high resource dependence ratio and the volatility of the revenues of investments during oil price variations, and they are characterized by various economic cycles caused by geopolitical instability, reconstruction, and shocks in the world economy. The insights into the variability of investment behavior as the distribution of its conditional and how it reacts to fiscal sustainability, structural change, and macroeconomic controls are critical implications of the evidence-based policymaking.

In [8]. introduced an integrated methodology of QARDL on the basis of Quantile Loss Function as a key estimation principle.This procedure was further developed by [11] by using a parametrically augmented approach to overcome autocorrelation in financial chains.

[20] proposed a likelihood-based estimation framework based on the EM (Expectation-Maximization) algorithm at the start of the present decade, which allows a superior fit of the model when analysing dynamics of various variables.[19] were concerned with the efficiency of QARDL estimation to identify structural shocks, and [9] reviewed lag order determination algorithms to make sure that the boundary tests are efficient.

In [21] used a standard quantum regression algorithm to track the location and size impact, whereas [20] introduced a quantum error correction parameter methodology to examine the impact of dynamical shocks .In [6] outlined the use of a Metropolis-within-Gibbs algorithm to the purpose of the Bayesian estimation of values, which is a highly successful algorithm in managing the effect of complex spatial and time and [15] reviewed the ultra fast Mata algorithm to select exemplary lags. However, in the meantime,[18] concentrated on an improved parametric estimation that incorporates Wald tests in statistical parameter trade-offs, which led to the study conducted by [22] who used the iterative estimation technique when estimating quantities.

The Research Contribution The main value of this study is that he introduces a hybrid model of analysis, which is a combination of the classical model of QARDL and Marine Predator Algorithm (MPA). Its novelty is that the algorithm is a two-fold weapon that is used to select the optimum lag and optimize the global parameters.

2. The Quantile Autoregressive Distributed Lag Model (QARDL)

QARDL model is a kind of integration of the dynamic ARDL model and quantitative regression, which helps to analyse the relationship between the variables at two different levels: a long-term level that takes account of the long-term stable relations between variables and a short-term level that takes into consideration the short-term and immediate impact of economic shocks and changes.

This is a distinctive model where it does not restrict itself to the analysis of relationships at the mean level like the traditional models, instead, it goes deeper to give an overall analysis of the relationships at various quantitative levels of the statistical distribution. This implies that one can appreciate the influence of independent variables on the dependent variable at varying levels of data that are low, medium, and high thus giving a better and combined picture of underlying economic processes.

This serves the purpose of having a better insight into the asymmetry of economic relations in various sections of the distribution.

We can define the independent variable changes over the time interval t in such a way that the dependent variable Y varies depending on a combination of a number of interrelated factors which affect at different levels of time.

The equation of state (QARDL) has order (p,q) with error correction model (ECM), and it can be obtained as the following equation [8] in general:

$$\triangle Y_t = \alpha(\tau) + \rho(\tau)[Y_{t-1} - \theta(\tau)X_{t-1}] + \sum_{i=1}^{p-1} \gamma_i(\tau) \triangle Y_{t-i} + \sum_{i=0}^{q-1} \delta_i(\tau) \triangle X_{t-i} + \epsilon_t(\tau) \quad ...(1)$$

Where the first part $\rho(\tau)[Y_{t-1} - \theta(\tau)X_{t-1}]$ refers to a crucial component for understanding long-term relationships between variables, It contains two essential elements that work together to determine the system's long-term behaviour.

The first element is the term $[Y_{t-1} - \theta(\tau)X_{t-1}]$ which represents the equilibrium difference or error in the long-term relationship. When the system deviates from its stable equilibrium path, this difference appears and takes on a positive or negative value depending on the nature of the deviation. The second element is $\rho(\tau)$, which represents the speed of adjustment. This coefficient must be negative and statistically significant to ensure the existence of a self-correction mechanism that gradually returns the system to equilibrium after any shock or disturbance.

The second part $\sum_{i=1}^{p-1} \gamma_i(\tau) \triangle Y_{t-i} + \sum_{i=0}^{q-1} \delta_i(\tau) \triangle X_{t-i}$ represents the short-term and immediate effects between variables.

$\sum_{i=1}^{p-1} \gamma_i(\tau) \triangle Y_{t-i}$, measures the relationship between current changes in the dependent variable and previous changes in it, allowing for autocorrelation in the series of differences.

Also $\sum_{i=0}^{q-1} \delta_i(\tau) \triangle X_{t-i}$,, measures the direct effect of changes in the independent variables on the change in the dependent variable. Both sets capture short-term dynamics whose effects end after a specific period.

Y_t: The endogenous variable, or dependent variable, is the variable whose changes and fluctuations over time are being explained. The symbol ΔYt represents the initial difference of this variable, which is calculated mathematically using the relationship ΔYt $= Y_t - Y_{t-1}$-, where Y_{t-1} represents the value of the variable in the previous time period. Transforming a variable into initial differences is a fundamental statistical procedure aimed at achieving stationarity, or statistical stability. Many economic variables are unstable at their initial level but become stable when differences are taken into account.

τ : Taking values in the interval (0,1) is one of the most important distinguishing features of this model, as it represents the quantile index, or what is known as the quantity level. This symbol indicates that all the model's coefficients are not constant values across the entire statistical distribution, but rather are functions that change with the quantile level of the dependent variable. This variation in coefficients across different quantile levels allows us to reveal the phenomenon of asymmetry in economic relationships.

$\alpha(\tau)$: The constant or secant for each quantile level represents the portion of the dependent variable's change that is not explained by the explanatory variables included in the model at that specific level of the distribution. This constant varies with the values of the τ.

$\theta(\tau)$: The long-term effect of independent variables.

$\gamma_i(\tau), \delta_i(\tau)$: The impact of current and past fluctuations in the short term.

$\epsilon_t(\tau)$: is an i.i.d with finite variance.

2.1 Assumption for the QARDL

To ensure the regularity properties, consistency, and asymptotic normality of the QARDL estimators, the following assumptions are imposed, consistent with the framework developed by **[8]**:

1- Error Process and Distribution is assumed to be an independently and identically distributed process with a continuous probability density function and cumulative distribution function It is required that $f(.) > 0$ to ensure the identification of τ^{th} quantile.

2- Properties of Regressors, The vector f regressors X_t is $k \times 1$vector of integrated processes, where its first difference $\triangle X_t$ is a general linear multivariate stationary and ergodic process with E $\triangle X_t = 0$ and finite variance.

3- Strict Exogeneity and Independence For each quantile $\tau\epsilon(0,1)$ the stochastic component $\epsilon_t(\tau)$ is independent of the regressors X_s for all t,s. This condition ensures that the model is free from endogeneity bias and allows for the accurate identification of the parameters.

4- Dynamic Stability Condition, the roots of the autoregressive polynomial are assumed to lie outside the unit circle for every $\tau\epsilon(0,1)$

5- Identification of Quantile Restrictions, the conditional τ^{th} quantile of the error term is assumed to be zero.

2.2 Marine Predators Algorithm (MPA)

The algorithm was initially introduced by [10], It is based on the natural principles of how the foraging behavior of marine predators, like sharks, tuna, and marlin is organized. MPA has a range of advantages that enable it to be statistically, geometrical superior:

A) Exploration and Exploitation Balance: The algorithm systematic combines Levy movements (to explore widely) with Brownian Motion movements (to exploit locally).

B) Fish Aggregation Effect (FADs): The algorithm replicates the behavior of predators around fish aggregation devices, which assist in preventing local optimum.

C) Marine Memory: The algorithm is able to remember places where successful fishing has occurred in the past and this increases its convergence to an optimal solution.

Within a number of aspects, MPA has shown exceptional excellence. It was applied to forecast the COVID-19 cases by [3] and the findings indicated that the algorithm is statistically accurate than the traditional algorithms, which indicates how the algorithm can process volatile and unstable data over time. It was also used by [1] in the selection of features, where binary versions of the algorithm were efficiently used to reduce the graphical size without compromising the accuracy of classification as an extremely important feature of contemporary statistical modelling. Perhaps in an almost recent study, [4] integrated MPA and other algorithms to enhance the choice of genes in complex health issues by stating that the introduction of the philosophy of the Levy and Brownian to the algorithm provides an advantage in processing high-dimensional data.

The reason we have chosen the MPA algorithm in our study is the statistical findings reported by [5] in their comparative analysis that validated the fact that MPA has a very high rate of convergence and can be used to find optimal solutions in conditions with the so-called random-generated landscapes, which is also aligned with the characteristics of the complex statistical data the present study is working with.

The algorithm is based on two fundamental theories:

1- **Levy Flight:** Describes the movement of organisms in a prey-scarce environment, where they follow long, random steps for exploration**,** where the Mantegna's algorithm method for generating random numbers based on Levy distribution.

$$Levy(\alpha) = 0.05 * \frac{x}{|y|^{\frac{1}{\alpha}}} \qquad ...(2)$$

$$x \sim N(0, \sigma_x^2), \qquad y \sim N\left(0, \sigma_y^2\right),$$

$$\sigma_y^2 = 1\,, \qquad \alpha = 1.5$$

$$\sigma_x = \left[\frac{gamma(1+\alpha)\sin(\frac{\pi\alpha}{2})}{gamma((1+\alpha)/2)\alpha 2^{\frac{\alpha-1}{2}}}\right]$$

2- **Brownian Motion:** A regular, random movement with nearly equal steps. Predators use this when prey is plentiful, following short steps for local exploitation. From the probability function defined by N Gaussian distribution $(M = 0, \sigma^2 = 1)$

2.3 Mathematical representation of the algorithm

1- Initialization the prey and elite arrays as follows:

$$\text{Prey} = \text{x} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} \\ \vdots & \vdots & \vdots \\ x_{n,1} & \cdots & x_{n,d} \end{bmatrix}_{n\times d}$$

n: Number of search elements (prey).

d: Number of dimensions (variables to be improved).

$x_{i,j}$: The element's value in dimensions i and j.

$$x_{i,j} = x_j^{min} + r * \left(x_j^{max} - x_j^{min}\right), \quad r \sim U(0,1) \qquad \text{... (3)}$$

Next, we select the most suitable solution to be the top predator to build an array called the elite. The arrays within this array oversee the search for and locating prey based on information about its location**.**

$$Elite = \begin{bmatrix} x_{best,1} & \cdots & x_{best,d} \\ \vdots & \vdots & \vdots \\ x_{best,1} & \cdots & x_{best,d} \end{bmatrix}_{n\times d}$$

2-Velocity setting and location update

The algorithm relies on the velocity ratio between predator and prey, and since any intelligent search operation requires moving between exploration and exploitation, the algorithm is divided into three phases as follows:

Phase1: High-Velocity Ratio or when predator is moving faster than prey

This stage occurs in the first third of the total number of repetitions $\left(Iter < \frac{1}{3}\max iter\right)$ for the purpose of (exploration). The step size is then calculated using the following formula:

$$StepSize_i = R_B \otimes (Elite_i - R_B \otimes x_i) \qquad \text{... (4)}$$

$$x_i^{new} = x_i + \text{P}.\text{R} \otimes StepSize_i \qquad \text{... (5)}$$

R_B : is a vector containing random numbers based on Normal distribution representing the Brownian Motion, and the notation ⊗ shows entry-wise multiplications.

The multiplication of R_B by prey simulates the movement of prey. P=0.5 is a constant number, and R is a vector of uniform random numbers in [0,1]. This scenario happens in the first third of iterations when the step size or the velocity of movement is high for high exploration ability.

$iter$: is the current iteration while $\max iter$ is the maximum one.

Phase 2: In Unit-Velocity ratio or when both predator and prey are moving at the same pace. A balance between exploration and exploitation occurs in the middle third of the iterations $\left(\frac{1}{3}\max Iter < Iter < \frac{2}{3}\max Iter\right)$. At this stage, the population is divided into two halves; The first half is explored using Lévy with a step size:

$$Stepsize_i = R_L \otimes (Elite_i - R_L \otimes x_i) \qquad \text{... (6)}$$

$$x_i^{new} = x_i + P.R \otimes Stepsize_i$$

Where, R_L: is a vector of random numbers based on Lévy distribution representing Lévy movement. The multiplication of R_L and Prey simulates the movement of prey in Lévy manner while the step size to prey position simulates the movement of prey. Since most of the Lévy distribution step size is associated with small steps, this section is helping to exploitation.

For In the second half, exploitation is based on Brownian motion with a step size:

$$Stepsize_i = R_B \otimes (Elite_i - x_i) \qquad \text{... (7)}$$

$$x_i^{new} = Elite_i + P.CF \otimes Stepsize_i$$

While, $CF = \left(1 - \frac{Iter}{Max_{Iter}}\right)^{2 \cdot \frac{Iter}{Max_{Iter}}}$ is considered as an adaptive parameter to control the step size for predator movement, this coefficient gradually decreases with the progression of iterations, reducing the step size and improving local exploitation.

Multiplication of R_B and Elite simulates the movement of predators in Brownian manner while prey updates its position based on the movement of predators in Brownian motion.

Phase 3: In Low-Velocity Ratio or when predator is moving faster than prey. This scenario happens in the last phase of the optimization process which is mostly associated with high exploitation capability $Iter \geq \frac{2}{3}.\max iter$

$$Stepsize_i = R_L \otimes (R_L \otimes Elite_i - x_i) \qquad \text{... (8)}$$

$$x_i^{new} = Elite_i + P.CF \otimes Stepsize_i$$

3-Fish Aggregating Devices (FADs Effect)

To avoid falling into localized solutions, a mechanism simulating the fish-gathering device effect is added:

$$x_i^{new} = \begin{cases} x_i + CF.[x_{min} + R \otimes (x_{max} - x_{min})] \otimes U\ , & if\ r \leq FADs \\ x_i + [FDA_S(1-r) + r].(x_{r1} - x_{r2})\ , & if\ r > FADs \end{cases} \quad ...(9)$$

Where **FADs=0.2:** is the probability of FADs effect on the optimization process.

U: is the binary vector with arrays including zero and one. This is constructed by generating a random vector in [0,1] and changing its array to zero if the array is less than 0.2 and one if it is greater than 0.2. r is the uniform random number in [0,1].

x_{max}, x_{min} is the vector containing the lower and upper bounds of the dimensions.

r_1 and r_2 subscripts denote random indexes of prey matrix.

The biological concept **FADs** In the oceans, there are devices (fish-gathering devices). Sharks are attracted to these devices and spend 80% of their time around them, but in the remaining 20%, they make long jumps searching for new prey distributions. In the algorithm, being around **FADs** represents the risk of falling into the trap of local solutions (stagnation), while long jumps represent the mechanism for escaping these traps and searching in entirely new areas within the search space.

2.4 *Optimal lag Selection using Marine Predators Algorithm (MPA)*

The determination of the optimal lag structure (p,q) is a fundamental cornerstone in Quantile Autoregressive Distributed Lag (QARDL) modeling. In econometric estimation, researchers have a tradeoff that is critical; the bias versus efficiency. Choosing a model that is underfitted (not enough lags) will not be able to represent the important underlying dynamics that result in omitted variable bias and serially correlated residuals.

In contrast, the over-fitted model (many lags) causes the exhaustion of degrees of freedom, and therefore, the high variance of the estimates, and the lack of predictive power of the model a phenomenon especially harmful in the quantile-based regressions which are sensitive to the distributional properties.

Conventionally the information criteria used to select the model include the Akaike Information Criterion (AIC) or the Schwarz Information Criterion (SIC). Although the methods are statistically based, they can also be based on a grid search that can be exhaustive, and which is computationally intensive and can also get trapped in local optima as the search space grows. In an effort to address these shortcomings, this paper incorporates the Marine Predators Algorithm (MPA), which is a high performance metaheuristic optimization algorithm that will be applied in automating and improving the lag selection process.

In order to make the lag selection operational in the context of the MPA model, we specify a specialized fitness function. The algorithm considers p and q as discrete search space decision variables and lag orders. This is aimed at minimizing information loss, which is measured by a penalized likelihood criterion (like AIC or BIC) within the quantile t The penalized likelihood criterion has the form as follows:

$$f(p, q|\tau) = \mathrm{Ln}(\hat{\sigma}_\tau) + \frac{2(p+q+1)}{T} \quad ....(10)$$

$f(p, q|\tau)$: represents the fitness value (to be minimized) for a given quantile.

$\hat{\sigma}_\tau$: is the estimated variance of the residuals from the QARDL model at quantile.

T: denotes the effective sample size.

(p + q + 1): represents the total number of estimated parameters, serving as the penalty term for model complexity.

The MPA iteratively explores the search space $\Omega = \{(p, q): 1 \leq p \leq P_{max}, 1 \leq q \leq Q_{max}\}$ to identify the global minimum:

$$(p^*, q^*) = \mathrm{argmin}_{(p,q)\in\Omega}\ f(p, q|\tau) \quad ...(11)$$

2.4.1 *The MPA algorithm to select the optimal Lag*

1- Initialization

Initialize a population of n predators (candidate lag vectors) x_i within the range $[1, P_{max}]$ for the first dimension and

$[1, Q_{max}]$ for the remaining m dimensions and apply $x_{i,d} = \text{round}\,(x_{i,d})$ to ensure lag orders are integers.

2-Initial Evaluation:
For each predator i = 1, 2, …, n; construct a QARDL model using lags in x_i and compute fitness in equation (10) using an Information Criterion.

3- Elite Matrix Identification:
Identify the best solution: Elite = equation (11), and construct the Elite matrix by replicating the best predator.

4- Optimization Loop (Iter = 1 to max iter):

- Phase Selection: Update positions based on the velocity ratio:

Phase 1 (High velocity): Use Brownian motion for global exploration.
Phase 2 (Unit velocity): Use both Brownian and Lev'y flights for transition.
Phase 3 (Low velocity): Use Lev'y flights for fine-tuned exploitation.

- FADs Effect: Apply Fish Aggregating Devices (FADs) effect to avoid stagnation in local optima.

- Fitness Update: Evaluate $f(x_{new})$

If $f(x_{i,new}) < f(x_{i,old})$ update the prey and the Elite matrix.

- Stability Check (Optional): Ensure the selected lags satisfy the QARDL stability conditions.

5- Termination
Return the global best lag structure: $(p^*, q_1^* \ldots q_2^*) = \text{Elite}$

2.5 The MPA algorithm to estimate the parameters of QARDL model

Estimating the parameters of the QARDL model is not simply a matter of reducing the sum of squared residuals as in ordinary least squares (OLS), but rather a complex search in a nonlinear space resulting from the check function. This function, although convex, is non-differentiable at the origin (U=0).

This discontinuity in the derivative makes it very difficult for traditional gradient based optimization methods to converge towards a global optimum, and they often fall into the trap of local solutions. In the original study that developed this model, Cho et al. (2015) used a linear programming algorithm to estimate the parameters. Although this method is efficient in traditional models, it relies on systematic searching which may lack flexibility when the search space becomes complex or the model has multiple dimensions (especially with multiple lag periods p, q).

Therefore, the methodological value of the study is that it employs the Marine Predators Algorithm (MPA) as a metaheuristic optimization. The use of MPA is needed to guarantee increased efficiency in investigating the study of complex parameter spaces via the motion schemes of Levy and Brownian. The main strength of it is that MPA could work with non-smooth functions and resolve the statistical stagnation through FDA which guarantees the proper global optimization of the lag structure and parameters without impairs the structural stability of the model.

Within the traditional model of QARDL, the estimation of parameters is achieved by minimizing the Quantile Loss Function. It is a purpose of this function to fit the model to the actual data with the least deviations possible and mathematically it is as follows:

Fitness function that serves to drive the MPA search is designed in order to have a quantitative loss function as well as structural stability constraints to obtain a consistent and representative estimate of the data structure. The target function with modification can be stated as follows:

$$\min \Im(\Xi(\tau)) = \sum_{i=1}^{n} \rho_\tau\left(\Delta Y_t - \Delta \hat{Y}_t(\Xi)\right) \quad \ldots (12)$$

Where

$$\Xi(\tau) = [\alpha(\tau), \rho(\tau), \theta(\tau), \gamma_1, .., \gamma_{p-1}, \delta_0, .., \delta_{q-1}]$$

Since traditional methods might find a solution that reduces error but is unstable (dynamically), we developed an objective function to suit the MPA algorithm. The structural penalty function $\Psi(\rho)$ was incorporated to ensure that the algorithm not only seeks the "least error" but also the "least error within the stability region.[-1,0]:

$$\min \mathfrak{I}^*(\Xi(\tau)) = \mathfrak{I}(\Xi(\tau)) + \lambda\, \Psi(\rho) \quad \dots (13)$$

Where, $\Psi(\rho)$ represents a statistical logic constraint. Its function ensure that the adjustment speed parameter ρ always falls within the range [-1, 0]. If the parameter falls outside this range, this function returns a positive value, triggering the penalty.

Since the stability condition in a QARDL model is satisfied when the sum of the autoregressive coefficients is less than unity $(\sum_{i=1}^{p}|\theta_i| < 1)$ to ensure that the characteristic roots lie within the unit circle, the stochastic logic constraint $\Psi(\rho)$,Furthermore, to guarantee the existence of a long-run equilibrium, an additional constraint is imposed on the error correction parameter $\rho(\tau)$, requiring it to be significantly negative and within the unit interval (-1, 0) to validate the cointegration relationship among the variables, is formulated as follows:

$$\Psi(\rho) = \max(0, \sum_{i=1}^{p-1}|\gamma_i(\tau)| - 1) + \max(0, \rho(\tau) + \max(0, -1 - \rho(\tau)) \quad \dots (14)$$

λ: The huge penalty factor, and its function is to eliminate any unstable solutions from the predators' "search space" in the MPA algorithm.

3 An Application to the Iraqi Economy

The proposed methodology was applied using monthly data for the Iraqi economy for the period (Jan/2008–Jan/2025). The model incorporates the following variables:

The Dependent Variable (Y): It refers to private investment, represented by credit facilities granted to the private sector.

Main Independent Variables:

1. Fiscal Sustainability (X1): Measured by the ratio of Domestic Debt to Gross Domestic Product (GDP). (Ministry of Planning, Central Bank of Iraq (CBI)).

2. Structural Transformation (X2): Measured by the ratio of Non-oil GDP to Total Gross Domestic Product (GDP), (Ministry of Planning, Central Bank of Iraq (CBI)).

Control Variables:

1. Oil Prices (C1): Monthly average crude oil prices (Investing.com) .
2. Inflation (C2): Represented by the Consumer Price Index (CPI), (Central Bank of Iraq (CBI)).
3. Exchange Rate (C3): Represented by the Parallel Market Exchange Rate of the Iraqi Dinar (IQD) against the US Dollar (USD). The parallel rate is employed as it captures the actual market dynamics and the real cost of foreign currency for private investors, providing a more realistic measure of exchange rate shocks on private investment than the official (basic) rate (Central Bank of Iraq (CBI). The analytical process commenced with an examination of the statistical properties of the time series, followed by the optimization of the lag structure, and culminated in the estimation of cointegration coefficients across different quantiles**.**

3.1 Unit Root Test

Prior to estimating a QARDL model, the Augmented Dickey-Fuller (ADF) test was conducted to ensure stationarity properties.

Table 1. ADF Unit Root Test Results (at First Difference)

Variable	ADF	P-value	Decision
Y	-5.2794	0.01*	stationary
X1	-4.3542	0.01*	stationary
X2	-6.2718	0.01*	stationary
C1	-6.1924	0.01*	stationary
C2	-10.099	0.01*	stationary
C3	-7.5186	0.01*	stationary

The results indicated that the variables (Private Investment, Fiscal Sustainability, Structural Transformation, and control variables) were non-stationary at their levels I(0) but achieved full stationarity after taking the first difference I(1) at a 1% significance level.

3.2 Selecting the Optimal Lag Structure Using the MPA Algorithm

In order to guarantee the model accuracy and preventing mischaracterization issues the Marine Predator Algorithm (MPA) was applied to compute the best lag intervals. This algorithm is described as having great ability to search complex spaces in an attempt to come up with a global solution. The fact that the MPA algorithm converges in less than 500 iterations, n prey=30, step size (p) =0.2, FDAs =0.5, lower bound=1, upper bound=12 to a fitness score of -7.022138 can be provided as evidence of the strength of the chosen QARDL(1, 1) model This guarantees that the estimated cointegration parameters are obtained with respect to a globally optimized lag structure, which provides the confidence of the asymmetric analysis at various quantiles. The negative score of the fitness criterion, which represents a minimized information criterion, implies that the model accounts for the dynamic association between the fiscal sustainability, structural transformation, and the private investment in the highest precision and information loss.

4. Results

Table (2) gives the empirical estimates of the Quantile Regression-based Error Correction Model (QR-ECM) model, optimized uniquely, through the Marine Predators Algorithm (MPA) to be able to obtain global convergence and precision of the model parameters. This is a hybrid model that involves the dynamics of asymmetric short runs and long-run equilibrium of various conditional quantiles (t =0.25, 0.50, 0.75), which takes into consideration potential nonlinearities and structural breaks. The model addresses the weaknesses of the conventional gradient-based approaches to non-convex objective functions by incorporating MPA. The findings give the impact of structural transformation (X1) and fiscal sustainability (X2) on the target variable of low, median, and high-growth regimes.

Table 2. QARDL Model Estimation Results Optimized by MPA Algorithm

Explanatory Variables	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$
Short-run Dynamics			
Intercept	0.11214***	0.13795***	0.23151***
LYt−1 (Speed of Adj.)	−0.00669***	−0.00771***	−0.01267***
ΔX_1 (Fiscal Sustainability)	−0.01283**	−0.02123**	−0.03105*
ΔX_2 (Structural Transformation)	0.03203***	0.03341	0.04817
ΔC_1 (Oil Prices)	−0.00951	0.00339	0.01782
ΔC_2 (Inflation)	−0.00177***	−0.00197**	0.00007
ΔC_3 (Exchange Rate)	−0.17518***	−0.09442	−0.15549
Long-run Analysis			
Long-run X_1	-1.91796***	-2.75528***	-2.44889***
Long-run X_2	4.78717***	4.33620***	3.79915***

Note: P-values are in parentheses, the symbols ***, **, * indicate statistical significance at 1%, 5%, and 10% respectively.

The results of estimation shown in Table (2) indicate that there do exist non-linear dynamics and non-symmetric responses of the private credit (private investment) to the macroeconomic variables in the three states of the distribution of the dependent variable, (τ=0.25,0.50,0.75) were chosen to capture three different conditions of the private credit, the lowest (τ=0.25) quantile depicts the recessionary or low-credit conditions, the median quantile τ=0.25 depicts normal market conditions, and the upper quantile t This choice is carefully made to set in the "Asymmetric Responses" of the private investment to macroeconomic shocks. It enables a strict comparison of the effects of fiscal and monetary policy on the situation in the vulnerable and resilient parts of the private sector such such parameters are understood in the following way:

a. Short-Run Dynamic

The intercept shows positive and highly significant values across all quantiles, increasing from (0.11) at the lower quantile to (0.23) at the upper quantile. This suggests a "self-sustaining growth" trend in Iraqi private credit that strengthens as overall credit levels improve, even in the absence of external shocks. The Error Correction Term (ECT) $\boldsymbol{LY_{t-1}}$ is negative and highly significant for all quantiles, confirming the existence of a Long-run Cointegration and a stable equilibrium relationship. The absolute speed of adjustment nearly doubles from (-0.006) at $\tau = 0.25$ to (-0.012) at $\tau = 0.75$, indicates that while private credit returns to its equilibrium path slowly in Iraq, the pace of adjustment is more flexibility during credit booms compared to recessionary periods, reflecting "structural rigidity" in financing channels during crises.

The ΔX_1 short-run impact is negative and significant across all quantiles, with the intensity of this effect increasing at higher quantiles. Statistically, shocks in domestic debt lead to an immediate contraction in private credit, confirming the direct and instantaneous impact of expansionary fiscal policy (via domestic borrowing) on crowding out the liquidity available to the private sector.

And the Structural Transformation ΔX_2, is positive and significant only at the lower quantile (0.032), while it loses significance at median and upper quantiles, This proves that enhancing non-oil activities acts as an effective "emergency catalyst" to revive credit during stagnation $\tau = 0.25$. In contrast, during expansionary phases, the impact is cumulative and long-term rather than an immediate statistical shock.

Inflation Change ΔC_2 is negative and significant at lower and median quantiles. This reflects the "uncertainty effect" created by inflation, which prompts banks to curtail credit . in the short run to protect asset quality and mitigate default risks.

The Parallel Exchange Rate ΔC_3 recorded a highly significant negative value (-0.175) exclusively in lower quantile ($\tau = 0.25$). This is crucial finding proving that exchange rate shocks in the parallel market specifically target "vulnerable investors" or startups that lack access to an official foreign exchange window. Larger investors, however, exhibit immunity to parallel market fluctuations in the short run.

b. Long-Run Analysis

Long-run Fiscal Sustainability X1 parameter is negative and its significance is very high on all levels of (-2.75) at the median. This is a strong confirmation of the Crowding- out Effect in the Iraq economy. The presence of domestic public debt would tend to suck out the bank liquidity to fund the government deficit, which would in turn Cause deprivation to the private sector of long-term sustainability financing. The strongest positive driver of the model is Long-run Structural transformation X 2. At lower quantile, its value was (4.787) as against (3.799) at upper quantile. The divergence of the economy out of oil becomes the leading strategic source of the investors on a private basis. It is most effective when there is stagnation in the credit and therefore, the real safety valve to sustainable growth beyond the oil industry is it. Figures (1) and (2) below show the dynamic change of these parameters in terms of the chosen quantiles

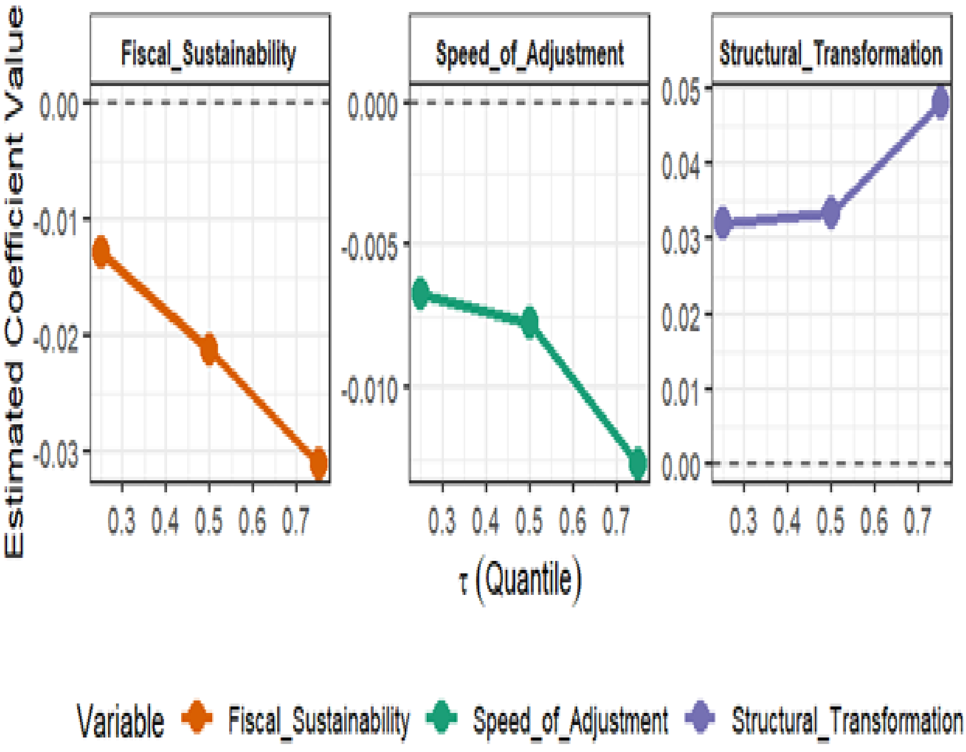

Figure 1. Short run dynamics optimized by MPA algorithm

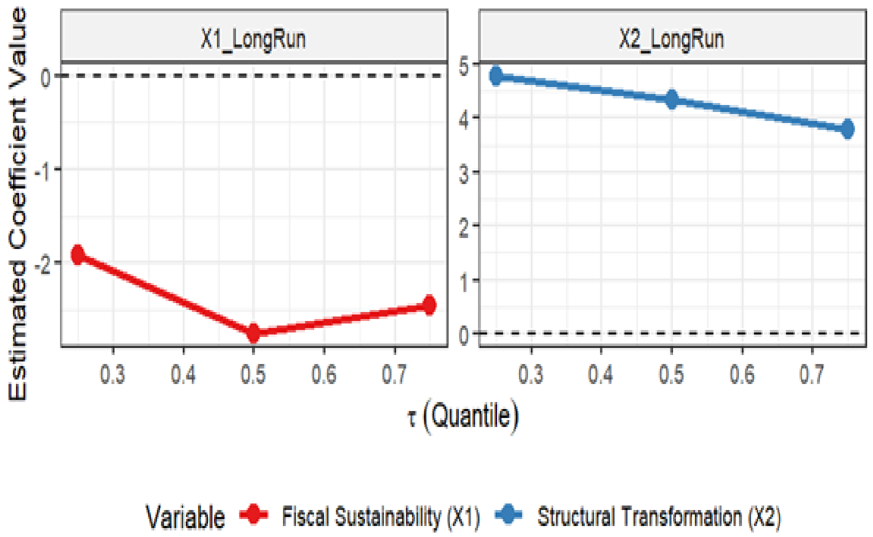

Figure 2. Quantile long run dynamics optimized by MPA algorithm

5. Conclusion

In this paper, we have shown that the Marine Predator Algorithm (MPA) with the QARDL model is an efficient way of developing an alternative touchscreen based structure in comparison with the conventional estimation systems. This algorithm was able to pick the time lags of the variables and deal with non-convexity of the quantum loss, when global estimates of parametric model specifications are optimal. This defeats local solution issues that may bedevil the traditional gradient algorithms.

It was also found in the results that there was significant asymmetry in the error correction parameters distributed over the quantities. This implies that the counteraction of the credit system to getting back to long-term equilibrium is mainly based on whether the system is in a state of contraction or recovery, and that the system would be more responsive to adjusting the system in the peak periods than in structural stagnation periods.

The authors statistically confirmed the hypothesis of crowding-out on all the quantities, which demonstrates that the effect of financial sustainability on private credit is a structural cross-level effect. This implies that the competition of the bank liquidity by the public sector is a constant hindrance that is not in relation to the amount of circulating credit.

The non-oil related structural change is an asymmetric factor, and the intensity and magnitude of the change reach a peak at the low end of the credit distribution. This highlights the high ability of the policies of economic diversification to hiss investment in bad recessions which has made it a better stabilizing policy than the traditional policy of monetary.

Quantitative models have revealed that sensitivity to parallel exchange rates changes and inflation is concentrated at lower levels of credit distribution. This observation implies that the risk of instant credit disconnection of the vulnerable categories of investors in case of monetary instability would only concern the vulnerable category of investors but not the system as a whole on its high levels.

6. Recommendation

We would suggest that we should have quantitatively flexible credit policies, which would consider the investment climate. This would entail augmenting support and safeguarding programs (especially on the exchange rate) to the investors at reduced credit limits, as they are highly sensitive as shown by the study. The funding of the fiscal deficits by domestic banks is important to be changed to take off the strain on the domestic private credit base and secure the sustainability of the structural transformation in the long term. We also suggest that hybridization of optimization methods (as in the case of QARDL-MPA) be also implemented in nonlinear time series analysis since they are superior to present more accurate and reliable results in economically uncertain environments.

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