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Non-Parametric Econometric Analyses of Algerian Inflation: An Application of KRLS and QQKRLS Methods

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Abstract:
This article reexamines the determinants of inflation in Algeria between 2002 and 2025 by mobilizing two advanced non-parametric econometric methods: Kernel Regularized Least Squares (KRLS) and Quantile-on-Quantile KRLS regression (QQKRLS). Unlike standard linear models, these approaches make it possible to capture nonlinearity, distributional heterogeneity, and complex dependencies between oil prices, exchange rates, and inflation. Preliminary specification tests (Ramsey RESET, Breusch Pagan, Jarque Bera, BDS) all reject the hypothesis of linearity and independence, fully justifying the use of these techniques. KRLS estimations reveal a positive and significant average marginal effect of oil prices on inflation, but with marked nonlinearity: the impact weakens for very high oil prices. In contrast, the average effect of the exchange rate is not statistically significant. The main contribution lies in the QQKRLS analysis, which highlights strong heterogeneity of effects across the quantiles of inflation and explanatory variables. For low inflation, the effect of oil prices is paradoxically negative, whereas under moderate to high inflation regimes, oil shocks exert an amplified effect. The exchange rate shows a strong negative effect when inflation is low (disinflationary appreciation of the dinar), but a positive and destabilizing effect during periods of high inflation. These results suggest that "one-size-fits-all" monetary policies are inappropriate: the response to external shocks must be conditioned by the prevailing inflation regime. The study contributes to the literature on the economics of rentier states by providing robust evidence of nonlinear and asymmetric dependencies, and proposes concrete implications for stabilization policy in Algeria.
Keywords: Algerian inflation; KRLS; QQKRLS; nonlinearity; distributional heterogeneity; monetary policy.

1. Introduction:

Algeria, a rentier economy highly dependent on hydrocarbons, has experienced persistent and volatile inflation since the beginning of the 2000s. Shocks in oil prices – the country's main export resource – and exchange rate fluctuations are often presented as the major determinants of domestic price dynamics. However, standard linear macro econometric models struggle to reproduce the multiple regimes, asymmetries, and threshold effects characterizing this relationship, particularly because of structural rigidities (fuel subsidies, exchange controls, discretionary monetary policy). Faced with these limitations, a non-parametric and nonlinear approach is required to better capture empirical reality.

This work proposes to exploit two state-of-the-art econometric methods – Kernel Regularized Least Squares regression (KRLS) and its quantile-on-quantile extension (QQKRLS) – in order to analyze in detail the role of oil prices (OP) and exchange rates (ER) in the formation of inflation (CPI) in Algeria over a monthly period from 2002 to 2025. A preliminary wavelet analysis makes it possible to characterize the time-frequency coherence between the series.
Main research question: To what extent do variations in oil prices and exchange rates explain inflation in Algeria, and is this relationship homogeneous across the conditional distribution of inflation and according to the regimes of each explanatory variable?

Sub-questions:

1. Is the relationship between oil prices and inflation linear and symmetric, or does it exhibit nonlinearities and threshold effects depending on the magnitude of oil shocks?
2. Does the exchange rate exert a significant impact on inflation, and does this impact vary depending on whether inflation is low or high (extreme quantiles)?
3. Is the coherence between inflation and its determinants stable over time and across different frequencies (short, medium, long term)?
4. Is there distributional heterogeneity: is the effect of oil prices more pronounced for high inflation rates (upper quantiles) and for strong oil price increases (upper quantiles of OP)?

Objective of the study

The central objective of this research is to evaluate, using advanced non-parametric econometric methods, the sensitivity of Algerian inflation to variations in oil prices and exchange rates, while accounting for nonlinearities, distributional heterogeneity, and time dynamics.
More specifically, the objectives are:
• To test the presence of nonlinearities and nonlinear dependencies in the relationship between inflation, oil prices, and exchange rates using diagnostic tests (RESET, BDS, etc.) and wavelet decomposition.
• To estimate the non-parametric marginal effects of oil prices and exchange rates on inflation using the KRLS (Kernel Regularized Least Squares) method, without imposing an a priori functional form.
• To characterize distributional heterogeneity through QQKRLS (Quantile-on-Quantile KRLS), by examining how the effect of a given quantile of oil prices (or exchange rates) varies according to inflation quantiles.
• To compare the explanatory power of the two determinants (oil versus exchange rate) across different time frequencies (short, medium, long term) using wavelet coherence analysis.
• To formulate monetary policy recommendations adapted to inflation regimes and oil shocks by identifying critical thresholds beyond which transmission becomes significant.

2. Literature Review

Numerous studies have examined the pass-through of oil prices to inflation[1] and the effect of exchange rate variations[2] . Others find a linear causality running from oil prices to prices, but ignore nonlinearities. Recent non-parametric methods (KRLS) [3] and (QQKRLS) [4] make it possible to model heterogeneous relationships according to the distribution of variables. Our work is the first to combine KRLS and QQKRLS with wavelet decomposition for the Algerian economy.

2.1 Theoretical Foundations of the Wavelet Transform

2.1.1 Wavelet Transform: A Time-Frequency Generalization

The wavelet transform is a time-frequency analysis tool that makes it possible to decompose a signal into a sum of localized elementary functions called wavelets. Unlike the Fourier transform, which uses stationary sinusoids, wavelets are oscillating functions of limited duration (compact support) capable of capturing both low and high frequencies of a non-stationary signal[5] , which is typical of macroeconomic series (inflation, oil prices, exchange rates).

The fundamental advantage of wavelets lies in their ability to provide multiresolution analysis (MRA). The wavelet coefficients of a function provide a time-frequency decomposition of that function, with finer temporal resolution for high-frequency components than for low-frequency components.

2.1.2 The Discrete Wavelet Transform (DWT): Mathematical Formalization

The discrete wavelet transform (DWT) is particularly suited to regularly sampled data (monthly observations). It relies on Mallat's algorithm, a filter bank composed of a low-pass filter and a high-pass filter, recursively applied to separate the signal into components of different scales (or resolutions).

Multiresolution analysis (MRA), as defined by Mallat, decomposes the space L2(R) of square-integrable functions into a nested sequence of approximation subspaces Vj and detail subspaces Wj such that: $V_j = V_{j+1} \oplus W_{j+1}$.

The information difference between resolutions 2j+1 and 2j is extracted by decomposing the signal on an orthonormal wavelet basis. [6]

The pyramidal algorithm proposed by Mallat consists of:

1. Filtering: the input signal is convolved with two filters:
   - Low-pass filter h → approximation coefficients,

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[1] **Hamilton, J. D.** (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy*, 91(2), 228-248.

[2] **McCarthy, J.** (2007). Pass-through of exchange rates and import prices to domestic inflation in some industrialised economies. *Eastern Economic Journal*, 33(4), 511-537.

[3] **Hainmueller, J., & Hazlett, C.** (2014). Kernel regularized least squares: Reducing misspecification bias with a flexible and interpretable machine learning approach. *Political Analysis*, 22(2), 143-168.

[4] **Sim, N., & Zhou, H.** (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking & Finance*, 55, 1-8.

[5] Lolanda LO CASCIO, Wavelet Analysis and denoising: new tools for economist, sur le site: https://www.qmul.ac.uk/sef/research/workingpapers/2007/items/600.html

[6] **Mallat, S. G.** (1989). A theory for multiresolution signal decomposition: the wavelet representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 11(7), 674-693.

• High-pass filter g → detail coefficients.

2. Downsampling: one sample out of two is removed (decimation by 2) to reduce redundancy.
3. Iteration: the approximation coefficients serve as input for the next level.

Reconstruction follows the reverse path (upsampling followed by filtering), guaranteeing perfect reconstruction in the absence of coefficient modification. This algorithm is described in detail in Mallat (1989). [7]

2.1.3 The Daubechies Wavelet of Order 4 (db4) [8]

Origin and Fundamental Properties

Daubechies wavelets, named after their creator Ingrid Daubechies, are a family of orthogonal wavelets defining a discrete wavelet transform. They are characterized by a maximum number of vanishing moments for a given support.

The foundational article establishes the theoretical basis. It demonstrates the existence of orthonormal wavelet bases with compact support and an arbitrary number of vanishing moments. These wavelets are orthogonal, meaning that the coefficients are non-redundant and the transform is reversible.

Mathematical Properties of db4

The choice of db4 (Daubechies order 4) in our analysis is justified by the following properties:
Compact support: the scaling function and the wavelet have a finite temporal support of length 2N−1 = 7 for N = 4.

• Orthogonality: the transform is reversible and non-redundant.

• Four vanishing moments: the first four moments (orders 0 to 3) are zero. This makes it possible to eliminate polynomial trends up to order 3 from the detail coefficients, retaining only non-polynomial variations. The economic interpretation of fluctuations thus becomes more robust.

Daubechies wavelets are denoted DbN where the number is either the number of coefficients (N) or the number of vanishing moments (N/2). The notation in theory by N actually designates half the number of filterings; for db4, N equals 2, hence 2N = 4 coefficients.

• Filter coefficients

The coefficients of the db4 wavelet come from a conjugate quadrature filter (CQF) with four coefficients (four tap filter). These coefficients are obtained by the db2 method in MATLAB and satisfy the constraints of perfect reconstruction (PR) and orthogonal moments. The wavelet is quasi-symmetrical, which limits nonlinear phase shifts, an important quality for the analysis of economic time series.

• Multi-resolution analysis (MRA) with db4

For monthly data, the period associated with each detail level is approximately 2j months (frequency band [2−j−1, 2−j] cycle per month). Thus:

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[7] **Mallat, S. G.** (1989). A theory for multiresolution signal decomposition: the wavelet representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 11(7), pp. 674-693.

[8] **Daubechies, I. (1988)** intitulé « **Orthonormal bases of compactly supported wavelets** » (Communications on Pure and Applied Mathematics, vol. 41, n° 7, pages 909-996)

• D1: 2–4 months (very short fluctuations, noise)
• D2: 4–8 months (seasonal variations, occasional shocks)
• D3: 8–16 months (intra-annual cycles)
• D4: 16–32 months (business cycles, 1.5–2.5 years)
• A4: longer-term trend (>32 months)

The multi-resolution decomposition is carried out via a filter bank whose structure depends on the coefficients of the db4 wavelet. Mallat's algorithm performs the computation through successive convolutions with quadrature mirror filters.

2.2 The KRLS Method (Kernel Regularized Least Squares): [9]

• Optimization problem:

The objective is to estimate a function f : Rd → R (with d = 2 in our study) that minimizes the sum of the quadratic cost on the data and a regularization term:

$$\min_{f \subset \mathcal{H}_K} \sum_{i=1}^{n} (y_i - f(\mathbf{x}_i))^2 + \lambda \|f\|_K^2$$

$$\min_{f \in \mathcal{H}_K} \sum_{i=1}^{n} (\mathrm{IPC}_i - f(\mathrm{PP}_i, \mathrm{TC}_i))^2 + \lambda \|f\|_K^2$$

where:
• n: number of observations,
• yi: dependent variable, CPI (inflation),
• xi ∈ Rd: vector of covariates (OP, ER),
• HK: reproducing kernel Hilbert space (RKHS), non-parametric space of smooth functions,
• ||f||K: norm in this space (penalizes the complexity of f),
• λ > 0: regularization parameter (chosen by cross-validation).

2.2.1 Representer theorem:

The optimal solution is written as a linear combination of kernels evaluated at the learning points:

$$f(\mathbf{x}) = \sum_{j=1}^{n} \alpha_j K(\mathbf{x}, \mathbf{x}_j)$$

$$f(\mathrm{PP}, \mathrm{TC}) = \sum_{j=1}^{n} \alpha_j K\big((\mathrm{PP}, \mathrm{TC}), (\mathrm{PP}_j, \mathrm{TC}_j)\big)$$

where αj ∈ R, α are the coefficients to be estimated.

2.2.2 Matrix form

Let K be the Gram matrix of size n × n defined by Kij = K(xi, xj). The problem becomes:

$$\min_{\boldsymbol{\alpha}} \|\mathbf{y} - \mathbf{K}\boldsymbol{\alpha}\|^2 + \lambda \boldsymbol{\alpha}^\top \mathbf{K}\boldsymbol{\alpha}$$

[9] Hainmueller, J. et Hazlett, C. (2014). Moindres carrés régularisés par noyau : réduction du biais de spécification erronée grâce à une approche d'apprentissage automatique flexible et interprétable. Political Analysis, 22(2)

The explicit solution is:

$$\widehat{\boldsymbol{\alpha}} = \left(\mathbf{K} + \lambda \mathbf{I}_n\right)^{-1} \mathbf{y}$$

$$\widehat{\boldsymbol{\alpha}} = \left(\mathbf{K} + \lambda \mathbf{I}_n\right)^{-1} \mathbf{IPC}$$

where In is the identity matrix n × n.

2.2.3 Prediction:

For a new point x*, the prediction is:

$$\widehat{\mathrm{IPC}}_* = \sum_{j=1}^{n} \widehat{\alpha}_j \, K(\mathbf{x}_*, \mathbf{x}_j)$$

2.2.4 Gaussian radial kernel (most commonly used)

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right)$$

where σ is the bandwidth, often chosen by cross-validation or by the automatic rule of Hainmueller & Hazlett.

2.2.5 Non-parametric marginal effects

For the variable OP (same reasoning for ER):

$$\frac{\partial f(\mathbf{x})}{\partial \mathrm{PP}} = \sum_{j=1}^{n} \widehat{\alpha}_j \, \frac{\partial K(\mathbf{x}, \mathbf{x}_j)}{\partial \mathrm{PP}}$$

For the Gaussian kernel, the derivative is:

$$\frac{\partial f(\mathbf{x})}{\partial \mathrm{PP}} = -\frac{1}{\sigma^2} \sum_{j=1}^{n} \widehat{\alpha}_j \, (\mathrm{PP} - \mathrm{PP}_j) \, K(\mathbf{x}, \mathbf{x}_j)$$

This effect is calculated for each observation i, which gives a distribution of marginal effects (non-parametric heterogeneity).

2.3 QQKRLS Extension (Quantile on Quantile KRLS)

2.3.1 Objective:

Estimate the effect of the quantile τ of oil prices (OP) on the quantile θ of inflation (CPI), denoted β(τ, θ). The relationship is no longer only nonlinear, but also heterogeneous across distribution regimes.

2.3.2 Double local weighting:

For each pair (τ, θ), weights are defined based on empirical ranks:

$$w_i(\tau, \theta) = \frac{1}{h_\tau h_\theta} K\left(\frac{\hat{F}_{\mathrm{PP}}(\mathrm{PP}_i) - \tau}{h_\tau}\right) K\left(\frac{\hat{F}_{\mathrm{IPC}}(\mathrm{IPC}_i) - \theta}{h_\theta}\right)$$

Where:

• F̂ is the empirical distribution function,

• K is a kernel (Gaussian or Epanechnikov),
• $h\tau$, $h\theta$ are bandwidths.

2.3.3 Locally weighted KRLS problem

Variables are centered around the neighborhood of quantiles:
One then solves:
The solution is written:
With:

2.3.4 Quantile-on-quantile coefficient:

For a Gaussian kernel:

2.3.5 Non-parametric interpretation:

• If $\beta(\tau, \theta) > 0$, an increase in oil prices (when they are at quantile τ) increases inflation at quantile θ.
• The surface $\beta(\tau, \theta)$ makes it possible to visualize nonlinearities: the effect may be null for low quantiles, strong for high quantiles, and variable depending on economic conditions.

2.4 Specificity of Non-Parametric Analysis:

In these equations, no parametric form (linear, polynomial, exponential) is presupposed. The function f is learned from the data through the kernel and regularization. Marginal effects are local and vary across observations. The QQKRLS approach adds a double quantile dimension, making it possible to capture distributional heterogeneity – a major advantage compared to linear models or even simple quantile regressions.

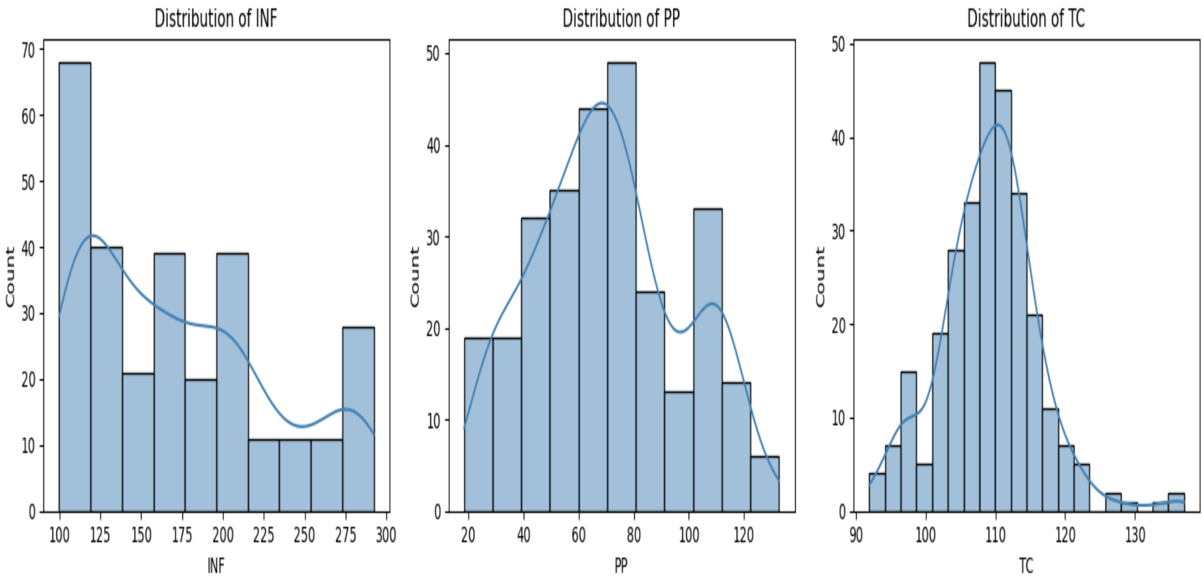
3. Empirical Results:

3.1 Data and Descriptive Analysis:

We use monthly series from January 2002 to December 2025 (288 observations). Inflation (INF: measured by the consumer price index (CPI)), oil prices (OP), and the exchange rate (ER). The series come from the Bank of Algeria, the National Office of Statistics (ONS), and the EIA.

Table 1: Statistical indicators of the variables (INF, OP, ER)

	INF	PP	TC
Mean	173.1540	70.14219	109.1456
Median	161.0350	68.54500	109.4100
Maximum	292.1600	132.7200	137.0300
Minimum	99.94000	18.38000	91.92000
Std. Dev.	56.88563	26.74897	7.002015
Skewness	0.571318	0.194879	0.381997
Kurtosis	2.190002	2.263020	4.657717
Jarque-Bera	23.54059	8.340616	39.98057
Probability	0.000008	0.015447	0.000000
Sum	49868.35	20200.95	31433.93
Sum Sq. Dev.	928724.8	205350.6	14071.10
Observations	288	288	288



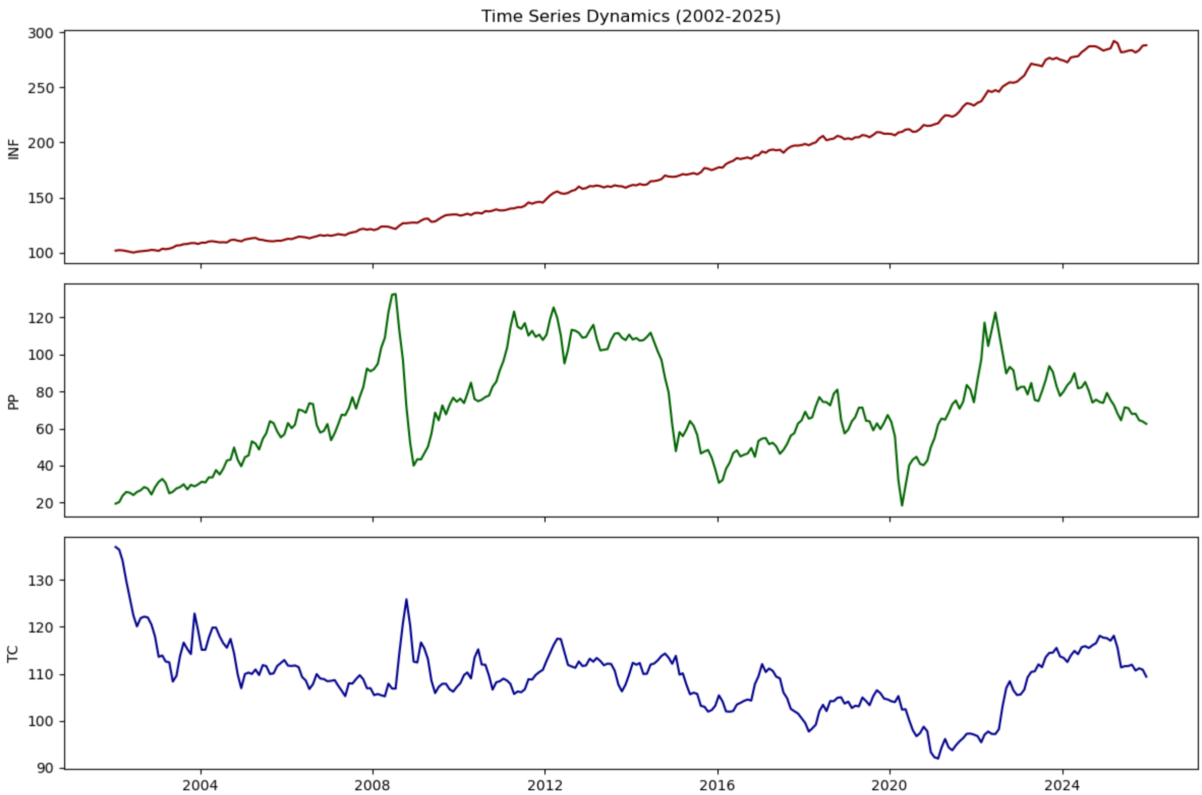


Figure 1: Dynamics of the series during the period 2002–2025 (INF, OP, ER)

Interpretation:

Inflation: high dispersion ($\sigma = 56.9$) and positive asymmetry (mean > median). Presence of extreme peaks (max = 292). The normality test is very clearly rejected ($p < 0.001$). The distribution is slightly platykurtic (flatter tails than normal), but extreme values are present.

Oil prices: moderate volatility (CV = 0.38). Nearly symmetrical (skewness close to 0). Normality marginally rejected at 5% ($p = 0.015$). The distribution is also platykurtic (kurtosis

< 3). Extreme negative shocks (min 18.38) and positive shocks (max 132.72) characterize the series.

Exchange rate: very low relative dispersion (CV = 0.064) but thick tails (kurtosis = 4.66). Moderate positive asymmetry. Strong rejection of normality (p = 0.000). The series remains stable on average but experiences significant occasional movements.

Synthesis: The three series violate the normality assumption. Inflation displays marked asymmetry, the exchange rate exhibits leptokurtosis, and oil prices show borderline but imperfect normality. These characteristics, combined with probable heteroskedasticity and nonlinearity (detected by BDS and Breusch Pagan tests in the preliminary diagnostics), prohibit the use of standard parametric linear models. They require flexible and robust approaches: wavelet analysis (for time-frequency dynamics), KRLS (non-parametric regression with regularization), and QQKRLS (to capture double quantile heterogeneity).

3.2 Preliminary Specification Tests

Before estimation, we verify the relevance of nonlinear models. The results are summarized in Table 2:

Test	**Statistic**	**p-value**	**Decision**
Ramsey RESET	0.3537	0.7024	Linearity not rejected
Breusch-Pagan	26.64	0	Heteroskedasticity
Jarque-Bera	49.63	0	Non-normality
BDS (dim = 2)	2.16E+09	0	Nonlinear dependence

The RESET test does not reject linearity, but the BDS test, which is more powerful against nonlinear alternatives, rejects the independence and identical distribution of residuals, indicating a nonlinear structure. Heteroskedasticity and non-normality also justify flexible methods such as KRLS and quantile regressions.

3.3 Wavelet Decomposition of Inflation:

The multiresolution decomposition (DWT) of inflation (INF) into five levels highlights:

• Trend (A4): smooth and increasing component over the period, capturing structural inflation (permanent factors: fiscal policy, expectations).

• Detail D4 (16–32 month period): large oscillations coinciding with major oil shocks (2008, 2014–2015, 2021–2022). This is the main source of cyclical variability.

• Details D3 and D2 (4–16 month periods): faster fluctuations of smaller amplitude, corresponding to short-term adjustments (shock transmission).

• Detail D1 (2–4 month period): almost negligible noise.

Inflation is dominated by a permanent trend and medium-term cycles (1–3 years). The presence of several time scales and changing regimes justifies the use of non-parametric methods (KRLS, QQKRLS) rather than linear models assuming homogeneous dynamics.

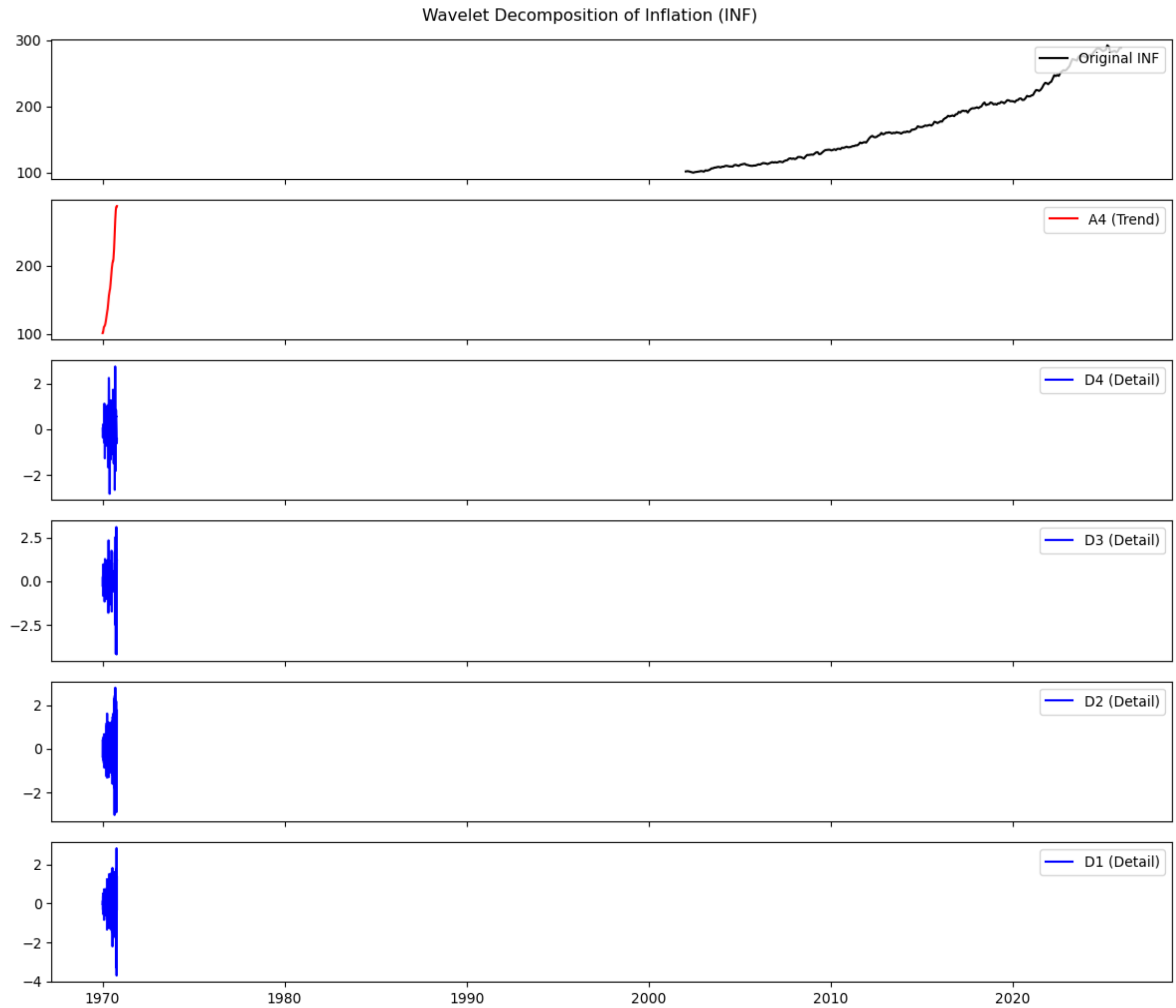
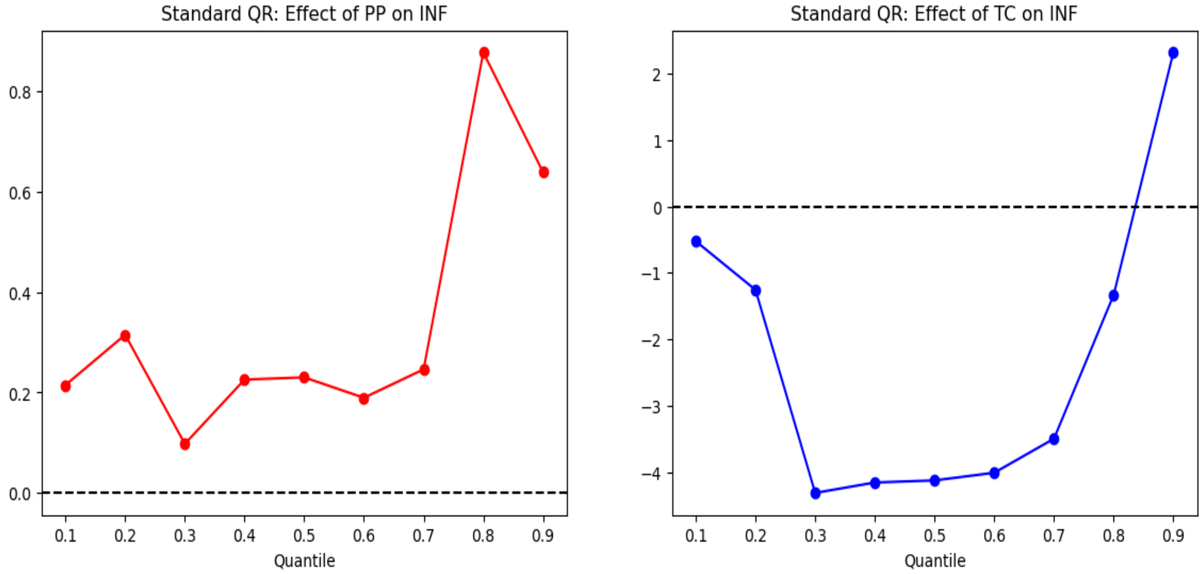


Figure 2: Wavelet Decomposition of Inflation

3.4 Standard Quantile Regression:

	q	PP_coef	PP_pval	TC_coef	TC_pval
0	0.1	0.214830	2.141181e-02	-0.524651	7.625642e-04
1	0.2	0.315084	1.847555e-03	-1.256114	8.217999e-09
2	0.3	0.097732	4.225451e-01	-4.311593	1.258774e-29
3	0.4	0.225822	4.776507e-02	-4.154642	4.059890e-23
4	0.5	0.230222	3.287290e-02	-4.123288	1.516646e-20
5	0.6	0.189567	5.923525e-02	-4.007943	4.223673e-18
6	0.7	0.246196	2.450285e-02	-3.495476	9.647243e-11
7	0.8	0.877645	4.033279e-10	-1.331890	3.264994e-02
8	0.9	0.639310	5.301863e-13	2.316447	9.333135e-04



The table presents the estimated coefficients of the effect of oil prices (OP) and the exchange rate (ER) on inflation (INF) for different inflation quantiles (from 0.1 to 0.9).

• Effect of oil prices (OP)

The coefficients are all positive. They are weak for low to medium inflation quantiles (0.1 to 0.6), but become significantly higher for upper quantiles (0.7 to 0.8).

Interpretation: The impact of oil prices on inflation increases with the level of inflation. When inflation is already high, an increase in oil prices amplifies it further. Clear asymmetry.

• Effect of the exchange rate (ER)

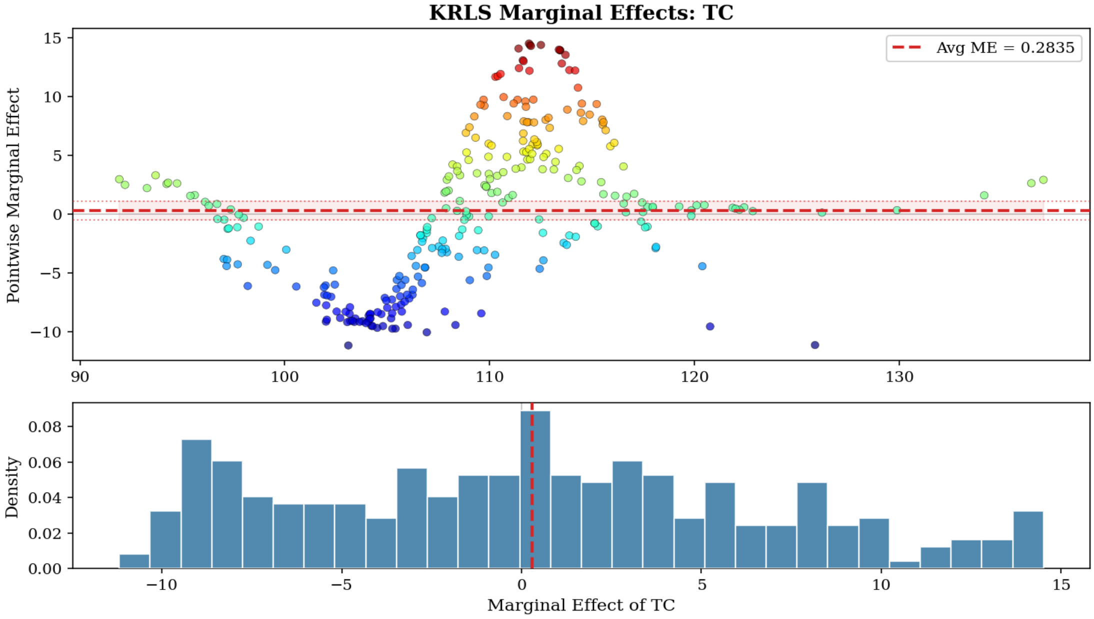
The coefficients are negative (approximately -0.52 to -1.31) for all quantiles, with very little variation across quantiles.

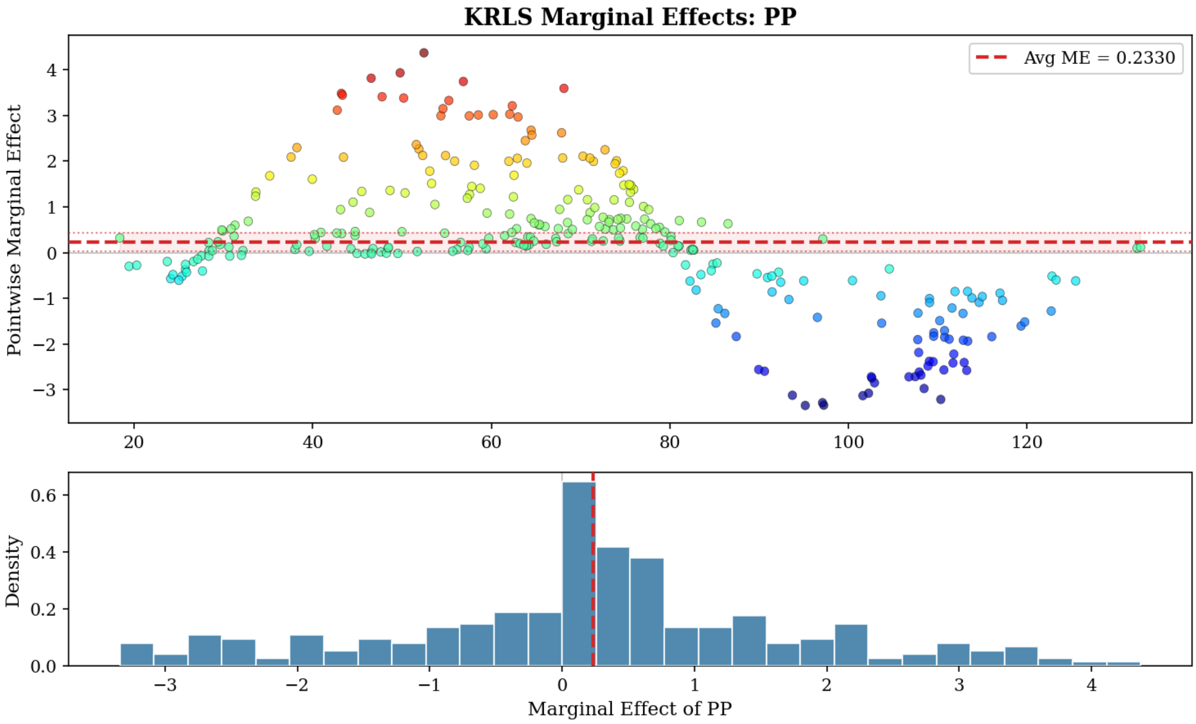
Interpretation: A depreciation of the dinar (increase in ER) reduces inflation, which is counterintuitive (a “deflationary” effect). This may reflect subsidies on imported products, exchange controls, or an inverse relationship through other channels.

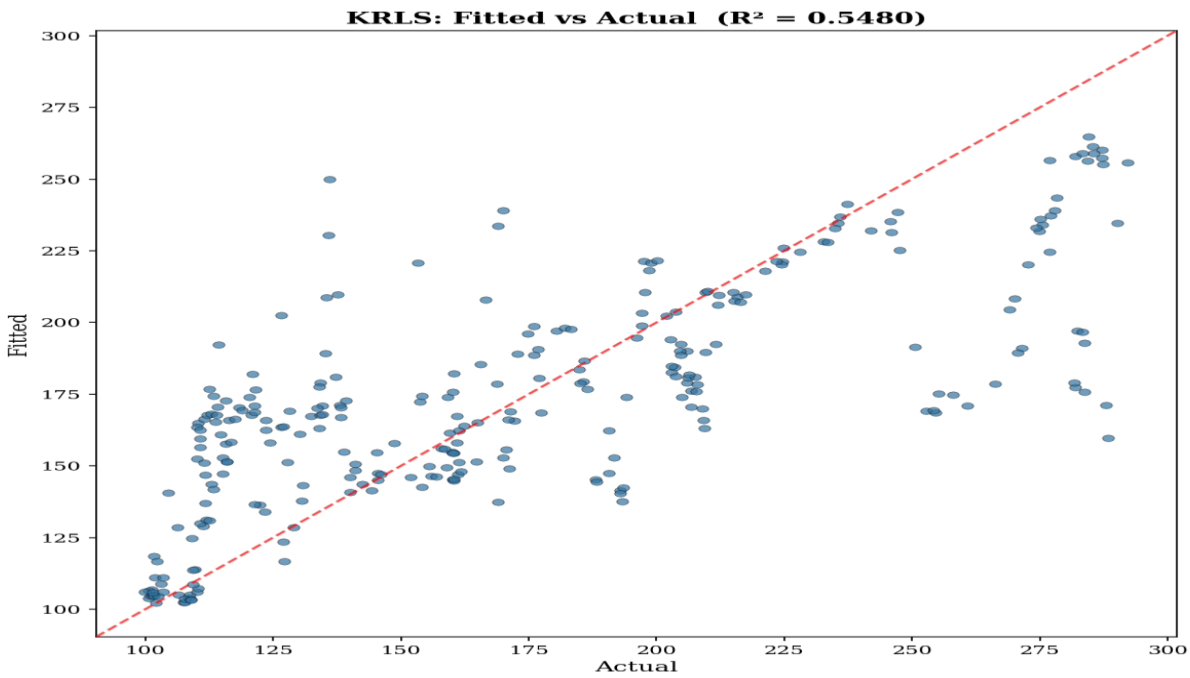
It is concluded that standard quantile regression reveals marked heterogeneity in the effect of oil prices: the higher the inflation, the stronger the oil price–inflation transmission.

The effect of the exchange rate is stable and negative, suggesting a secondary and atypical role. These results justify the use of a more sophisticated method (QQKRLS) to explore double quantile dependence (quantile of OP × quantile of INF).

3.4 KRLS Model (Kernel-Regularized Least Squares):







Main results:

• Effect of oil prices (OP):

The average marginal effect is positive (0.233) and statistically significant (p-value ≈ 0.023). An increase in oil prices therefore tends to increase inflation on average.

• Effect of the exchange rate (ER):

The average marginal effect is positive (0.284) but not significant (p-value ≈ 0.486). On average, the exchange rate has no statistically detectable impact on inflation.

• Goodness of fit:

The R^2 is 0.548, indicating that the model explains approximately 55% of the variance in inflation.

• Nonlinearity:

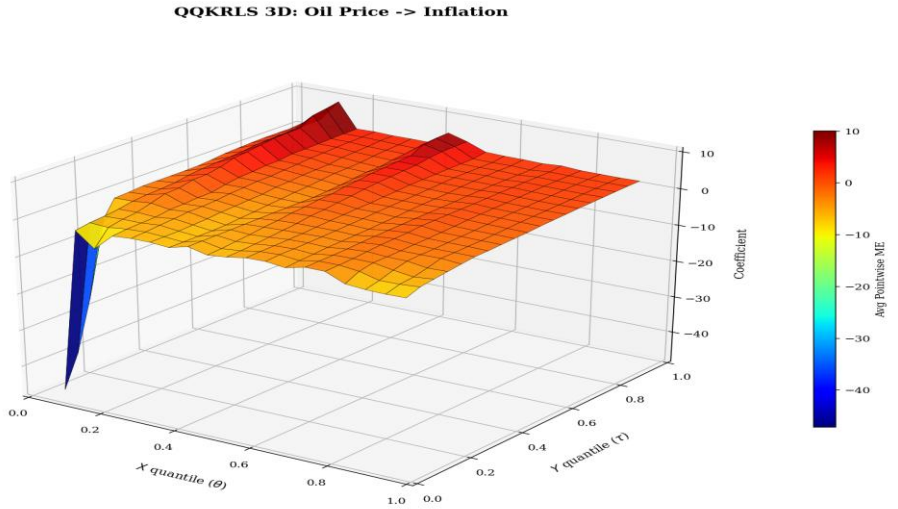
The graphs of the marginal effects of OP show that the impact varies according to the level of OP (non-constant effect), justifying the non-parametric approach.

Oil prices significantly and positively influence inflation in Algeria, whereas the average effect of the exchange rate is not significant. The relationship is nonlinear.

3.5.2 QQKRLS Model (Quantile-on-Quantile KRLS)

The application of the QQKRLS (Quantile-on-Quantile Kernel Regularized Least Squares) methodology to the study of the determinants of inflation in Algeria (2002–2025) highlights strong heterogeneity in the effects of oil prices and exchange rates depending on the inflation regime considered. These results contradict the assumption of a linear and constant relationship usually assumed in standard models.

• Effect of oil prices (OP):



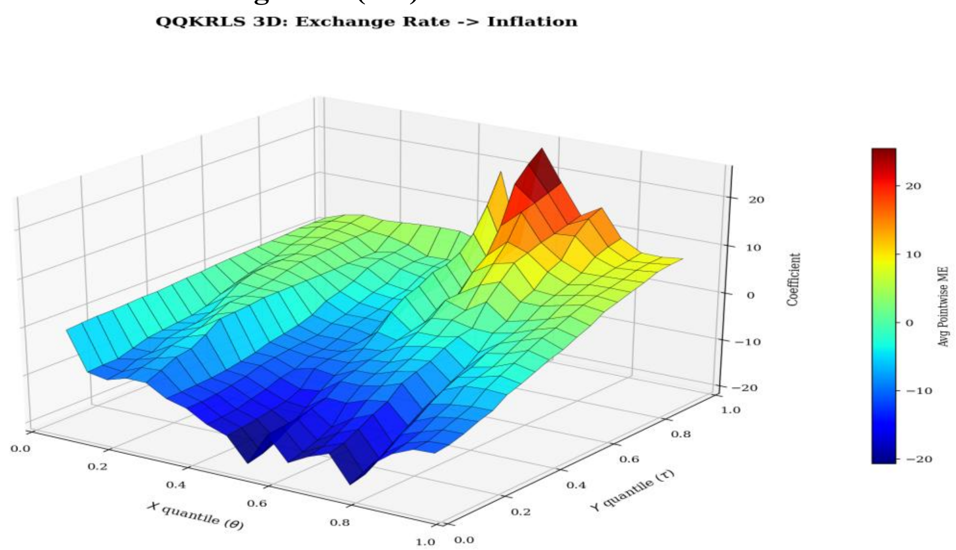
For episodes of low to moderate inflation ($\tau \leq 0.4$), the marginal effect of oil prices is negative or non-significant, suggesting that increases in oil prices are not mechanically transmitted to domestic inflation, probably because of subsidy or stabilization policies.

• When inflation is high ($\tau \in [0.5; 0.8]$), the effect becomes positive and statistically significant, confirming standard theory: an increase in oil prices fuels inflation in a context where tensions are already present.

• At the extremes (very high inflation, $\tau = 0.9$), the effect becomes negative again, which could reflect a regime change (expectations of monetary tightening or a "fatigue" effect in transmission).

Conclusion on OP: The effect is not constant. An increase in oil prices stimulates inflation only when inflation is already in a high regime ($\tau > 0.5$). During periods of low or very low inflation, the effect is null or negative.

• Effect of the exchange rate (ER)



For low to moderate inflation regimes ($\tau \leq 0.6$), an appreciation of the exchange rate (decrease in ER) significantly reduces inflation, with negative and highly significant coefficients. This validates the exchange rate channel in the Algerian economy.

• As inflation rises ($\tau = 0.7$–0.8), the magnitude of this effect decreases, then reverses for $\tau = 0.9$ (positive effect). This reversal suggests that in situations of very high inflation, other forces (indexation, loss of credibility) dominate the traditional transmission mechanism, or that the estimated sign captures an endogeneity bias linked to the monetary crisis.

Conclusion on ER: The exchange rate is a highly significant determinant of inflation, especially when inflation is low or moderate. Its effect is consistent with theory (appreciation = disinflation). However, at the extremes ($\tau = 0.9$), the relationship reverses, probably because of regime changes or the predominance of other mechanisms.

General Conclusion

This study mobilizes the KRLS and QQKRLS methods, coupled with wavelet decomposition, to reexamine the nonlinear determinants of Algerian inflation between 2002 and 2025 in the face of violations of classical assumptions. The results invalidate the hypothesis of a linear and homogeneous transmission of oil price and exchange rate shocks. The effect of oil prices proves to be nonlinear and conditioned by the inflation regime: null or negative for low inflation, strongly positive for moderate to high inflation (quantiles 0.5–0.8), then reversing at the extremes. The exchange rate exerts on average no significant effect (KRLS), but QQKRLS analysis reveals a disinflationary impact consistent with theory when inflation remains moderate (quantiles ≤ 0.6), which disappears and then reverses under conditions of very high inflation. Wavelet analysis confirms a dynamic dominated by a permanent trend and medium-term cycles (16–32 months) aligned with major oil shocks. From a methodological perspective, the KRLS–QQKRLS combination offers unprecedented flexibility for capturing double quantile heterogeneity, going beyond the limits of linear or standard quantile regressions. For monetary policy, these results argue in favor of differentiated monitoring of inflation thresholds, cautious use of the exchange rate according to the economic regime, and abandonment of linear specifications in forecasting models.

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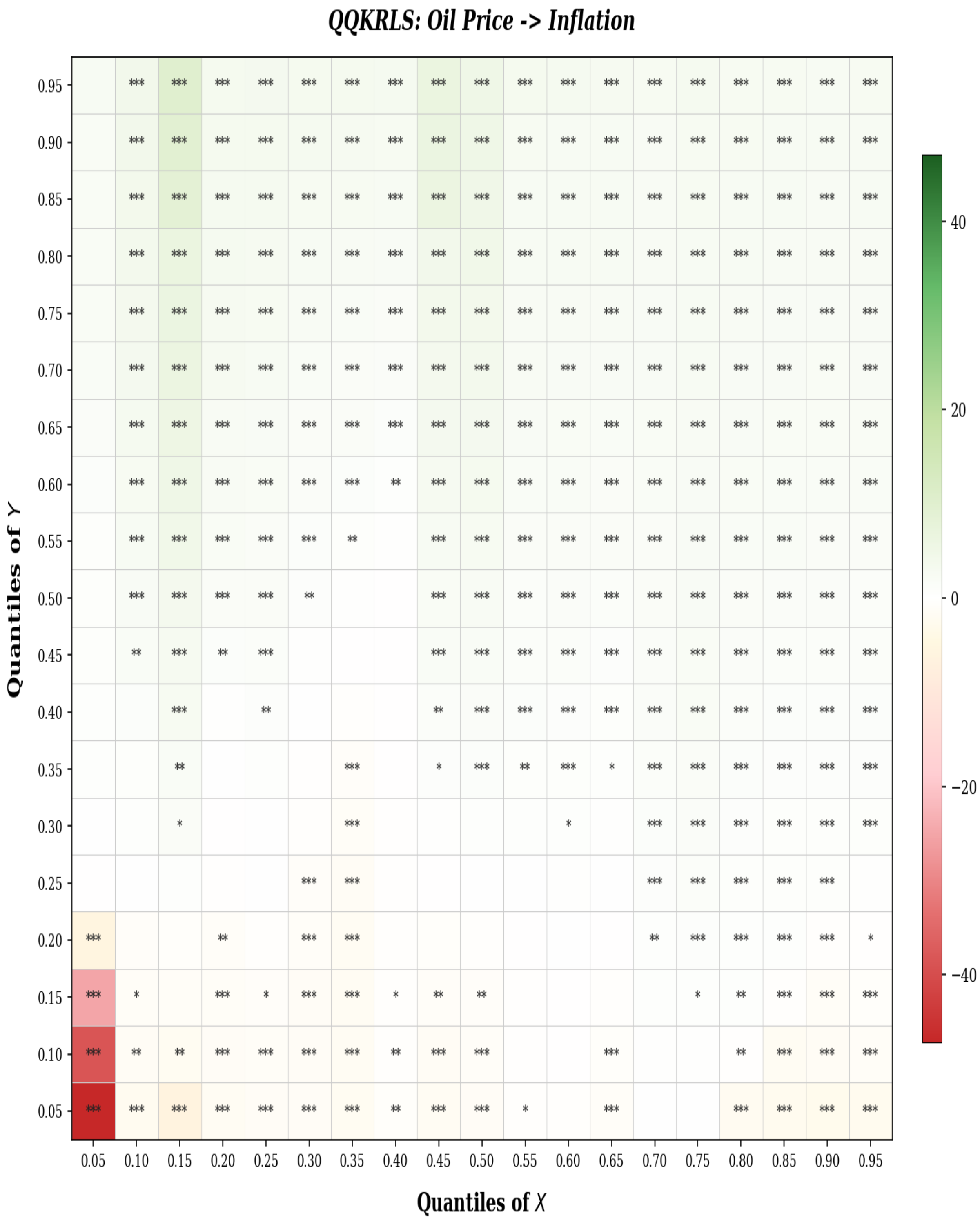
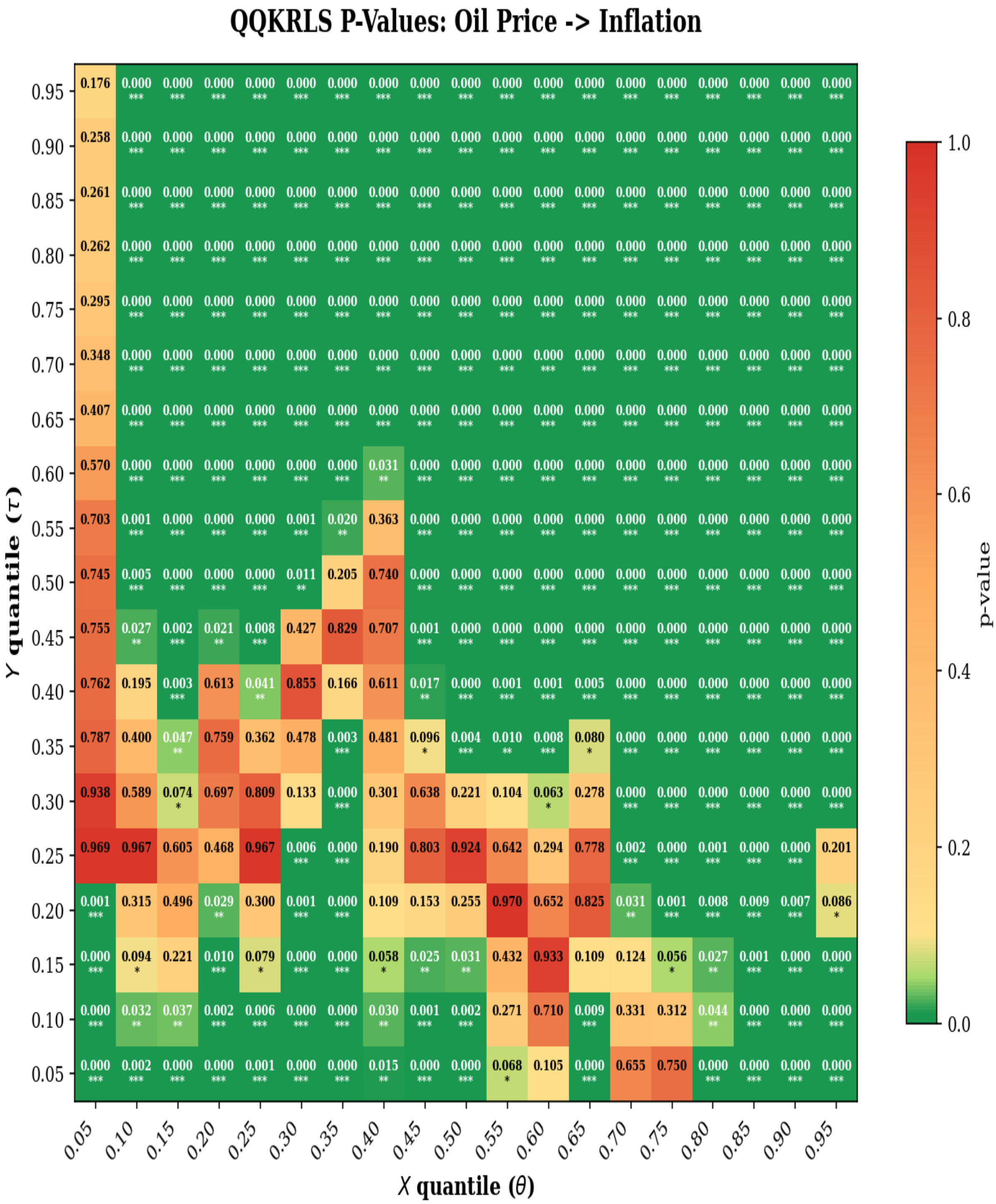
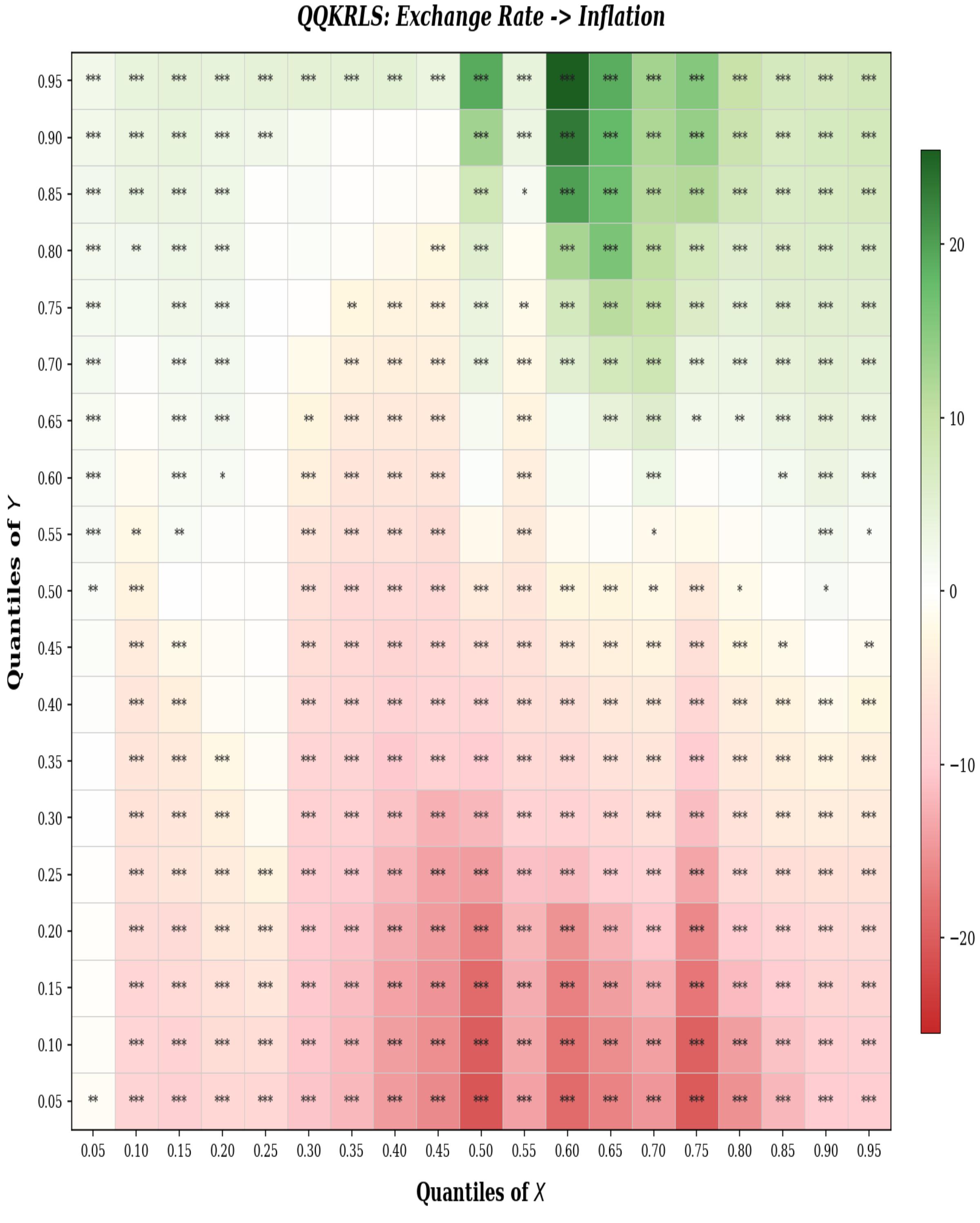
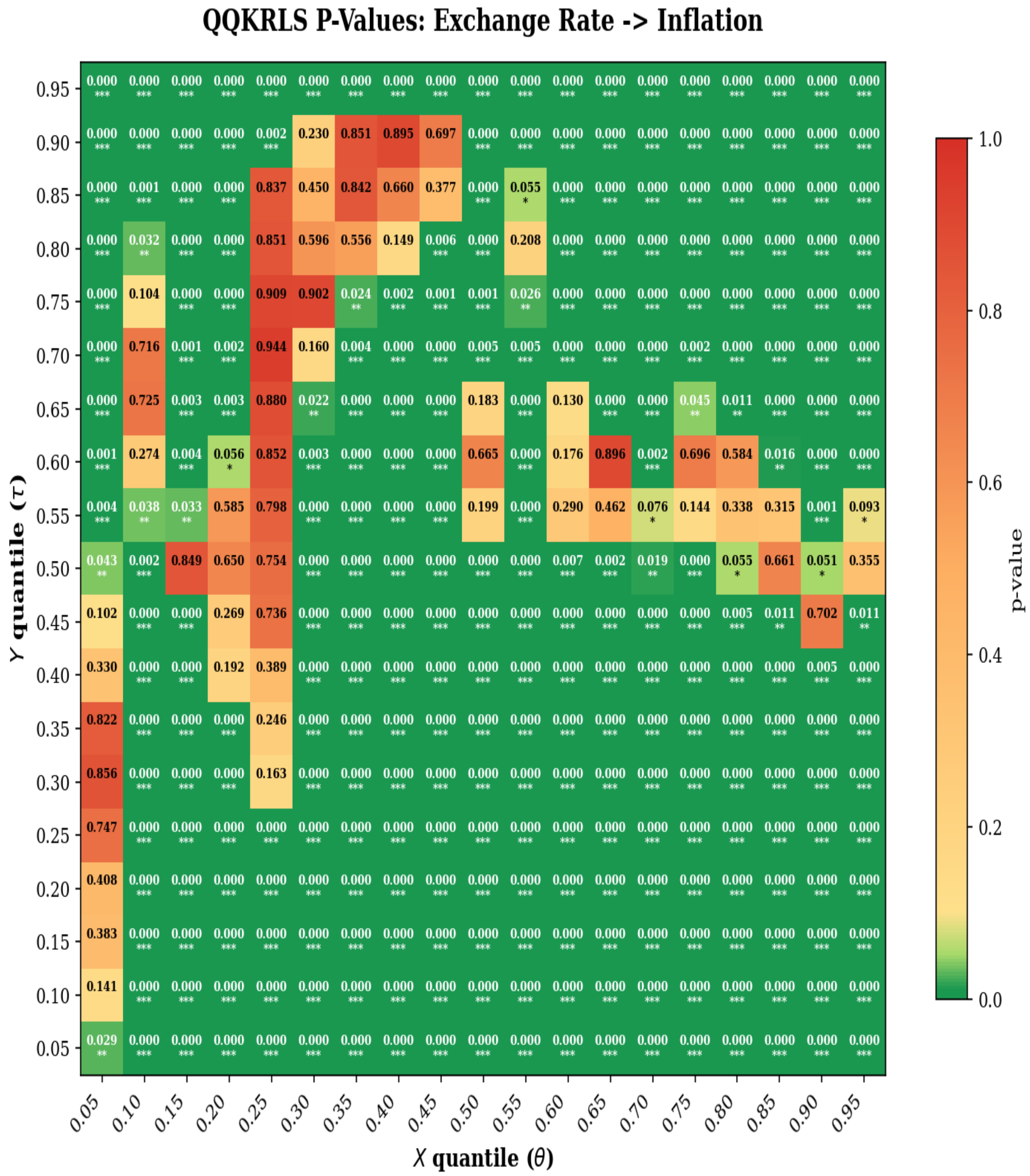
ANNEX:




QQKRLS P-Values: Oil Price -> Inflation
Y quantile (τ)
X quantile (θ)
p-value
0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40 0.45 0.50 0.55 0.60 0.65 0.70 0.75 0.80 0.85 0.90 0.95
0.0 0.2 0.4 0.6 0.8 1.0


QQKRLS: Exchange Rate -> Inflation
Quantiles of Y
Quantiles of X
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85
0.90
0.95
20
10
0
−10
−20


QQKRLS P-Values: Exchange Rate -> Inflation
Y quantile (τ)
X quantile (θ)
p-value