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Domestic and External Inflation Drivers in Oil-Exporting Countries:

Empirical Evidence from the UAE

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Abstract

This paper examines the key drivers of inflation in oil-exporting economies with an empirical application to the UAE. Results show that the primary domestic sources of inflation are housing rents and PMI, as measured by the Purchasing Managers' Index. On the external side, interest rates, the nominal effective exchange rate, and global non-energy commodity prices emerge as significant contributors to inflation dynamics. Oil prices also play a notable role, especially following the deregulation of fuel prices in August 2015. These findings hold across the frequency spectrum (monthly, quarterly).

Keywords: inflation expectations, non-oil GDP, rent prices, non-energy inflation, United Arab Emirates.

JEL classification: C13, C22, E31, E37.*

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1. Introduction

The debates among economists on inflation tend to intensify during periods of surging inflation. This was evident during the oil shocks of the 1970s and the debt crises of the 1980s. After a period of disinflation and sustained growth (Great Moderation, 1986–2007), punctuated by major recessions in 2008–09 and 2020, inflation has returned as a central concern in the early 2020s. In fact, global inflation has surged to multi-decade highs in the post-2020 period – reaching around 8–9% in many advanced economies by 2022 – prompting monetary tightening worldwide. By contrast, the UAE's inflation rate has risen only moderately, averaging 4.8% in 2022. This divergence between the global inflation spike and the United Arab Emirates (UAE)'s more contained price growth underscores the importance of understanding country-specific inflation dynamics from the outset.

Determining the main drivers of inflation is a vital task for central banks, as it helps anchor the public's inflation expectations and prevent persistent inflationary spirals. Recent studies emphasise that well-anchored expectations are crucial to avoiding self-fulfilling inflation inertia (Alcidi et al., 2022; Schafer, 2022). However, analysing inflation dynamics in the UAE presents unique challenges due to several data limitations. The available time series for key macroeconomic variables are relatively short (reflecting the UAE's newer statistical history), and are reported infrequently or with delays. These data constraints complicate conventional modelling and forecasting of inflation in the UAE, necessitating careful methodological choices.

In practice, short-term inflation forecasts (up to one or two quarters ahead) often rely on granular assumptions about individual price index components (e.g., food, transport, housing). Beyond a very short horizon, however, such component-by-component forecasting becomes questionable, as it fails to capture the lagged second-round effects and cross-variable pass-throughs that shape overall inflation. For example, energy and food prices are sometimes projected exogenously (based on futures or global trends), separate from core inflation, even though these components eventually feed into costs and prices across the broader economy. Therefore, an appropriate modelling approach that internalises these dynamics is paramount for medium-term inflation forecasting.

While oil prices are known to affect inflation in both exporting and importing countries, the inflation dynamics of oil-exporting economies warrant special attention. Notably, much of the existing inflation literature has focused on large advanced or oil-importing economies, whereas individual case studies on oil-exporting countries remain relatively scarce. This paper seeks to contribute to narrowing this gap by introducing a short-term inflation forecasting model for the UAE, as an oil-exporting, open economy with a fixed exchange rate and limited labour market rigidities due to its large expatriate workforce.

Empirically, we develop a short-term inflation forecasting model inspired by the New Keynesian Phillips Curve (NKPC) framework, incorporating both domestic and external determinants relevant to the UAE. The specification includes variables such as oil prices, the nominal effective exchange rate (NEER), interest rate, rent, and the purchasing managers index (PMI). The model is estimated using quarterly and monthly data between 2015:Q1 and 2024:Q2, with robust regression techniques and appropriate variable selection methods. The results show that the main domestic inflation drivers for the UAE are rent and PMI, while external drivers include interest rate, the NEER, and oil price.

The remainder of the paper is structured as follows. Section 2 reviews the literature on inflation drivers in oil-exporting countries, section 3 introduces the model and data, section 4 presents estimation results and robustness checks, and section 5 concludes.

2. Literature Review

A wide range of tools and economic models have been designed to forecast inflation, drawing on formal theoretical frameworks (Atkeson and Ohanian, 2001; Stock and Watson, 2009). These models are often rooted in established concepts of economic theory, such as the (Augmented) Phillips curve and the wage-price spiral. However, these standardised formulations are limited in their applicability to oil-exporting countries, as such economies are subject to specific structural features that standard formulations may fail to capture. Consequently, more tailored specifications are needed to track inflation dynamics in these contexts, incorporating relevant domestic and external determinants, beyond conventional theoretical models (Arezki et al. 2018).

For oil-exporting countries, particularly in the GCC, the literature remains relatively scarce. Alsabban et al. (2023), using an ARDL model with quarterly data for Saudi Arabia, found that domestically, inflation is driven by the Purchasing Managers' Index (PMI), net government spending and broad money (M3), while external drivers include imported inflation and the nominal effective exchange rate (NEER). Similarly, Fareed et al. (2023), applying a global VAR model to the GCC countries, concluded that inflation dynamics are largely shaped by external factors, particularly the NEER and imported inflation from major trading partners. Earlier, Kandil and Morsey (2009) also highlighted the role of imported inflation, along with oil revenues, during the 2001-2007 period.

In many economies, oil prices play an important role in shaping economic activity and inflation. However, their influence is particularly pronounced in oil-exporting economies, where oil revenues are a central driver of fiscal policy, external balances, and overall macroeconomic conditions. In such contexts, oil prices can affect domestic inflation through both direct and indirect channels. Direct effects arise when fuel and other energy products are de-subsidised, making consumer prices more sensitive to fluctuations in global oil markets. Indirect effects are transmitted through broader macroeconomic channels, notably fiscal policy. Figure A.1 (Appendix A) illustrates a framework of potentially direct and indirect drivers of inflation in an oil-exporting country with a pegged exchange rate and a large foreign labour force. The main pass-through to domestic inflation can be grouped into three categories: (i) fiscal channel, (ii) exchange rate and reserves accumulation channels, and (iii) other exogenous or foreign channels, such as expectations (Alcidi et al., 2022; Schafer, 2022) and technology shocks (Dieppe et al., 2021). Oil prices influence each of these channels differently.

The Fiscal Channel: A sustained increase in oil prices typically boosts fiscal revenues, allowing governments to build stronger fiscal buffers. Oil exporters thus benefit from oil windfalls, especially in times of expansionary phases and commodities booms, except in the recent pandemic crisis, though the dual shocks of COVID-19 and the oil price slump in 2020 were notable exceptions. The analysis of the effect on inflation could be captured through the global aggregate demand and/or the composition and shares of different government expenditures. Government expenditures can have a mixed effect on inflation, where a high presence of subsidies can dampen a portion of imported inflation, while social transfers and mega-government projects may boost aggregate demand and push up inflation.[1]

1 Despite that energy and food products are subsidised, the pass-through from international commodity prices to the domestic prices was estimated to be important, particularly for food prices in developing countries due to their high weights in the consumer basket (IMF, 2011).

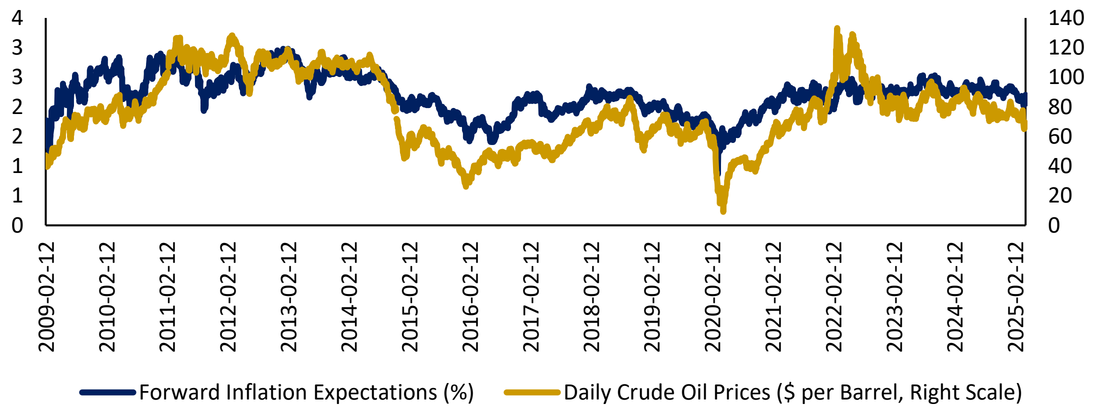
The pro-cyclical fiscal policy in the GCC countries, as evidenced in various publications (IMF, 2020, 2021, 2022), involves an increase in public spending that shifts aggregate demand upward through the non-oil GDP channel. This likely leads, *ceteris paribus*, to pressures on domestic prices. Inflation originating from aggregate demand is empirically measured through the gap between actual GDP and its potential, or interchangeably, the purchasing managers' index (PMI). When the economy is overheating, an increase in GDP exceeding its potential is associated with inflation, as the economy is running beyond its capacity. Conversely, a decrease in GDP is often a precursor to downturns. Besides the active role of fiscal policy in stimulating the aggregate demand, its flexibility is vital for exchange rate arrangements, particularly under a pegged regime (Eichengreen et al., 1998; El Hamiani et al., 2020).

The accumulation of reserves channel: Rising oil prices often translate into higher reserves (Net Foreign Assets) and increased capital inflows. Many studies argue that the build-up of reserves can exert inflationary pressures on domestic prices.[2] Two main mechanisms have been identified. First, reserve accumulation may expand the monetary base, and in the case of incomplete sterilisation, this fuels domestic price increases. Second, large reserves can create a sense of confidence and security that may encourage governments to adopt imprudent expansionary policies, reflecting a form of moral hazard (Chitu, 2021). Beyond oil prices, other external shocks may also affect inflation. For example, fluctuations in global food prices are highly relevant for the UAE, given its dependence on food imports. These prices are shaped by transportation costs, supply chain disruptions, and bottlenecks, particularly during crises such as the COVID-19 pandemic. In addition, technological shocks linked to digitalisation and fintech may help ease inflationary pressures.

The inflation expectations channel: Identifying inflation drivers is crucial for central banks to anchor expectations and guide monetary policy effectively. A wide body of recent research recognises inflation expectations as a major determinant of actual inflation (Alcidi et al., 2022; Schafer, 2022), as they strongly influence economic agents' decisions. However, measuring expectations remains complex.[3] Increasingly, central banks rely on surveys to assess them—for instance, the ECB employs the Survey of Professional Forecasters (SPF) (Alcidi et al., 2022). Still, evidence highlights notable biases in individual forecasts, which can amplify inflationary trends. In particular, surveys of households and business managers often overlook the dynamics of inflation and show limited awareness of monetary policy measures and objectives (Schafer, 2022).

With regard to international oil prices, they may also play a significant role in shaping inflation expectations. For instance, data from the Federal Reserve Bank of St. Louis indicates a strong correlation (83%) between daily oil prices and U.S. inflation expectations over the period from December 2009 to April 2025 (Figure 1).[4]

Figure 1. Inflation Expectations and Oil Prices in the United States



Source: FRED data retrieved on April 25, 2025.

2 For more details, refer to Heller (1981), Jones (1983), Aizenman and Glick (2009) and Steiner (2017).

3 For the monetary authorities, the more they anchor inflation expectations to their objectives, the better the monetary transmission and the more inflation persistence is reduced. Inflation persistence could have risen had the monetary policy failed to anchor inflation expectations to its monetary objectives.

4 The measure of expected inflation is a 5-Year Forward Inflation Expectation Rate, derived from 10-Year and 5-Year Treasury Inflation-Indexed Constant Maturity Securities, retrieved from: FRED; https://fred.stlouisfed.org/series/T5YIFR, April 25, 2025.

The labour market channel: Inflation originating from the labour market is primarily driven by wages and salaries through labour cost inflation, meaning wage growth adjusted for productivity changes. Inflation is thus connected to real unit labour costs via structural equations that also incorporate inflation expectations (Gali and Gertler, 1999; Smets and Wouters, 2007; King and Watson, 2012), and to wages through the wage price spiral mechanism (Blanchard, 1986; Kandil, 2003). Recent empirical evidence, however, suggests a weakening of this channel, as the pass-through from labour costs to inflation has been declining over time. This trend is often attributed to rising trade openness, increased firm market power, and better-anchored inflation expectations (Bobeica et al., 2021a).

The wage–price spiral is most prominent in industrialised economies, where collective bargaining through labour unions plays a central role in wage determination. In contrast, this mechanism appears less relevant in oil-exporting countries, where labour market frictions are limited due to the heavy reliance on expatriate workers, particularly in the private sector, reducing the significance of cost-push inflation (as seen in GCC economies). Nonetheless, the pass-through from the labour market to inflation may still operate indirectly through labour demand, which is often linked to oil prices and production cycles. Labour demand tends to rise during oil booms and contract during downturns. Over the long term, structural reforms, economic diversification, and transformation processes may further influence inflation dynamics (Bobeica, 2020; 2021b).

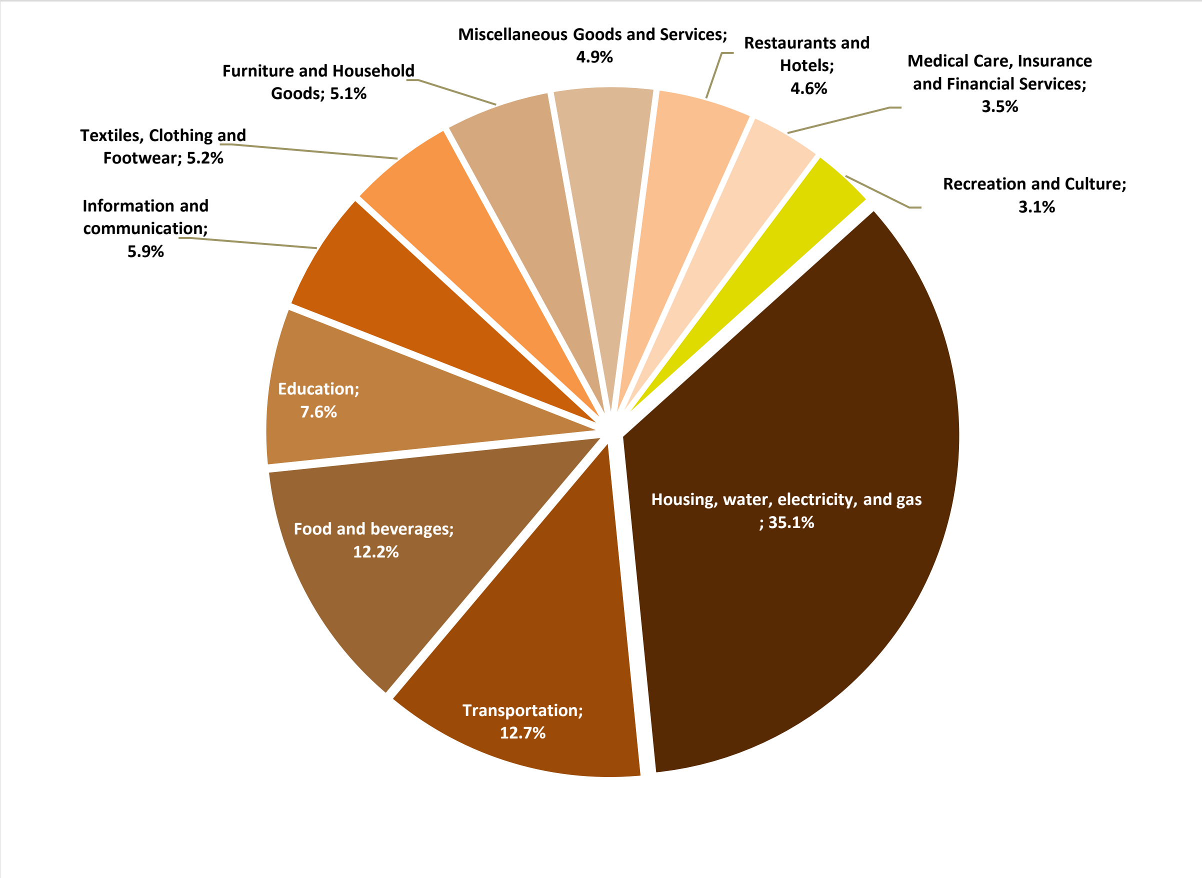
3. CPI Analysis, Model Specification, and Data Description

3.1. *Sectoral Analysis of the UAE CPI*

Examining the composition of the consumer price basket provides insight into the main components driving domestic prices. In the UAE, housing and related services represent the largest share of household expenditure, accounting for 35.1% of the basket according to 2019 data (Figure 2). Transportation constitutes the second-largest component (12.7%), followed closely by food and beverages (12.2%).

At the micro level, fluctuations in international oil prices directly influence consumers via their pass-through to local fuel and gasoline prices.[5] Moreover, all industries that rely on these deregulated products as intermediate inputs, such as airline industries, and public and common private transportation, are likely to transfer their higher cost of produced goods and services to end users, thereby contributing to the overall price increase. Food commodities, which are largely imported, are also exposed to external shocks, including changes in global transportation costs and supply chain disruptions.

Figure 2. Weightage of Items in the UAE's Customer Expenditure Basket



Source: Federal Competitiveness and Statistics Centre (FCSC).

Accordingly, the three largest components, housing, transportation, and food, account for more than 60% of the UAE's expenditure basket. These categories are also, to varying degrees, influenced by international oil prices. In particular, global oil prices directly pass through to gasoline products, which have been liberalised in the UAE since August 2015.

Housing prices likewise tend to follow oil market dynamics. For instance, real estate prices in the UAE peaked in 2013, coinciding with a period of sustained high oil prices from 2011 to 2014. Further analysis could reveal housing cycles that partially correlate with oil price movements. Evidence from other countries supports this linkage: Padilla (2005) documented a lag of seven quarters for the impact of oil prices on housing prices in Calgary (Canada). At the national level, Kilian and Zhou (2022) found that real oil price shocks account for around 11% of the variability in Canada's real house price growth. They also show that oil price shocks transmit to housing markets in non-oil-producing regions through government redistribution of oil revenues and interprovincial trade. A similar mechanism may apply in the UAE, where oil production is uneven across the seven emirates. In this case, oil wealth from resource-rich emirates could affect real estate markets in less oil-abundant emirates via the federal budget and inter-emirate trade.

5 In the UAE, fuel prices were deregulated as of 1 August 2015 (https://u.ae/en/information-and-services/environment-and-energy/water-and-energy/energy-and-fuel-prices).

3.2. A New Keynesian Phillips Curve for the UAE

To empirically assess the key drivers of inflation in the UAE, we estimate a hybrid New Keynesian Phillips Curve (NKPC) augmented with domestic and external variables that reflect the structural characteristics of the UAE economy (Figure A.1). The NKPC framework is particularly flexible, allowing the inclusion of both foreign and domestic determinants, and is widely applied in empirical studies by central banks, monetary authorities, and academia (Banerjee et al., 2024; Aginta, 2023; Ball and Mazumder, 2021; Eser et al., 2020; Dur and Martínez García, 2020; Gabrielyan, 2018; Mihailov et al., 2011; Rumler, 2007).

We include variables such as oil prices to capture direct energy-driven inflation, government expenditure to reflect fiscal policy effects, the non-oil GDP output gap and the global output gap (interchangeably tested with the global non-energy commodity price index), as well as additional factors like inflation inertia, the nominal effective exchange rate (NEER), and interest rates. Following Kamber et al. (2020), the baseline hybrid NKPC for an open economy is expressed as:

$$\pi_t = \alpha_0 + \alpha_1\pi_{t-1} + \beta_1\tilde{Y}_t + \beta_2\tilde{Y}_t^w + \gamma_1\tilde{E}_t + \gamma_2\tilde{p}_t^{oil} + \gamma_3 i_t + \theta_1\tilde{G}_t + \theta_2\widetilde{W}_t + \theta_3\widetilde{H}_t + \varepsilon_t$$ [6]

Where π_t is inflation measured as percent change of the consumer price index (CPI), $\tilde{Y}_t$ and $\tilde{Y}_t^w$ are respectively domestic and World output gaps in percent change, $\tilde{E}_t$ measures variations of the nominal effective exchange rate, and $\tilde{p}_t^{oil}$ denotes the world oil prices growth. Given the Dirham's peg to the U.S. dollar, we augment the specification with the U.S. Federal Funds rate (i_t) to capture the exogenous effects of the U.S. monetary policy on domestic inflation. We also add government expenditure growth $\tilde{G}_t$ to capture fiscal policy effects,[7] private sector wages ($\widetilde{W}_t$) [8] and housing prices ($\widetilde{H}_t$) which is highly relevant in the UAE's CPI structure, and, ε_t is a residual term which assumes classical properties. The money supply growth (M3) is also tested as a domestic driver for inflation, while the global non-energy inflation is tested interchangeably with the World output gap as a potential external driver. The non-oil GDP gap is tested but insignificant, and is then interchangeably replaced with the PMI index, used as another alternative for assessing the economy's position in the business cycle (Clancy,2013).

3.3. Data Description and Preliminary Tests

The dataset includes a set of domestic and foreign variables, which are likely the main internal and external drivers of inflation in the UAE, as discussed in the literature section for the case of an oil-exporting country. Sources are listed in Appendix B (Table B.1). The non-oil output gap is estimated using the Hodrick-Prescott (1997) filter. Stationarity is tested using unit-root tests; all year-on-year growth rate variables are stationary, while the interest rate is stationary in level and used as such (Table B.2). Kendall's tau statistics, suitable for small samples, show significant correlations are more induced by external than domestic determinants (Table B.3).

6 Inflation expectations in the Kamber et al. (2020) model are expressed as a weighted average of Backwards (π_t^{be})and forward (π_t^{fe}) inflation expectations ($\alpha.\pi_t^{be} + (1-\alpha).\pi_t^{fe}$). Since there is no data on inflation expectations in the UAE, we follow common practice and proxy expectations by inflation inertia (π_{t-1}), assuming that expectations are habit-based.

7 We also test the effect of the pro-cyclicality of fiscal policy and its effects on inflation through the government expenditure cyclicality ($\tilde{G}_t$).

8 The public sector's compensations are included in the government expenditures variable.

4. Estimations

4.1 Estimations and Results Discussion

Several specifications of the UAE NKPC are estimated using the selected variables. Details of variables selection and methodological steps are provided in Appendix C.

The final chosen model identifies past inflation (inertia), rent prices and purchasing managers' index (PMI) as the most significant domestic drivers of inflation in the UAE. On the external side, the nominal effective exchange rate (NEER), U.S. federal funds rate, global non-energy commodities inflation, and oil prices emerge as key foreign (Table 1). All coefficients are highly significant and display the expected signs. Thus, during expansions, rent prices, PMI, global non-energy inflation, and oil prices tend to push up inflation. Conversely, dirham appreciation (via the NEER) and higher interest rates exert downward pressures on inflation as observed during the 2022–2023 tightening cycle.

Inflation in the UAE also displays significant inertia (around 0.6), suggesting that expectations anchored in past inflation continue to influence current inflation dynamics. Dummy variables for 2018:Q1 and 2019:Q1 improve model fit, capturing the inflationary impact of the introduction of VAT in 2018 and the subsequent deflationary correction in 2019 (Figure A.2, Appendix A). [9]

Table 1. NKPC Estimations for the UAE (Quarterly)

	Model with VAT effect		Model without VAT effect	
Variables	Coefficient	Prob.	Coefficient	Prob.
Constant, α_0	0.747***	0.006	0.818***	0.001
Inertia, π_{t-1}	0.557***	0.000	0.508***	0.000
Rent, H_{t-2}	0.120***	0.005	0.117***	0.000
PMI_{t-1}	0.134***	0.000	0.127***	0.000
Interest rate, i_{t-1}	-0.238***	0.004	-0.224***	0.004
NEER, $\tilde{E}_{t-2}$	-0.011**	0.027	-0.014*	0.059
Oil prices, $\tilde{P}_t^{oil}$	0.025***	0.000	0.027***	0.000
Global non-energy inflation, $\widetilde{WI}_{t-2}^{w}$	0.054**	0.022	0.048**	0.022
VAT Dummy	---	---	2.155***	0.000
Adjusted R-squared	0.867		0.923	
F-statistic	34.662		54.049	
Durbin-Watson statistic	1.983		2.138	

*Notes: *, **, ***: significant at the level of 10%, 5% and 1% respectively. Period of estimations: 2015:Q1-2024:Q2; included observations: 37 after adjustments. We use the OLS regression method with the option of Heteroskedasticity and Autocorrelation-Consistent (HAC) standard errors to produce standard errors that are robust to autocorrelation as well as heteroscedasticity, and the covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).*

9 Statistically, the dummy effect is detected from the residuals equation and confirmed using influential statistics tests detecting outliers (Belsley et al., 2004).

Figure A.1 illustrates that oil price effects can be transmitted through various channels, including fiscal policy, the accumulated official reserves via net foreign assets, and transportation as a direct channel. For the UAE, empirical evidence over the past decade indicates that oil prices act as a direct driver of inflation, primarily through the transportation component, the second largest component after housing in the consumer basket (Figure 2). This effect has been more pronounced since August 2015, when the government subsidies on petroleum derivatives, such as gasoline, were removed. Monthly data confirm this finding.[10] Table 2 reports the final results for the monthly model estimated for the post-subsidy period, showing a direct effect of oil prices on inflation. Mien (2022) found an oil coefficient ranging between 0.07 and 0.09 for four African oil countries, while Galesi and Lombardi (2009) found a direct effect of oil prices on inflation, mostly in developed countries.

Table 2. NKPC Estimations for the UAE (Monthly)

Variables	Coefficient	Std. Error	t-Statistic	Prob.
Constant, α_0	0.556***	0.123	4.511	0.000
Inertia, π_{t-1}	0.780***	0.052	14.987	0.000
Rent, H_{t-7}	0.042***	0.014	2.946	0.004
PMI_{t-6}	0.027**	0.011	2.519	0.014
Interest rate, i_{t-1}	-0.241**	0.097	-2.477	0.016
NEER, $\tilde{E}_{t-5}$	-0.037*	0.019	-1.965	0.053
Oil prices, $\tilde{P}_t^{oil}$	0.003**	0.002	2.067	0.042
Global non-energy inflation, $\widetilde{WI}_{t-4}^{w}$	0.015*	0.008	1.792	0.077
Adjusted R-squared	0.94			
F-statistic	184.83			
Durbin-Watson statistic	1.70			

*Notes: *, **, ***: significant at the level of 10%, 5% and 1% respectively. Period of estimation: 2015:M06-2024:M07; the number of included observations: 107.*

The effect of money supply (M3) on inflation is statistically insignificant. Similarly, government expenditure does not appear significant in our model, despite evidence from earlier periods suggesting a pro-cyclical relationship between government spending and oil prices in the GCC and particularly in the UAE (IMF 2020, 2021). For the more recent period, however, empirical results reject a measurable impact of government expenditures on inflation. [11]

10 We run regressions over the two periods with only oil prices and inflation inertia as explanatory variables and using different lags. Results (Appendix, Table B.4) confirm the effect of oil prices on inflation based on monthly data, particularly after the subsidy was removed in August 2015.

11 The reason could also be related to the content of the data on the consolidated government budget. Indeed, the latter contains only government expenditures for the general government, while major important capital expenditure projects are likely implemented through government-related entities.

4.2. *Robustness Check*

The reliability of econometric estimations depends on sufficient degrees of freedom, which in this case are constrained by the short time series and the inclusion of multiple relatively correlated determinants. Correlations among regressors raise additional econometric concerns, such as multicollinearity, that can weaken the statistical and economic significance of some variables. Given the wide range of potential inflation drivers in the UAE, their correlations (Table B.3), and the relatively short sample available for certain variables, we conduct six different estimations to identify the most relevant determinants. The selection process relies on two econometric methods: the stepwise forward regression method [12] and the coefficients' variance decomposition method (see methodological supplement in Appendix C).

Table 3 summarises the estimation results. Across specifications, the models are relatively well fitted with an adjusted R2 of around 90%. All models include a constant and an inflation inertia (AR[1]).[13] For robustness, we applied both parametric and non-parametric diagnostic tests, including residual autocorrelations (Table B.5, Appendix B) and heteroskedasticity (Table B.6, Appendix B).[14] In addition, Vector Autoregressive (VAR) models were estimated to confirm the relative size and expected economic signs of each inflation determinant (Figures 4 and 5).

Inflation inertia is statistically significant in all specifications, with coefficients ranging between 0.5 using quarterly data and 0.8 with monthly data. This not only improves the correction of serial correlation in the residuals but also aligns with previous findings: Asfuroglu (2021) and Loungani and Swagel (2001) report inertia values between 0.5 and 0.7 for developing economies, while Kandil and Morsy (2011) find a coefficient of 0.8 using UAE annual data for 1970–2007. We further tested inertia against the sample structure and explanatory variables, confirming its robust statistical significance.[15]

Model 2 indicates that inflation inertia, rents, private-sector wages, and the Purchasing Managers' Index (PMI) are the main domestic drivers of inflation in the UAE, while government expenditure and money supply (M3) growth are statistically insignificant (Table 3). These two variables were excluded after checks for multicollinearity, residual serial correlation, stepwise regression, and variance decomposition (Table B.9, Appendix B). The model remains highly robust, with an adjusted R^2 of 91%. On the external side, Model 3 highlights oil prices, the NEER, the interest rate, and global non-energy commodity inflation as significant determinants. Model 5 is the selected model after mixing all the domestic and foreign drivers and reapplying all the appropriate tests, leading to a final set of selected domestic and foreign drivers of UAE inflation (Model 6). The latter concludes that the main inflation drivers are rent, PMI, oil price, NEER, interest rate and global non-energy commodities prices.

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12 This starts with no explanatory variables and consecutively includes variables, based on statistical significance, until no remaining statistically significant variables. Backward selection could also be used, but is challenged by the large number of potential explanatory variables (Smith, 2018).

13 Results considering the non-oil GDP gap instead of PMI are also presented (Table B.10, Appendix B).

14 Breusch-Godfrey serial correlation LM tests show that there are no autocorrelations of the residuals (Table B.5, Appendix B) for the three chosen models. For the heteroskedasticity, Breusch-Pagan-Godfrey tests show that the errors are homoscedastic (Table B.6, Appendix B).

15 Wald test (Table B.7; Appendix B) confirmed that, despite its relatively high value, inertia remains less than 1, suggesting that the expectations are not adaptive.

Table 3. Estimation Results for the Selection of the Main Inflation Determinants (Quarterly Model)

Variable	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
Constant, α_0	0.473	0.315	0.416**	0.038	0.385	0.164	0.470	0.107	0.689***	0.001	0.818***	0.001
Inertia, π_{t-1}	0.587***	0.000	0.584***	0.000	0.866***	0.000	0.834***	0.000	0.620***	0.000	0.508***	0.000
Rent, H_{t-2}	0.062***	0.005	0.066***	0.005	..	..	..	..	0.063**	0.015	0.117***	0.000
Wages, W_{t-1}	0.074**	0.050	0.078***	0.008	..	..	..	..	-0.005	0.897	..	..
PMI_{t-1}	0.064**	0.014	0.060**	0.026	..	..	..	..	0.104***	0.006	0.127***	0.000
Government spending, $\tilde{G}_{t-1}$	0.007	0.333	..	..	..	..	..	..	0.004	0.611	..	..
Money M3, $\tilde{M}_{t-1}$	-0.010	0.860	..	..	..	..	..	..	..	..	..	..
Oil prices, $\tilde{P}^{oil}_{t-1}$	..	..	..	..	0.010	0.121	0.008**	0.049	0.007	0.251	0.027***	0.000
NEER, $\tilde{E}_{t-2}$	..	..	..	..	-0.006	0.320	..	..	-0.009	0.169	-0.014*	0.059
Interest rate, i_t	..	..	..	..	-0.364*	0.089	-0.411**	0.048	-0.240*	0.100	-0.224***	0.004
Global non-energy inflation, WI^{w}_{t-2}	..	..	..	..	0.020	0.402	..	..	0.016	0.161	0.048**	0.022
VAT Dummy, D	2.874***	0.000	2.836***	0.000	2.583***	0.000	2.557***	0.000	2.380***	0.000	2.155***	0.000
Adjusted R-squared	0.913		0.917		0.879		0.885		0.946		0.923	
Durbin Watson	1.933		1.826		1.728		1.698		2.224		2.155	

*Note: *, **, ***: Significant at 10%, 5% and 1% respectively. Period of estimation: 2015:Q1-2024:Q2; number of included observations: 37. Model 1 includes domestic drivers with constant and in-ertia, model 2 is the selected model for domestic drivers after an appropriate set of tests as described in the methodology section, model 3 is for all foreign drivers, model 4 is the selected model after appropriate tests, model 5 is the selected model after mixing all the domestic and foreign drivers and reapplying all the appropriate tests leading to model 6. In the presence of the lagged dependent variable as an explanatory variable, the Durbin-Watson measure is not conclusive on the residual autocorrelations. Thus, we examined serial correlations using the Breusch-Godfrey Serial Correlation LM Test (Table B.5, Appendix B).*

4.3. *Additional Validation Tests*

We conduct a series of statistical tests to assess model stability, forecasting performance, and potential nonlinearities through quantile simulations.

- **Model stability**: Several diagnostic tools are applied to evaluate stability (Figures A.3, A.4, and A.5, Appendix A). Leverage plots are used to visualise the unique contribution of each predictor while controlling for other variables. The Cusum test tracks cumulative deviations between actual and expected values to detect gradual structural shifts. Recursive estimates trace how the estimated coefficients evolve as additional data are incorporated. Figure A.5 shows that the coefficients remain relatively stable, with no significant fluctuations. A strong indication of instability would have been visible through sharp coefficient jumps, signalling structural breaks, which are absent here.
- **Forecasts performances (in-sample and out-of-sample)**: The model is estimated over 2015Q1-2024Q2. We generate an in-sample forecast by re-estimating the model over 2015Q1-2021Q4, then producing an out-of-sample forecast for the period 2022Q1-2024Q2 (Table 4; Figure A.6, Appendix A). Results are reported for both OLS and Robust M-regression. The model performs well in forecasting inflation out-of-sample, as confirmed by standard statistical criteria used in the literature, including the Theil inequality criterion. Theil inequality coefficient lies between 0 and 1, where zero indicates a perfect fit (the model forecasts exactly the actual figures). For the out-of-sample forecast, the Theil criterion equals 13.6% (OLS) and 13.1% (robust regression),[16] while for the in-sample forecast, it is around 10% for both regressions. In addition, the bias proportion, which measures how far the forecast mean deviates from the actual series mean, is found to be very small, especially under robust regression.

Table 4. In-sample and Out-of-sample Forecasts Evaluation

	OLS regression		Robust OLS	
Sample forecast: 2022Q1-2024Q2	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample
Theil inequality coefficient	0.101	0.136	0.110	0.131
Bias Proportion	0.024	0.205	0.004	0.007
Variance Proportion	0.307	0.236	0.371	0.590
Covariance Proportion	0.669	0.558	0.624	0.403

Note: Bias proportion indicates how far the mean of the forecast is from the mean of the actual series. Variance proportion indicates how far the forecast variation is from the actual series variation. The covariance proportion measures the remaining unsystematic forecasting errors. The quality of the forecast decreases with the Theil, Bias and Variance proportion increases, which means a good forecast corresponds to smaller values of these measures, so that most of the bias should be concentrated on the covariance proportions.

- **Non-linearity assessment**: The overall model is simulated through in-sample forecasts at different quintiles: 0.25 (lower), 0.5 (the median) and 0.75 (upper). Historical in-sample forecasts (Figure A.7, Appendix A) show that quintile simulations follow similar trajectories, hence ruling out the linearity issue.
- **Feedback effects and endogeneity**: Endogeneity arises when one or more predictors are correlated with the error term, violating the assumption of regressor independence and potentially biasing OLS estimates.[17] Common sources of endogeneity include (i) measurement errors, (ii) omitted variables, and (iii) simultaneity bias, the latter occurring when feedback exists from the dependent variable (domestic inflation, in this case) to the explanatory variables. In our model, measurement errors are assumed to be negligible, and a sufficient number of explanatory variables have been included. Thus, simultaneity bias remains the main potential concern. In our case, all explanatory variables, except oil prices, which are exogenous and determined in global markets, are considered lagged by at least one period, lags that are endorsed by different VAR models, thereby mitigating simultaneity.

16 Three methods for robust least squares are performed: M-estimation (Huber, 1973), S-estimation (Rousseeuw and Yohai, 1984), and MM-estimation (Yohai 1987).

17 In this case, Generalised Method of Moments (GMM) is appealed to account for potential endogeneity issues and test for the exogeneity of the regressors endorsing the validity of the estimations.

- **Robust regressions**: Since OLS estimates can be sensitive to outliers, we employ robust regression methods such as M-estimation, MM-estimation and S-estimation to test against influential observations. Results indicate that all estimated coefficients remain stable across specifications (Table 5). [18]
- **Impulse response functions (IRFs)**: Using stationary VAR models with lags determined by information criteria (Table B.8, Appendix B), impulse response functions of inflation are computed based on Cholesky one-standard-deviation shocks. The IRFs are consistent with the results obtained from the NKPC model estimations at both quarterly (Figure 3) and monthly (Figure 4) frequencies.

18 M-estimation addresses dependent variable outliers where the value of the dependent variable differs markedly from the regression model norm (large residuals). S-estimation is a computationally intensive procedure focusing on outliers in the regressor variables (high leverages). MM-estimation is a combination of S-estimation and M-estimation. The procedure starts by performing S-estimation and then uses the estimates obtained from S-estimation as the starting point for M-estimation. Since MM estimation combines both methods, it addresses outliers in the dependent and independent variables.

Table 5. Robust Regression Results (Monthly Model)

	Robust Regression								
	M-Estimation			S-Estimation			MM-Estimation		
Variable	Coefficient	z-Statistic	Prob.	Coefficient	z-Statistic	Prob.	Coefficient	z-Statistic	Prob.
Constant, α_0	0.473***	4.043	0.000	0.506***	4.174	0.000	0.472***	4.063	0.000
Inertia, π_{t-1}	0.785***	16.787	0.000	0.824***	18.655	0.000	0.785***	16.746	0.000
Rent, H_{t-7}	0.043***	3.223	0.001	0.045***	3.724	0.000	0.044***	3.246	0.001
PMI_{t-6}	0.017*	1.698	0.090	0.004	0.545	0.586	0.016*	1.682	0.093
Interest rate, i_{t-1}	-0.171**	-2.271	0.023	-0.122*	-1.650	0.099	-0.170**	-2.253	0.024
Oil prices, $\tilde{P}_t^{oil}$	0.003*	1.897	0.058	0.006*	1.832	0.067	0.003*	1.913	0.056
NEER, $\tilde{E}_{t-5}$	-0.034*	-1.781	0.075	-0.037**	-2.079	0.038	-0.035*	-1.808	0.071
Global non-energy inflation, $\widetilde{WI}_{t-4}^{w}$	0.020*	1.882	0.060	0.008	0.672	0.502	0.020*	1.907	0.057
Fit and robust statistics	Adj-R^2	Adj. Rw2	P(Rn^2 stat.)	R^2	Adj-R^2	P(Rn^2 stat.)	Adj-R^2	Adj. Rw^2	P(Rn^2 stat.)
	0.813	0.969	0.000	0.845	0.831	0.000	0.797	0.970	0.000

*Note: *, **, ***: Significant at 10%, 5% and 1% respectively. Adj-R2 is the adjusted R-squared, DW stands for Durbin Watson statistics, P(F-stat.) is the probability of Fisher, Adj. Rw2 is the Adjusted Rw-Squared, and P(Rn2 stat.) is the probability of the Rn-squared statistic. The latter two are robust statistics for robust regression. For the robust estimations, we use the following options: weight is Bisquare with Huber type III Standard Errors and Covariance. Period of estimation: 2015:M06-2024:M07; number of included observations: 107.*

Figure 3. Inflation Response to Impulses of Selected Determinants: Quarterly Model

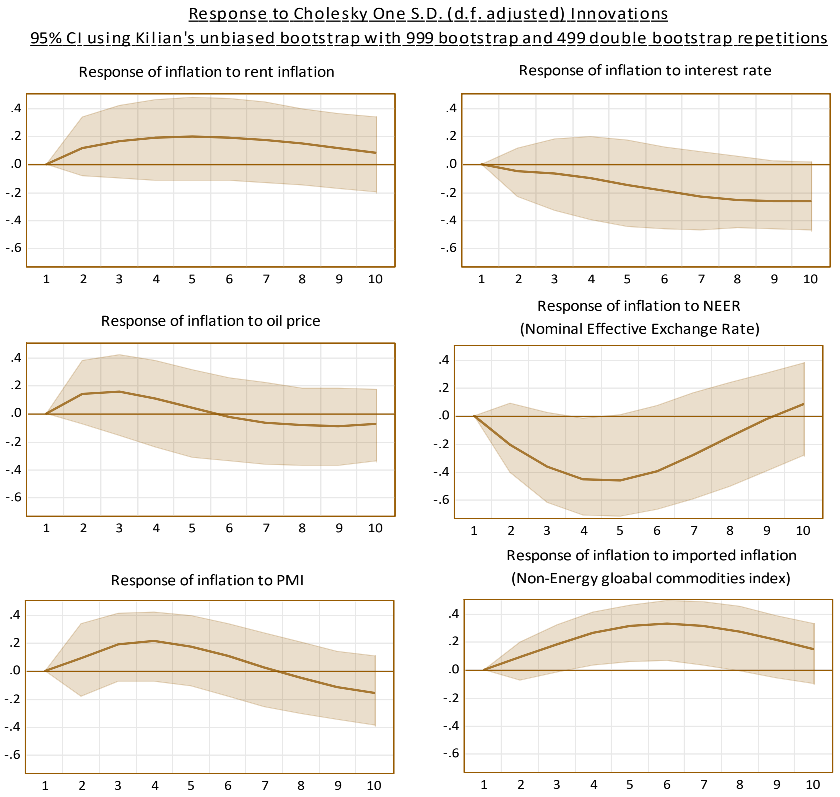
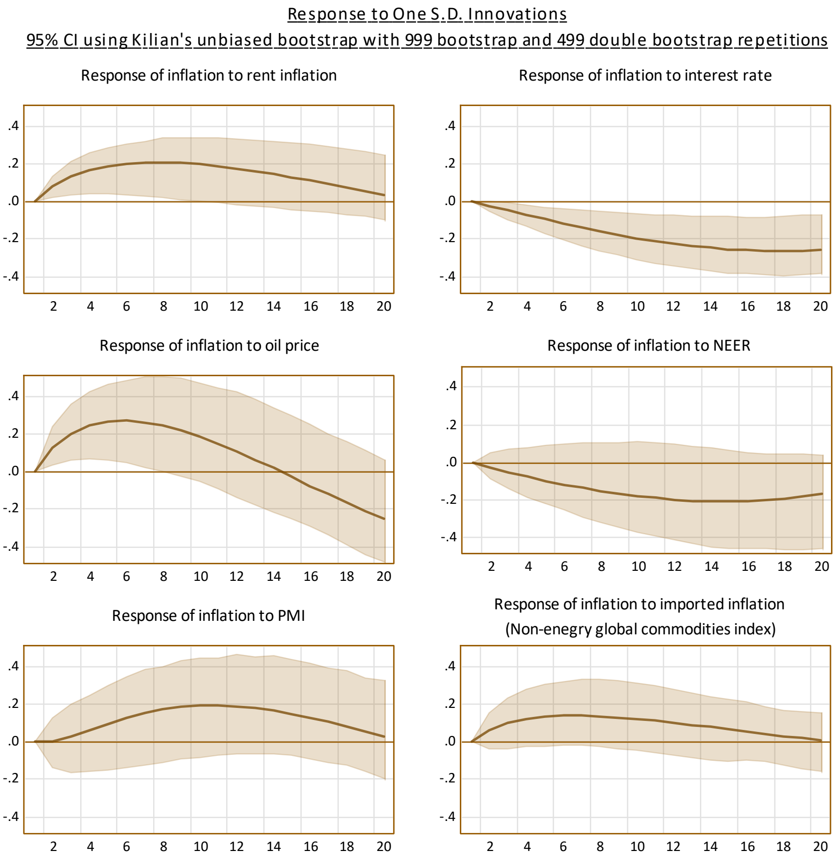


Figure 4. Inflation Response to Impulses of Selected Determinants: Monthly Model



5 Conclusion

This paper investigates the main drivers of inflation in an oil-exporting economy characterised by a fixed exchange rate and a labour market dominated by foreign workers. For the UAE, evidence suggests that inflation dynamics are shaped by a combination of domestic and external factors.

On the domestic side, price developments are largely driven by inertia and rental costs. On the external side, oil and other international commodity prices are the primary inflationary forces, although their impact is mitigated by the appreciation of the nominal effective exchange rate and by monetary tightening. The analysis also shows that inflation in the UAE displays persistence, with an inertia coefficient of around 0.6, indicating that past inflation has an influence on future price movements. This persistence suggests that inflation expectations may exert meaningful feedback effects on actual inflation.

Despite the UAE's high degree of openness, sustained economic growth and the dynamism of domestic sectors—supported by ongoing reforms aimed at economic diversification—are gradually reducing exposure to external inflationary shocks and imported inflation. At the same time, maintaining equilibrium in key domestic drivers, such as the housing market, helps moderate overall inflationary pressures in the country.

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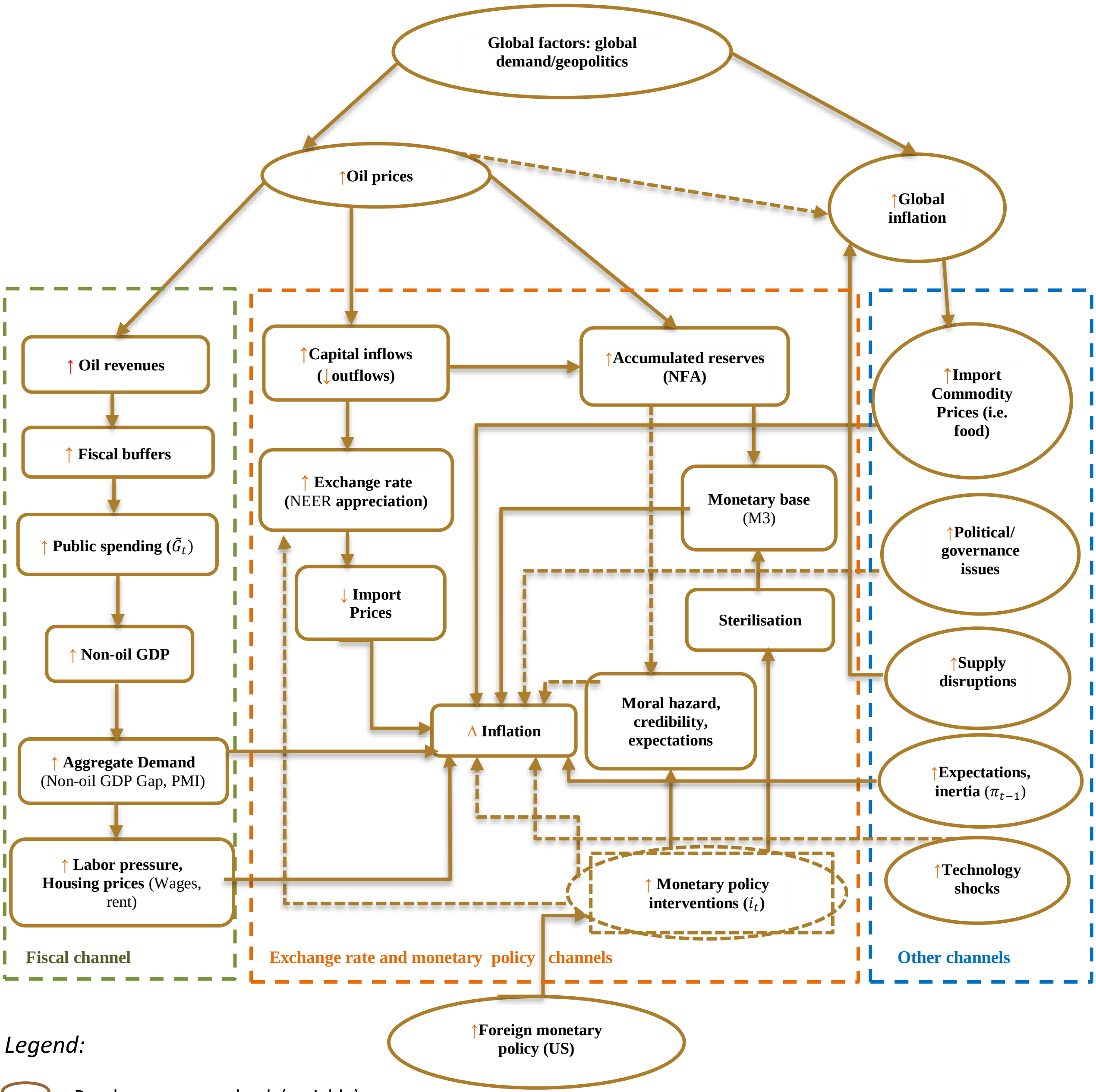
7 Appendices

7.1 *Appendix A. Figures*

Figure A.1. Pass-through Channels to Domestic Inflation in an Oil-exporting Country with a USD-Pegged Fixed Exchange Rate



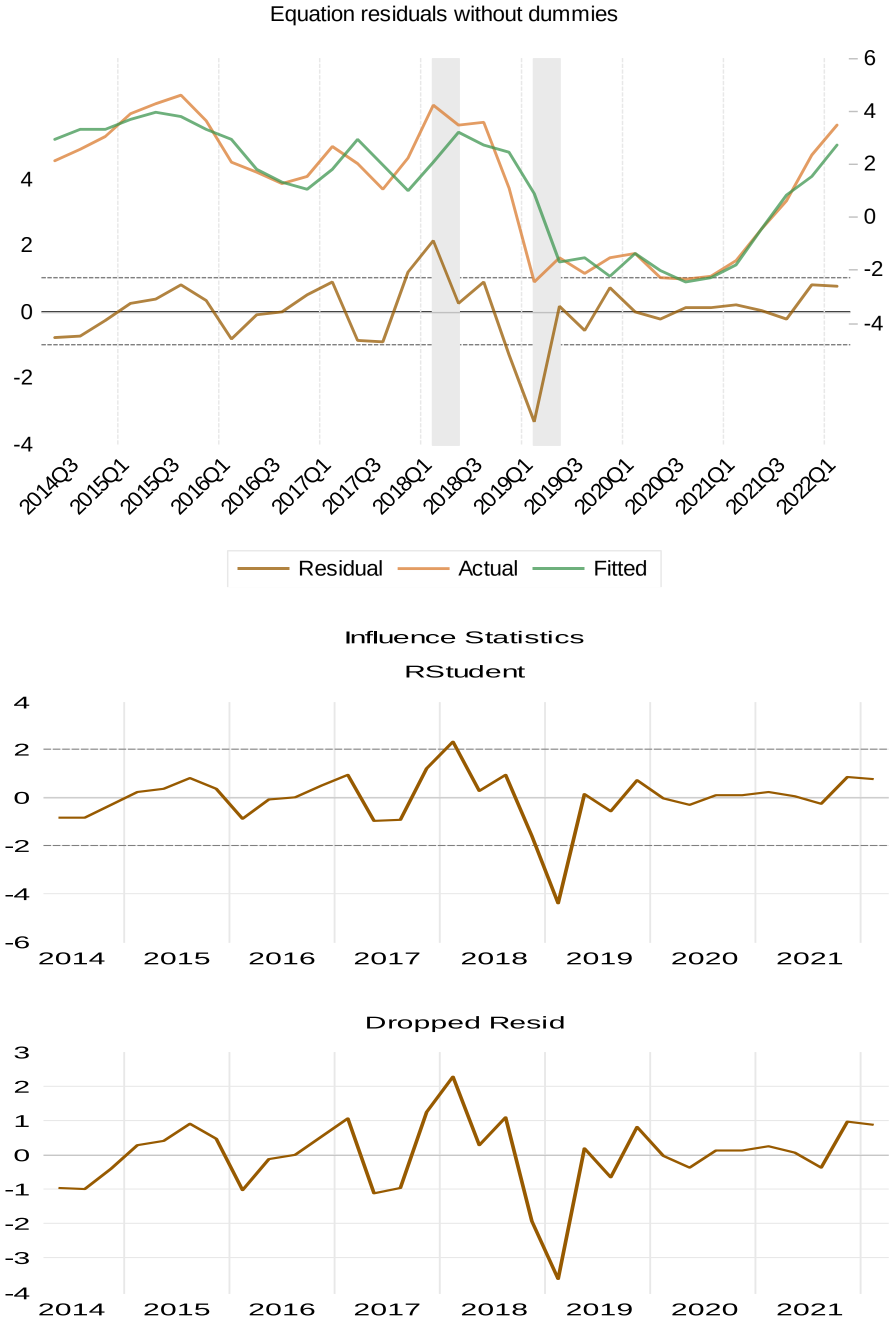
Legend:

: Purely exogenous shock (variable).
: Endogenous variable (domestically determined).
: Exogeneity depends on the target (the exchange rate for the pegged regime).
: Direct impact/shock (from the source variable to the end arrow variable).
: Indirect impact.
↑ (↓) : Increase (Decrease)
∆ : The sign of the impact is determined by the result of a mixture of variables.

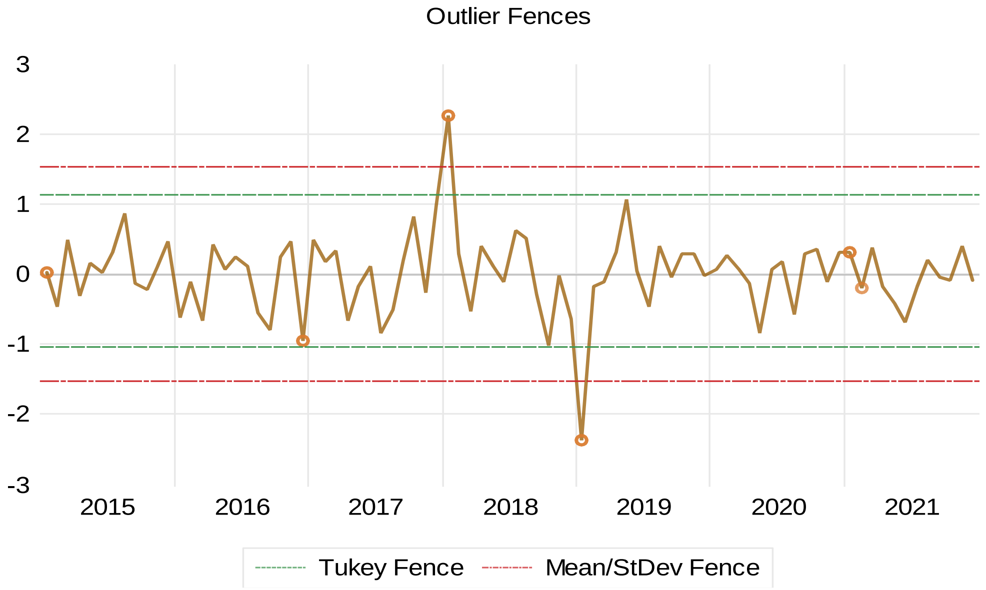
Note : NEER, $\tilde{G}_t$, PMI, i_t, M3 and π_{t-1}, respectively, stand for Nominal Effective Exchange Rate, Government expenditures, purchasing managers' index, interest rate, money supply and lagged inflation (inertia).

Source: Author

Figure A.2. Detection of Outliers and VAT Introduction Effect

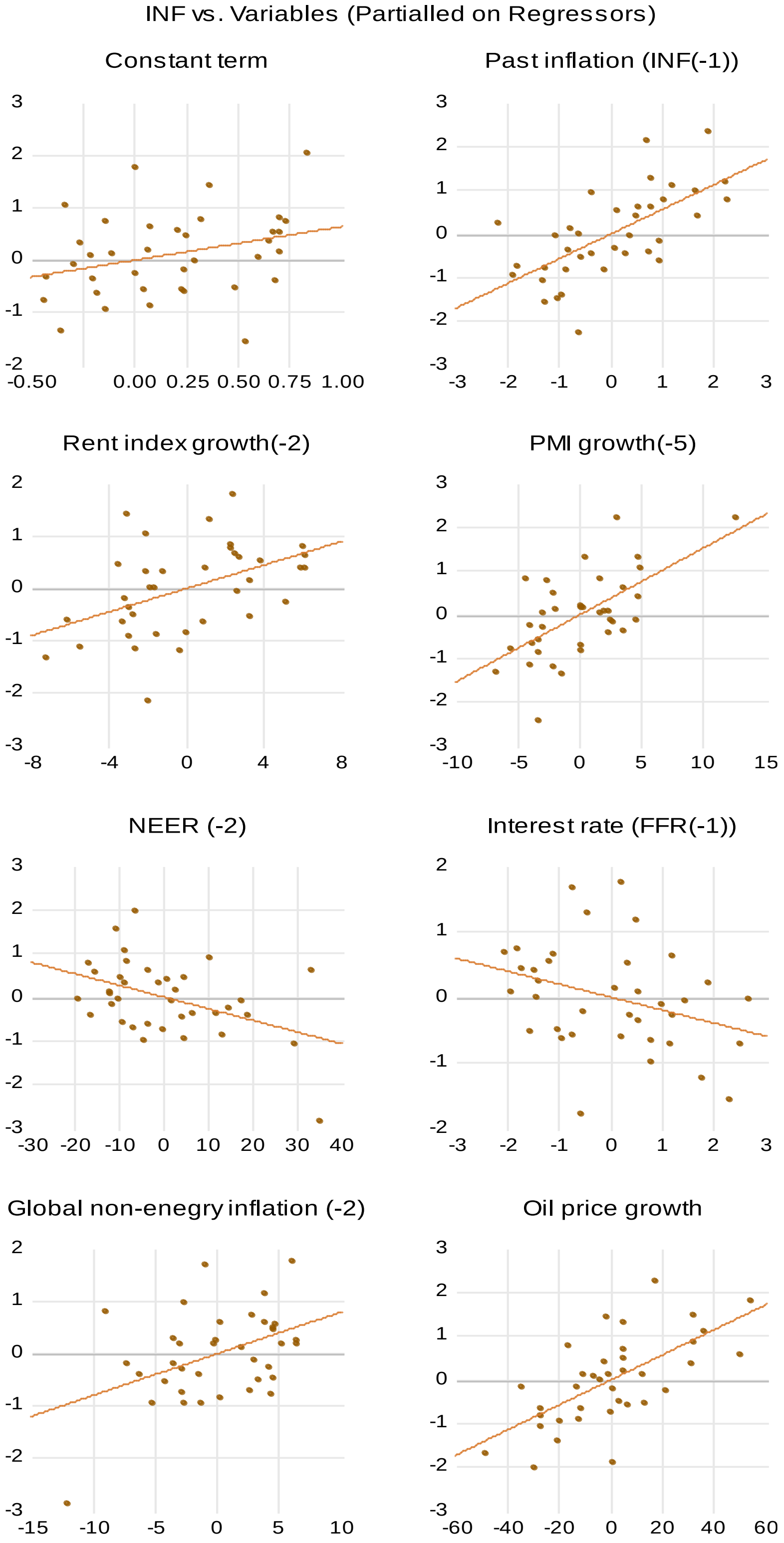


Note: Influence statistics tests, particularly the RStudent and the dropped residual DRResid, are estimates of the residual for that observation had the equation been run without that observation (Belsley et al., 2004). The RStudent is numerically identical to the t-statistic that would result from putting a dummy variable in the original equation, which is equal to 1 on that particular observation and zero elsewhere. Thus, it can be interpreted as a test for the significance of that observation.



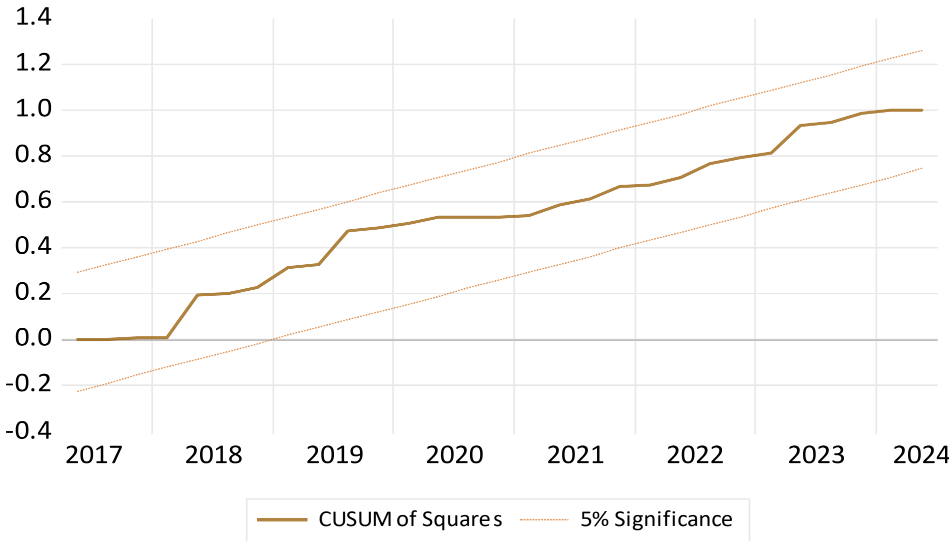
Note: Outlier fences are statistical boundaries, calculated using quartiles and the Interquartile Range (IQR), that define what is considered a "normal" data point versus an outlier in a dataset, commonly visualised in box plots.

Figure A.3. Leverage Plots



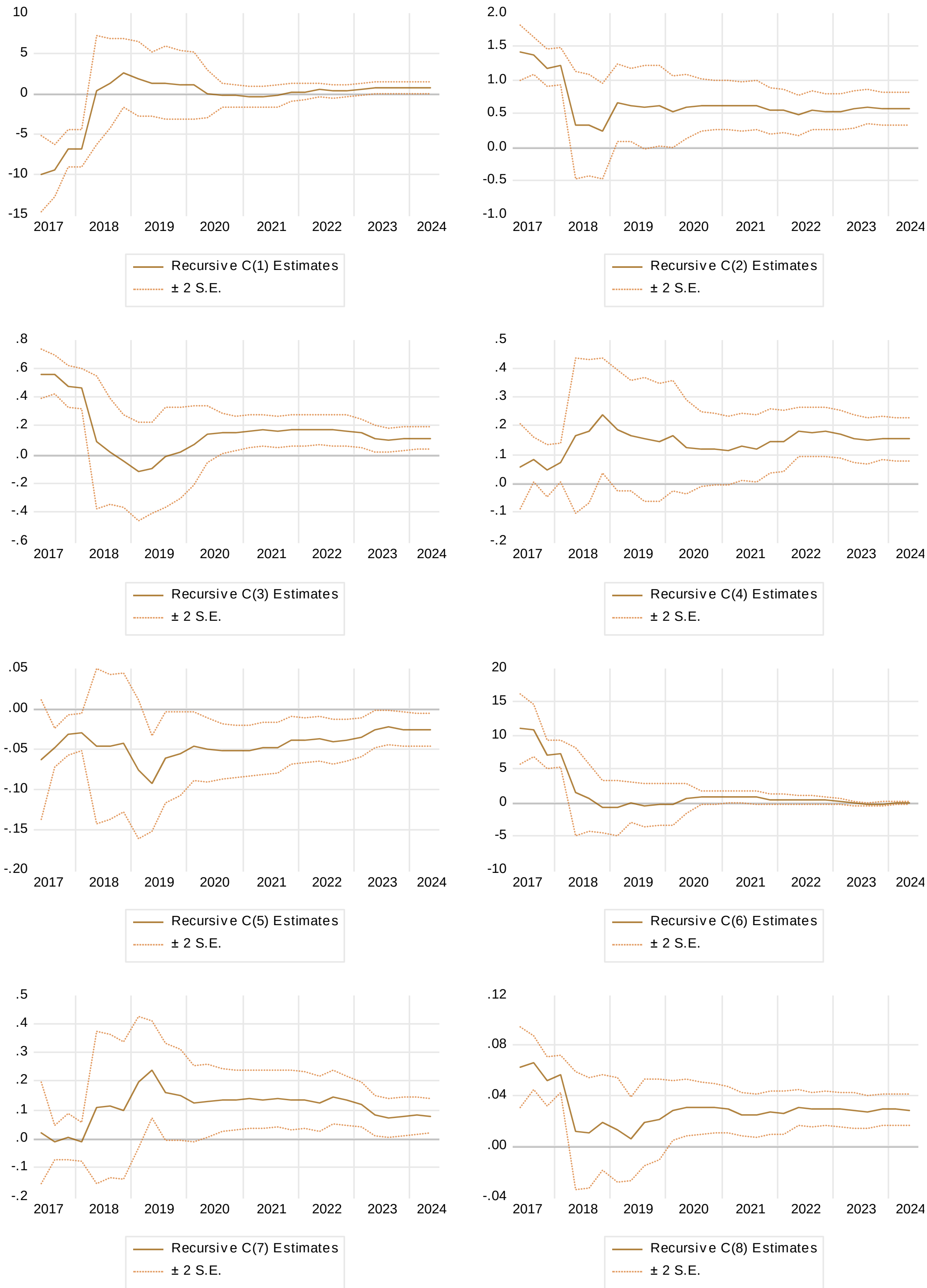
Note: Leverage plots are partial regression plots used as diagnostic tools in regression analysis, showing the unique contribution of each predictor variable, revealing influential points (outliers) that heavily affect model coefficients, by plotting the predictor against the dependent variable after partialling out other model variables. This helps assess the model fit, identify unusual data points, and understand variable relationships beyond collinearity.

Figure A.4. Cumulative Sum of Squares (CUSUM) Test



Note: The CUSUM (Cumulative Sum) test detects structural breaks or parameter instability in a model over time by plotting the cumulative sum of recursive residuals. If the blue line (CUSUM statistic) stays within the red critical bands, the model is stable, but if it crosses the bands, it signals significant parameter drift or a structural change, indicating the model's coefficients aren't stable.

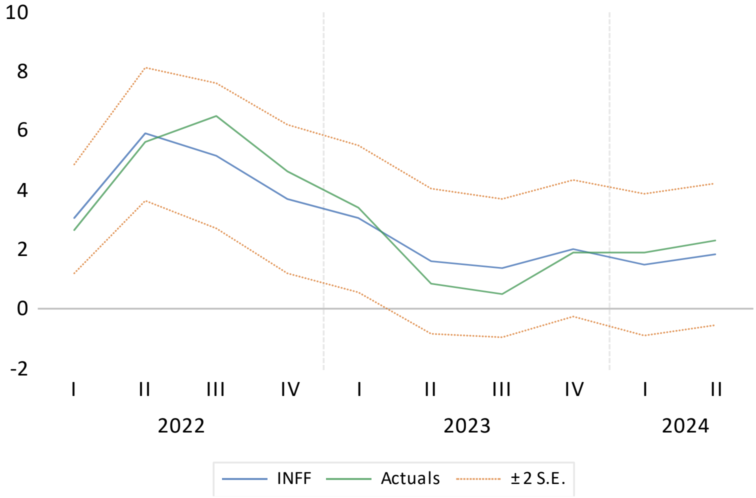
Figure A.5. Recursive Coefficient Estimates for the UAE Quarterly Inflation Model



Note: C(1) is the constant term, C(2) is the coefficient associated with the inflation inertia (lag), C(3) with rent inflation, C(4) with the PMI, C(5) with the NEER, C(6) with the interest rate, C(7) with the global non-energy commodities inflation and C(8) with oil price. Recursive coefficient estimates are continuously updated parameters in models that adapt to new data, using methods like Recursive Least Squares (RLS).

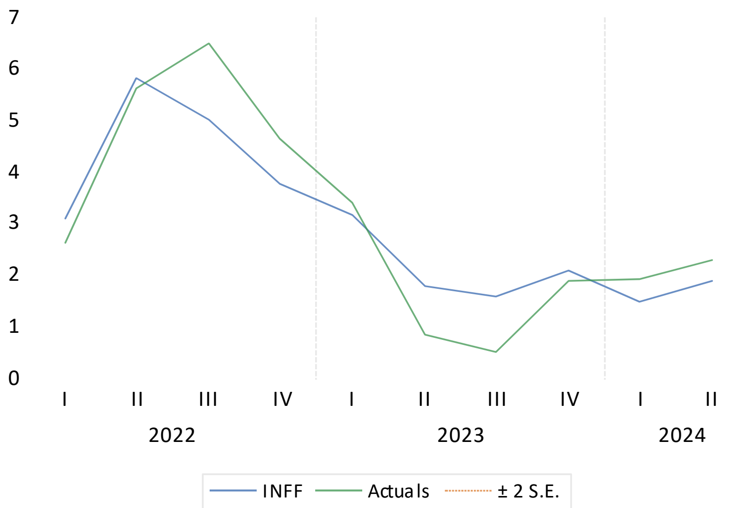
Figure A.6. In-sample and Out-of-sample Quarterly Inflation Forecasts

Figure A.6.1 OLS Model In-sample Dynamic Forecast



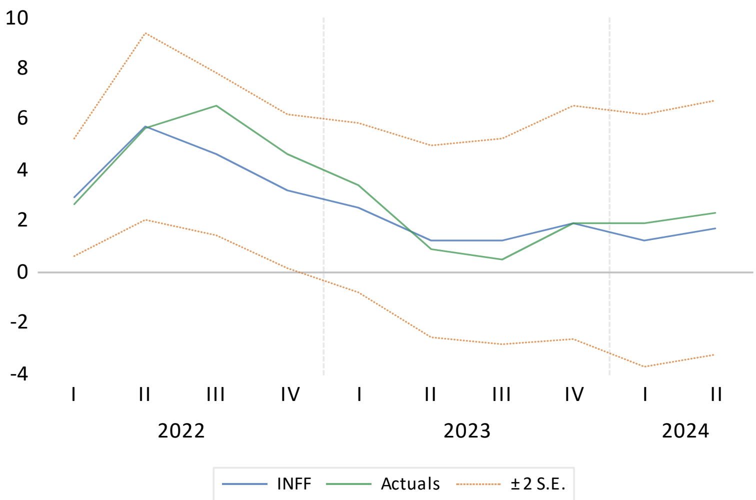
Forecast: INFF	
Actual: INF	
Forecast sample: 2022Q1 2024Q2	
Included observations: 10	
Root Mean Squared Error	0.687121
Mean Absolute Error	0.596526
Mean Abs. Percent Error	38.73422
Theil Inequality Coef.	0.100851
Bias Proportion	0.023963
Variance Proportion	0.306698
Covariance Proportion	0.669338
Theil U2 Coefficient	0.360915
Symmetric MAPE	28.72111

Figure A.6.2 Robust OLS Model In-sample Dynamic Forecast



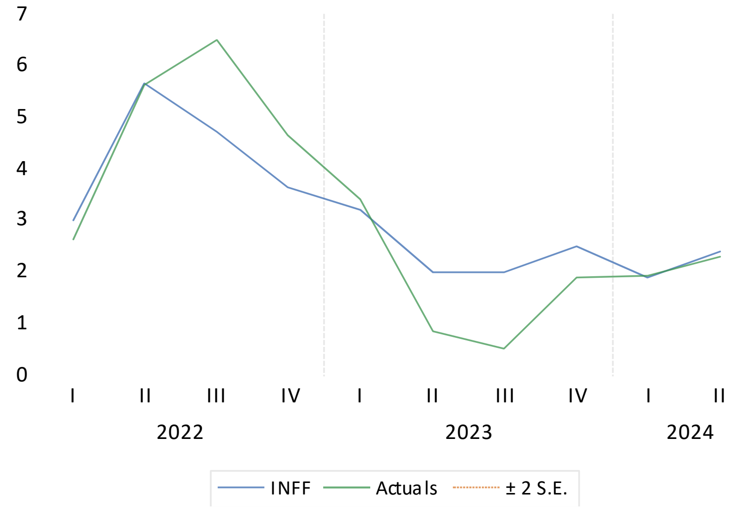
Forecast: INFF	
Actual: INF	
Forecast sample: 2022Q1 2024Q2	
Included observations: 10	
Root Mean Squared Error	0.749473
Mean Absolute Error	0.626822
Mean Abs. Percent Error	45.38447
Theil Inequality Coef.	0.109715
Bias Proportion	0.004099
Variance Proportion	0.371396
Covariance Proportion	0.624505
Theil U2 Coefficient	0.443997
Symmetric MAPE	30.39152

Figure A.6.3 OLS Model Out-of-Sample Dynamic Forecast



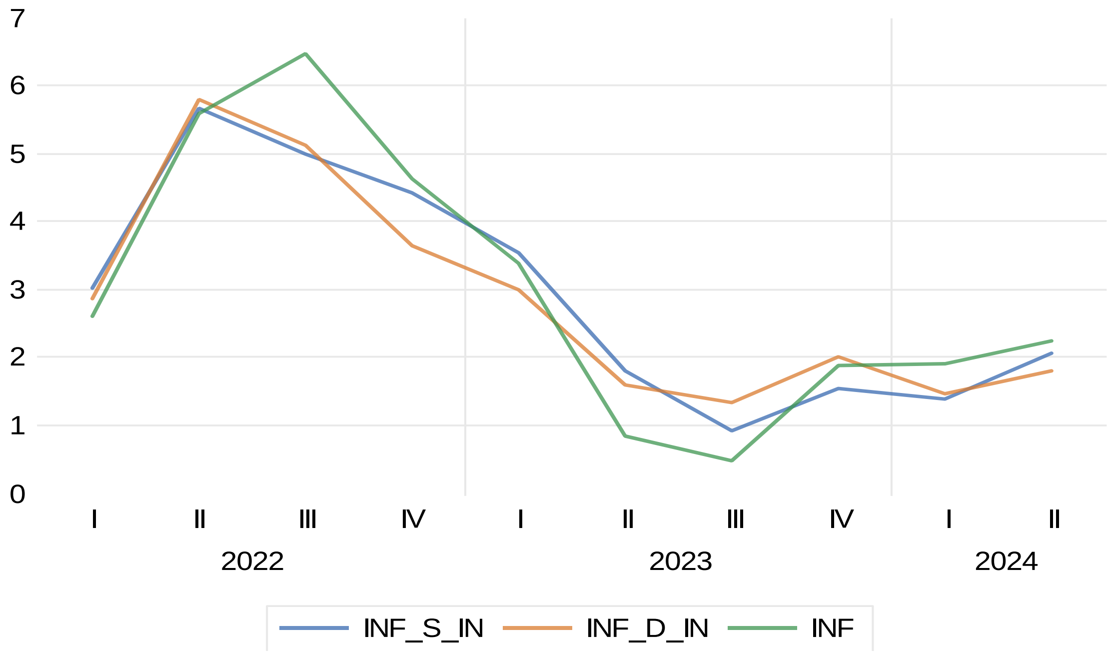
Forecast: INFF	
Actual: INF	
Forecast sample: 2022Q1 2024Q2	
Included observations: 10	
Root Mean Squared Error	0.890580
Mean Absolute Error	0.689821
Mean Abs. Percent Error	34.56433
Theil Inequality Coef.	0.136446
Bias Proportion	0.205318
Variance Proportion	0.236086
Covariance Proportion	0.558596
Theil U2 Coefficient	0.330209
Symmetric MAPE	30.35955

Figure A.6.4 Robust OLS model Out-of-sample Dynamic Forecast



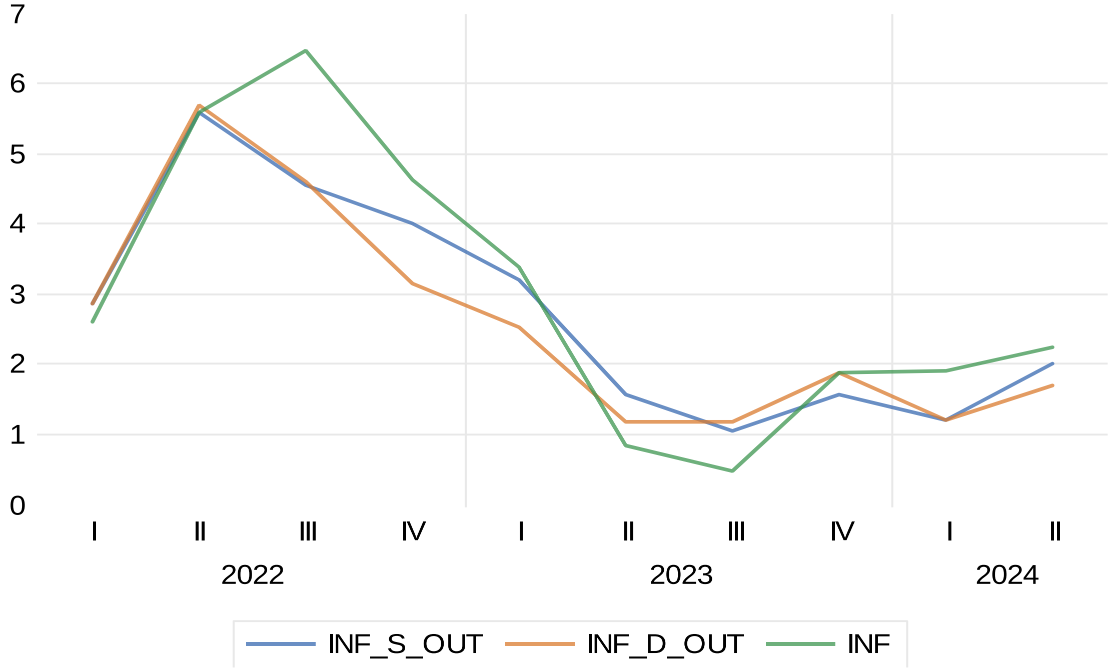
Forecast: INFF	
Actual: INF	
Forecast sample: 2022Q1 2024Q2	
Included observations: 10	
Root Mean Squared Error	0.900248
Mean Absolute Error	0.673427
Mean Abs. Percent Error	54.82180
Theil Inequality Coef.	0.131435
Bias Proportion	0.006848
Variance Proportion	0.589726
Covariance Proportion	0.403426
Theil U2 Coefficient	0.681148
Symmetric MAPE	31.13370

Figure A.6.5 Actual versus In-sample Static and Dynamic Simulations



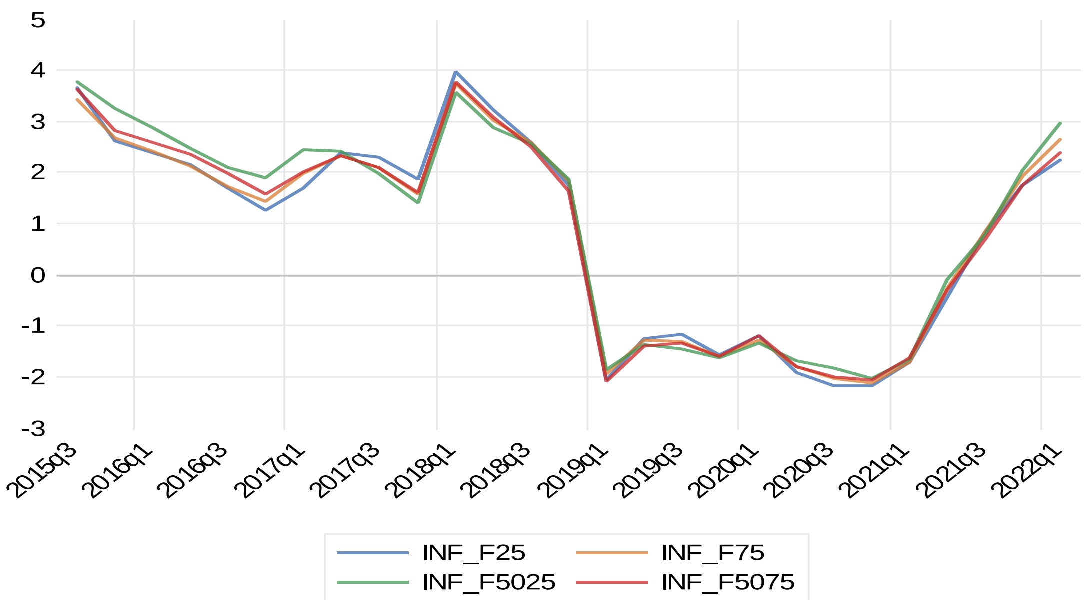
Note: INF=actual inflation; INF_S_IN stands for in-sample static simulation and INF_D_IN for in-sample dynamic simulation.

Figure A.6.6 Actual versus Out-of-sample Static and Dynamic simulations



Note: INF=actual inflation; INF_S_OUT stands for out-of-sample static simulation and INF_D_OUT for out-of-sample dynamic simulation.

Figure A.7. Quantile Average In-sample Forecasts



Note: INF_F25, INF_F5025, INF_F507525, and INF_F75 stand respectively for the 0.25, 0.25-0.50, 0.50-0.75 and 0.75 quintiles.

7.2 Appendix B. Tables

Table B.1. Variables' Sources, Ranges and Frequencies

Variable	Sample range	Frequency	Source	Remarks
Inflation	2009q1-2024q2	Monthly	FCSC	Available on monthly frequencies too
Non-oil GDP	2012q1-2024q1	Quarterly	FCSC	Used to calculate the non-oil GDP gap variable
Rent Inflation	2013:1-2024:09	Monthly	DLD/REIDIN	Other measures of housing inflation were tested from the REIDIN source
Federal Funds Rate	2007q1-2024q3	Quarterly	FedSLouis	
Private Wages	2010q1-2024q3	Monthly	CBUAE	Wage Protection System
Oil Prices	2009: 1 -2024:09	Monthly	EIA	Average Brent Crude prices ($)
NEER	2009:1-2024:09	Monthly	BIS	Nominal effective exchange rate
Government Spending	2013q1-2024q3	Quarterly	Ministry of Finance	UAE Consolidated government
Money (M3)	2009:1-2024:09	Monthly	CBUAE	
World GDP	2009q1-2024q2	Quarterly	OECD	OECD quarterly GDP
World Inflation	2009q1-2024q3	Quarterly	World Bank	Global non-energy commodities index
Global Non-Energy Index	2009q1-2024q3	Quarterly	FedSLouis	
PMI Index	2013:02-2024:10	Monthly	S&P Global	Purchasing Managers' Index for non-oil business activities

Note: CBUAE stands for Central Bank of the UAE; DLD stands for Dubai Land Department; FCSC for Federal Competitiveness and Statistics Centre; BIS for Bank of International Settlements; FedSLouis for Federal Reserve of Saint Louis, and EIA is the Energy Information Administration.

Table B.2. Stationarity Tests.

Phillips-Perron test statistic: Null Hypothesis: the variable has a unit root			
Consumer Price Index (%, YoY)		Nominal Effective Exchange Rate (, YoY)	
Adj. t-Stat	Prob.*	Adj. t-Stat	Prob.*
-2.6253	0.0943	-2.7294	0.0761
Housing Price Index (% change, YoY)		Oil Prices (% change, YoY)	
Adj. t-Stat	Prob.*	Adj. t-Stat	Prob.*
-1.8672	0.0598	-2.7099	0.0793
Private Wages (% change, YoY)		Federal Funds Rate (percent per annum)	
Adj. t-Stat	Prob.*	Adj. t-Stat	Prob.*
-4.8729	0.0004	-3.2648	0.0209
Non-oil GDP gap (%)		Non-energy World inflation (% change)	
Adj. t-Stat	Prob.*	Adj. t-Stat	Prob.*
-4.1599	0.0031	-3.8499	0.0041
Government Expenses (% change, YoY)		Rent prices (% change, YoY)	
Adj. t-Stat	Prob.*	Adj. t-Stat	Prob.*
-6.3246	0.0000	-2.2925	0.1781
Money M3 (% change, YoY)		World commodities prices index (%, YoY)	
Adj. t-Stat	Prob.*	Adj. t-Stat	Prob.*
-4.6440	0.0008	-4.6740	0.0003
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel; *MacKinnon (1996) one-sided p-values; Exogenous: Constant.			

Table B.3. Covariance Analysis: Kendall's Tau Correlation Test

Tau-b (Probability)		RING	GAP	WPG	GEG	M3G	NEERG	OPG	FFR	WGDPG
RING	tau	1.0000								
	prob	-----								
GAP	tau	0.1576	1.0000							
	prob	0.2373	-----							
WPG	tau	0.0739	0.0788	1.0000						
	prob	0.5865	0.5609	-----						
GEG	tau	0.0148	0.2365	-0.2020	1.0000					
	prob	0.9253	**0.0747***	0.1287	-----					
M3G	tau	0.0049	0.1182	0.0837	-0.0049	1.0000				
	prob	0.9850	0.3780	0.5359	0.9850	-----				
NEERG	tau	0.1034	0.0690	0.1034	0.1626	0.0148	1.0000			
	prob	0.4418	0.6125	0.4418	0.2227	0.9253	-----			
OPG	tau	0.0345	0.2266	0.0640	-0.1330	0.1823	-0.3793	1.0000		
	prob	0.8073	**0.0878***	0.6391	0.3201	0.1709	**0.0041****	-----		
FFR	tau	-0.3753	0.1333	-0.1630	0.0049	0.1086	0.0889	0.0988	1.0000	
	prob	**0.0046****	0.3200	0.2226	0.9850	0.4197	0.5113	0.4643	-----	
GNEI	tau	0.2956	0.2709	0.1478	0.0099	-0.0493	-0.1675	0.4926	-0.1728	1.0000
	prob	**0.0256****	**0.0409****	0.2684	0.9551	0.7215	0.2088	**0.0002*****	0.1954	-----

*Note: *, **, ***: significant at respectively, 10%, 5% and 1%. Number of included observations: 37. RING stands for rent price index growth, GAP for non-oil GDP output gap, WPG for private wages growth, GEG for government expenditures growth, M3G for broad money (M3) growth, NEERG for the nominal effective exchange rate growth, OPG for oil prices growth, FFR for Federal Funds, and GNEI is the global non-energy inflation. All the variables are quarterly year-on-year growth in percent, except the FFR is percent per annum.*

Table B.4. Inflation and Oil Prices Effects Before and After Subsidy Reform (Monthly Regressions)

Estimated specifications		Sample (adjusted): 2009M01-2024M08		Sample (adjusted): 2009M01-2015M07		Sample (adjusted): 2015M08-2024M08	
		Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
Equation 1: $\pi_t = c + \alpha\pi_{t-1} + \beta P_t^{oil}$	c	0.0146	0.7706	0.0906	0.2780	-0.0332	0.6598
	π_{t-1}	0.943	0.0000	0.9260	0.0000	0.9245	0.0000
	P_t^{oil}	0.0032***	0.0011	0.0008	0.6436	0.0045***	0.0021
	Adj. R-squared	92.09%		90.40%		92.32%	
Equation 2: $\pi_t = c + \alpha\pi_{t-1} + \beta P_{t-1}^{oil}$	c	0.0229	0.6477	0.0596	0.4696	-0.0188	0.8056
	π_{t-1}	0.9434	0.0000	0.9512	0.0000	0.9219	0.0000
	P_{t-1}^{oil}	0.0028***	0.0055	0.0013	0.4431	0.0038***	0.0090
	Adj. R-squared	91.69%		89.46%		92.03%	
Equation 3: $\pi_t = c + \alpha\pi_{t-1} + \beta P_{t-2}^{oil}$	c	0.0322	0.5204	0.0087	0.9090	-0.0018	0.9821
	π_{t-1}	0.9497	0.0000	0.9977	0.0000	0.9270	0.0000
	P_{t-2}^{oil}	0.0016	0.1046	0.0018	0.2364	0.0022	0.1379
	Adj. R-squared	91.52%		90.23%		91.50%	
Equation 4: $\pi_t = c + \alpha\pi_{t-1} + \beta P_{t-3}^{oil}$	c	0.0384	0.4369	-0.0224	0.7381	0.0064	0.9351
	π_{t-1}	0.9574	0.0000	1.0338	0.0000	0.9329	0.0000
	P_{t-3}^{oil}	0.0009	0.3923	0.0022	0.1080	0.0011	0.4908
	Adj. R-squared	91.74%		92.16%		91.30%	
Equation 5: $\pi_t = c + \alpha\pi_{t-1} + \beta P_{t-4}^{oil}$	c	0.0441	0.3668	0.0017	0.9779	0.0079	0.9206
	π_{t-1}	0.9609	0.0000	1.0313	0.0000	0.9339	0.0000
	P_{t-4}^{oil}	0.0006	0.5711	0.0010	0.4189	0.0010	0.5266
	Adj. R-squared	91.97%		93.26%		91.29%	
Equation 6: $\pi_t = c + \alpha\pi_{t-1} + \beta P_{t-5}^{oil}$	c	0.0492	0.3123	0.0268	0.6426	0.0085	0.9143
	π_{t-1}	0.9614	0.0000	1.0241	0.0000	0.9337	0.0000
	P_{t-5}^{oil}	0.0006	0.5304	0.0002	0.8658	0.0012	0.4247
	Adj. R-squared	92.11%		93.86%		91.32%	
Equation 7: $\pi_t = c + \alpha\pi_{t-1} + \beta P_{t-6}^{oil}$	c	0.0565	0.2459	0.0567	0.3067	0.0101	0.8987
	π_{t-1}	0.9609	0.0000	1.0133	0.0000	0.9352	0.0000
	P_{t-6}^{oil}	0.0003	0.7611	-0.0006	0.5760	0.0009	0.5529
	Adj. R-squared	92.19%		94.31%		91.28%	

Table B.5. Residual Serial Correlation Tests

Breusch-Godfrey Serial Correlation LM Test for Model 2			
Null hypothesis: No serial correlation at up to 3 lags			
F-statistic	0.715470	Prob. F(3,22)	0.5533
Obs*R-squared	2.844526	Prob. Chi-Square(3)	0.4162
Breusch-Godfrey Serial Correlation LM Test for Model 4			
Null hypothesis: No serial correlation at up to 3 lags			
F-statistic	1.107190	Prob. F(3,38)	0.3581
Obs*R-squared	3.858406	Prob. Chi-Square(3)	0.2772
Breusch-Godfrey Serial Correlation LM Test for Model 5			
Null hypothesis: No serial correlation at up to 3 lags			
F-statistic	1.576934	Prob. F(3,20)	0.2262
Obs*R-squared	5.930050	Prob. Chi-Square(3)	0.1151

Table B.6. Heteroscedasticity Breusch-Pagan-Godfrey Tests

Heteroskedasticity Test: Breusch-Pagan-Godfrey for Model 2			
Null hypothesis: Homoskedasticity			
F-statistic	1.067175	Prob. F(6,25)	0.4080
Obs*R-squared	6.524767	Prob. Chi-Square(6)	0.3670
Scaled explained SS	3.178883	Prob. Chi-Square(6)	0.7861
Heteroskedasticity Test: Breusch-Pagan-Godfrey for Model 4			
Null hypothesis: Homoskedasticity			
F-statistic	1.286690	Prob. F(6,41)	0.2848
Obs*R-squared	7.606029	Prob. Chi-Square(6)	0.2684
Scaled explained SS	8.801522	Prob. Chi-Square(6)	0.1851
Heteroskedasticity Test: Breusch-Pagan-Godfrey for Model 5			
Null hypothesis: Homoskedasticity			
F-statistic	1.495262	Prob. F(7,23)	0.2183
Obs*R-squared	9.695326	Prob. Chi-Square(7)	0.2065
Scaled explained SS	4.152020	Prob. Chi-Square(7)	0.7621

Table B.7. Wald Restriction Test for Adaptive Expectations (Coefficient of Lagged Dependent Variable = 1)

Test Statistic	Value	df	Probability
t-statistic	-5.644704	23	0.0000
F-statistic	31.86269	(1, 23)	0.0000
Chi-square	31.86269	1	0.0000
Null Hypothesis: C(2)=1			
Null Hypothesis Summary:			
Normalized Restriction (= 0)	Value	Std. Err. 0.060644	
-1 + C(2)	-0.342317		

Note: Restrictions are linear in coefficients. EViews reports an F-statistic and a Chi-square statistic with associated p-values. In cases of a single restriction, it reports the t-statistic equivalent to the F-statistic. In addition, EViews reports the value of the normalised restriction and an associated standard error. The p-value indicates that we reject the null hypothesis of adaptive expectations.

Table B.8. VAR Lag Order Selection Criteria of Selected Drivers' Inflation Model

Quarterly Sample: 2015:Q1 2024:Q2						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-425.1570	NA	5265840.	29.66600	29.90174	29.73983
1	-349.3655	120.2209*	163416.7*	26.16314	27.57758*	26.60613*
2	-324.1829	31.26117	191108.5	26.15055	28.74369	26.96269
3	-292.4002	28.49485	195773.2	25.68277*	29.45462	26.86407
Monthly Sample: 2010:M1 2024:M07						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-606.0192	NA	78415.49	25.45913	25.65405	25.53279
1	-436.7560	296.2105	193.5150	19.44817	20.61767*	19.89012*
2	-407.0520	45.79367	164.7145	19.25217	21.39625	20.06242
3	-378.1166	38.58062*	153.1179*	19.08819*	22.20686	20.26674

Note: LogL, LR, FPE, AIC, SC, and HQ are statistical criteria used to determine the optimal lag length for VAR models, where LogL stands for the log-likelihood, LR for likelihood ratio, FPE for final prediction error, AIC for Akaike Information Criterion, SC for Schwarz Criterion and HQ for Hannan-Quinn criterion.

Table B.9. Application of Coefficient Variance Decomposition on Domestic Determinants

Step 1: All variables introduced							
Eigenvalues	0.2420	0.0117	0.0012	0.0003	0.0001	0.0000	0.0000
Condition	0.0001	0.0020	0.0203	0.0751	0.3246	0.6502	1.0000
Associated Eigenvalue Variable	1	2	3	4	5	6	7
C	0.9987	0.0013	0.0000	0.0000	0.0000	0.0000	0.0000
INF(-1)	0.2887	0.7084	0.0026	0.0001	0.0000	0.0001	0.0000
RING	0.6336	0.3306	0.0175	0.0030	0.0004	0.0135	0.0014
WPG	0.2658	0.0943	0.3803	0.1961	0.0555	0.0071	0.0009
GAP	0.1195	0.0609	0.6529	0.1655	0.0010	0.0002	0.0000
GEG	0.2736	0.3139	0.1890	0.0413	0.0097	0.0225	0.1502
M3G	0.9156	0.0126	0.0536	0.0102	0.0079	0.0001	0.0000
Step 2: M3g is removed for its high-associated eigenvalue							
Eigenvalues	0.0301	0.0068	0.0006	0.0003	0.0001	0.0000	
Condition	0.0010	0.0046	0.0510	0.1013	0.2440	1.0000	
Associated Eigenvalue Variable	1	2	3	4	5	6	
C	0.9910	0.0088	0.0001	0.0001	0.0000	0.0000	
INF(-1)	0.1305	0.8645	0.0007	0.0026	0.0016	0.0000	
RING	0.0907	0.7701	0.0276	0.0211	0.0889	0.0016	
WPG	0.4599	0.1242	0.0130	0.3850	0.0180	0.0000	
GAP	0.2825	0.0003	0.7066	0.0003	0.0103	0.0000	
GEG	0.5746	0.1838	0.0012	0.0054	0.0395	0.1955	
Step 3: GEG is removed for its high-associated eigenvalue							
Eigenvalues	0.0210	0.0073	0.0007	0.0003	0.0001		
Condition	0.0066	0.0189	0.2073	0.4246	1.0000		
Associated Eigenvalue Variable	1	2	3	4	5		
C	0.9826	0.0170	0.0003	0.0000	0.0000		
INF(-1)	0.1227	0.8730	0.0020	0.0003	0.0021		
RING	0.0755	0.7917	0.0315	0.0026	0.0987		
WPG	0.0309	0.0121	0.0417	0.9129	0.0024		
GAP	0.3128	0.0098	0.6607	0.0049	0.0118		

Explanation of the decision rule: In each step, the top line displays the eigenvalues, sorted from largest to smallest, along with the corresponding condition numbers below. Practically, a smaller condition number than 1% may indicate a collinearity issue. The rest shows the decomposition proportions. The proportions associated with the smallest condition number are located in the first column. The rule is to exclude each variable for which the condition proportion is larger than 0.5.

Table B.10. Estimation Using the Non-oil GDP Gap Instead of PMI (Quarterly Model)

Variables	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
Constant, α_0	0.441	0.358	0.165	0.126	0.394***	0.007	0.395***	0.005	0.541***	0.008	0.472***	0.000
Inertia, π_{t-1}	0.616***	0.000	0.657*	0.063	0.767***	0.000	0.769***	0.000	0.580***	0.000	0.624***	0.000
Rent, H_{t-2}	0.078***	0.009	0.064**	0.022	..	..	..	..	0.067***	0.005	0.065**	0.017
Wages, W_{t-1}	0.062**	0.018	0.070**	0.028	..	..	..	..	0.033	0.217	..	..
Non-oil gap, $\tilde{Y}_{t-1}$	0.011	0.790	..	..	..	..	..	..	..	..	..	..
Gov. Spending, $\tilde{G}_{t-1}$	0.012	0.119	0.014***	0.008	..	..	..	..	0.004	0.653	..	..
Money M3, $\tilde{M}_{t-1}$	-0.038	0.564	..	..	..	..	..	..	..	..	..	..
Oil prices, $\tilde{P}_{t-1}^{oil}$	..	..	..	..	-0.002	0.732	..	..	..	..	..	..
NEER, $\tilde{E}_{t-2}$	..	..	..	..	-0.051	0.135	-0.042*	0.085	-0.084**	0.027	-0.087**	0.050
Interest rate, i_t	..	..	..	..	-0.502***	0.000	-0.506***	0.000	-0.301**	0.036	-0.303**	0.050
Global non-energy inflation, WI_{t-2}^{w}	..	..	..	..	0.1118***	0.006	0.105***	0.001	0.094*	0.051	0.133***	0.001
Dum:2018-19 Q1	2.909***	0.000	2.932***	0.000	2.539***	0.000	2.545***	0.000	2.630***	0.000	2.393***	0.000
Adjusted R-squared	0.89		0.90		0.89		0.90		0.92		0.91	
Durbin Watson	2.15		2.20		1.92		1.92		2.19		1.93	

*Notes: *, **, ***: Significant at 10%, 5% and 1% respectively. Period of estimation: 2015:Q1-2024:Q2; the number of included observations: 37. Model 1 includes domestic drivers with constant and inertia, model 2 is the selected model for domestic drivers after an appropriate set of tests as described in the methodology section, model 3 is for all foreign drivers, model 4 is the selected model after appropriate tests, model 5 is the selected model after mixing all the domestic and foreign drivers and reapplying all the appropriate tests. In the presence of the lagged dependent variable as an explanatory variable, the Durbin-Watson measure is not conclusive on the residual autocorrelations. Thus, we examined serial correlations using the Breusch-Godfrey Serial Correlation LM Test.*

7.3. Appendix C. Methodological Supplement

The Hodrick-Prescott (HP) filter is a widely used smoothing method among researchers. The method first appeared in a working paper in the early 1980s, was applied to analyse the post-war US business cycles and was published later in 1997 (Hodrick and Prescott, 1997). The HP filter algorithm works to smooth the original series by estimating its trend component (smoothed component with a parameter of smoothing λ), while the cyclical component results as the difference between the original series and its trend. The higher the data frequencies, the larger the smoothing parameter. Practically, $\lambda = 100$ for annual data, and $\lambda = 1600$ for quarterly data.

We perform the two commonly used tests, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests (Dickey and Fuller, 1979; Phillips and Perron, 1988). The latter builds on the former specification, which runs statistical inference based on an autoregressive model but makes a nonparametric correction to the t-test statistic. Compared to ADF, the PP test offers greater robustness to general forms of heteroscedasticity (Afriyie et al., 2020). Besides, setting a lag length is not required for its implementation. Table B.2 (Appendix B) displays PP test results. The ADF and PP tests' null hypothesis rejection probabilities could differ substantially for the time series that are integrated at order 2 (Leybourne and Newbold, 1999).

The cross-correlations of the variables are examined using Spearman's rank and Kendall's tau statistics as a non-parametric test suitable for small samples. Non-parametric tests are often used when probability distributions are not converging to normality. This happens with small samples, violating the convergence condition as assumed by the Central Limit Theorem (CLT). Besides, non-parametric tests tend to deliver accurate and powerful results.

Table B.3 presents Kendall's tau correlations between all the potential drivers of inflation in the UAE. It shows that more significant correlations are induced by foreign than domestic determinants. For the latter, correlations are only significant between the non-oil GDP gap and government expenditures. Besides, the non-oil GDP gap is correlated to oil price growth and the global non-energy inflation. Furthermore, housing inflation is negatively correlated to the federal funds rate and positively correlated to the global non-energy inflation. Oil prices are also negatively correlated with the exchange rate variability and positively correlated with the global non-energy inflation.

Methodology of Estimations: Steps for the Selection of the Main Inflation Drivers

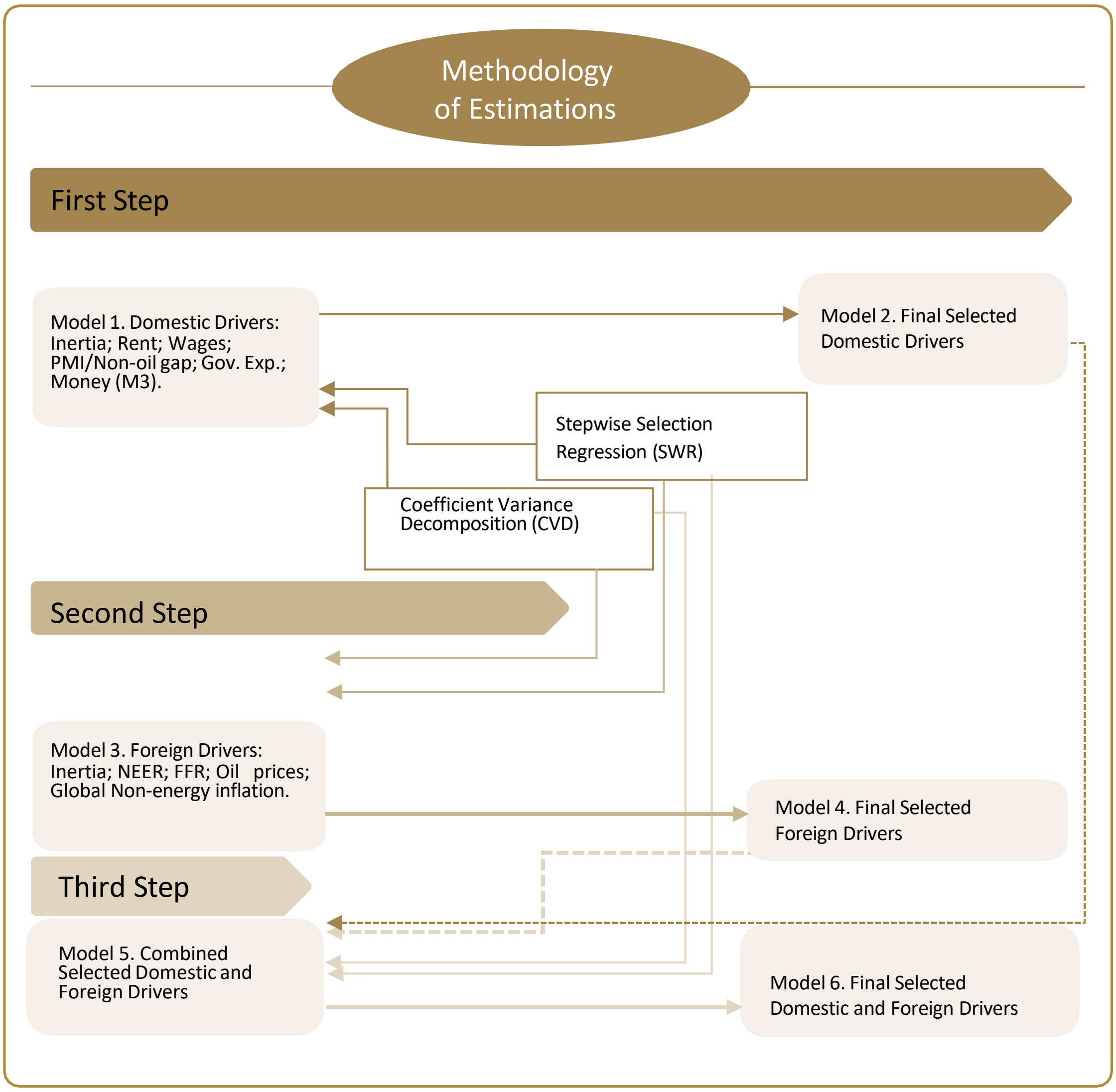
To choose the most important drivers of inflation in the UAE, we use two econometric methods: the stepwise forward regression method and the coefficients' variance decomposition method, since stepwise regression may not be relevant (Smith, 2018). A forward-selection begins with no explanatory variables and includes variables, one by one, based on which is the most statistically significant, until there are no remaining statistically significant variables. A backward-selection introduces all possible explanatory variables and proceeds by eliminating, one by one, the least statistically significant regressors. The process stops when each variable remaining in the equation is statistically significant. The Coefficient Variance Decomposition of an equation is an important method to diagnose potential collinearity issues amongst the regressors. It provides information on the eigenvector decomposition of the coefficient covariance matrix as in Belsley et al. (2004).

We split the sample into domestic and foreign determinants samples and proceed in three steps:

1. First, testing the domestic drivers of inflation (model 1) and proceeding by using the procedure of variable selection method based on stepwise forward regression and the coefficients' variance decomposition to select the best determinants (model 2).

2. We repeat the first 2 steps for a model of only foreign variables and constant and inflation inertia (model 3), to select the main foreign drivers of inflation in the UAE based on the stepwise forward regression variable selection and the Coefficient Variance Decomposition (model 4).

3. In the final step, we mix the selected determinants of the two sets of variables and run the final model (model 5), for which the validity and accuracy are examined through a set of econometric tests leading to model 6, and a VAR confirmation of effects using the inflation responses function following the drivers' impulses.


Methodology
of Estimations
First Step
Model 1. Domestic Drivers:
Inertia; Rent; Wages;
PMI/Non-oil gap; Gov. Exp.;
Money (M3).
Model 2. Final Selected
Domestic Drivers
Stepwise Selection
Regression (SWR)
Coefficient Variance
Decomposition (CVD)
Second Step
Model 3. Foreign Drivers:
Inertia; NEER; FFR; Oil prices;
Global Non-energy inflation.
Model 4. Final Selected
Foreign Drivers
Third Step
Model 5. Combined
Selected Domestic and
Foreign Drivers
Model 6. Final Selected
Domestic and Foreign Drivers