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ORIGINAL PAPER

Granger predictability of real oil prices by us money and inflation in Markov-switching regimes

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Abstract

This paper presents new evidence that US money supply growth and inflation rates Granger predict real oil prices in a two-regime Markov switching vector autoregression (MS-VAR) model. An asset pricing theory motivates the empirical work by showing how jumps in real oil prices approximately follow jumps in the discount factor to keep constant the competitive return to oil capital. Using monthly data from January 1978 to June 2024, we consider alternative data combinations of US money supply growth rates, US inflation rates, and real oil prices to establish volatility regimes through goodness of fit testing. We set baseline model as that model with the highest likelihood in explaining the real oil price, which combines M2, the CPI less energy prices (CPIE), and real oil prices. Robustness considers two M2 variants combined with the CPIE that have the next highest likelihoods, for two alternative models. In the high volatility regime, results show robust Granger predictability of real oil prices by the baseline M2 and the M2 variants. In the low volatility regime for the baseline model, the CPIE inflation rate Granger predicts real oil prices. The paper contributes these new MS-VAR results that combined with the theory provide nuanced non-conventional support that monetary factors contribute to heightened real oil price episodes in volatile times as well as in calmer periods.

Keywords US inflation and money supply, real oil prices · Volatility regimes · Present value · Granger-predictability · Impulse responses

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1 Introduction

Do oil prices cause inflation, or can it also be the other way around? Theory has used variants of Taylor rules to justify as in Natal (2012) that the monetary authority should lower interest rates by increasing the money supply in response to an oil price shock to lessen its real consequences for the economy. This is a theory about the feedback from oil prices to money supply. The degree to which the feedback from oil prices to the money supply occurs empirically has been debated since Bernanke et al. (1997), Hamilton and Herrera (2004), and Bernanke et al. (2004). In this paper, we focus instead on the opposite effect: theory and empirical evidence on how oil prices respond to monetary policy.

Because oil is traded in US dollars (USD), there can be effects on oil prices from US money supply and inflation. If there is an effect of US money on oil prices, then the dictum that accelerated money supply growth leads to higher inflation suggests that both the money supply growth rate and the inflation rate may contribute to periods of high oil prices. Growing evidence has found money and inflation Granger predicting real oil prices, using linear assumptions for the testing, to suggest a money non-neutrality that yet remains outside of the conventional explanations of major episodes of heightened real oil prices. Recent work identifying the monetary shocks that explain changes in oil prices further enforces a non-neutrality explanation by finding that monetary shocks dominate in explaining three of the four major oil price increase episodes of the 1970s–1980s, post-2008, and 2021–2023, but excepting the early 2000s-2008 episode that is instead found to be driven by oil demand.

This paper contributes the first such corroborating evidence in a Markov-switching vector autoregression (MS-VAR) framework of the role of US money supply and inflation in Granger predicting real oil prices during low and high volatility regimes. After a literature review in Sect. 2, we provide in Sect. 3 data to motivate the potential relation between real oil prices and inflation, supply in Sect. 4 an asset pricing present value model for real oil prices that provides the intuition for the results, present the econometric methodology in Sect. 5, and then in Sect. 6 contribute robust Granger predictability empirical findings that back the model intuition.

As discussed further in Sect. 7, for the intuition consider that with USD oil prices set by sequences of nominal oil price contracts in the market, the balanced growth path equilibrium of the model requires real oil prices to jump in correspondence with the nominal market discount factor. If real oil prices stay in line with jumps in the discount rate, then the present discounted value of dividends to the oil producer of the profits from the oil flow remains constant. This means that the oil reserve capital continues to earn the competitive market real rate of return on its income flow from oil sales. Jumps occur in the market discount factor due to jumps in the government debt nominal interest rate, which changes often in capital markets. The nominal interest rate has been regulated in the US since 2008, but theoretically it can be expressed in terms of the inflation rate and/or in the money supply growth rate, as shown mathematically. Then jumps in the inflation rate and/or jumps in the money supply growth rate warrant approximately proportional jumps in the real oil price to keep the present discounted value constant and the real return on capital invested in the oil production earning the competitive market real return to capital. Such real oil price volatility from jumps in the factors entering the discount rate on the stream of oil flow earnings often take place during periods of relatively high volatility when there are jumps in the US inflation rate and/or the US money supply growth rate. Concluding in Sect. 8, our results present new robust MS-VAR Granger predictability evidence from these nominal variables to real oil prices in high volatility regimes as well as in the baseline model's low volatility regime.

2 Related literature

Bobasu et al. (2024) update the literature on the effect of oil shocks on monetary policy by finding that for the Euro area passive monetary policy better accommodates oil price shocks. And ample evidence finds that monetary policy follows regime switching properties (Owyang & Ramey, 2004) and that financial stability concerns figure prominently in US monetary policy (Dibooglu et al., 2022). But Hamilton & Herrara (2004) find that the possible response of monetary policy to oil shocks is muted at best relative to the magnitude of the oil price shocks. And Mork (1989), Barsky & Lutz (2002), Lardic and Mignon (2006), Blanchard & Gali (2009), and Katayama (2013) dispute that oil shocks have been a major source of output growth volatility. Kormilitsina (2011), Kilian and Vigfusson (2017) and Gunter and Linsbauer, (2018) further study transmission between oil prices and the macroeconomy.

This leaves open the converse that monetary shocks may affect real oil prices that are suspected to build in expected inflation as do gold prices. Towards this thesis, Hamilton (1983) famously found that no macroeconomic variable Granger-predicts oil prices, but used data only up to 1973 when oil prices fluctuated little; Mork et al. (1994) for example update this. Restarting the monetary hypothesis, Crowder (1998), Gillman and Nakov (2009), Haug and Dewald (2012), Alquist et al. (2013), Benk and Gillman (2020), and Matthews and Ong (2022) all find evidence of linear Granger-predictability from the money supply growth rate to inflation. And of these, Gillman and Nakov (2009), Alquist et al. (2013), and Benk and Gillman (2020) all find Granger predictability of real oil prices by US money supply and inflation. In further support for how money supply in practice cause inflation, Leeper and Zhou (2021) find that 50% of new Treasury debt during crises is financed through the inflation tax, with these crisis periods possibly including times of high oil price episodes.

Relatedly, Fratzscher et al. (2014) find evidence of bidirectional causality between the US dollar and oil prices. Couderta and Mignon (2016) find a significant relationship between oil prices and the real US dollar exchange rate. And Arfaoui & Rejeb (2017) find that both gold prices and the US dollar exchange rate affect oil prices.

If nominal variables exert influence on real oil prices, then one approach is to first identify the shocks affecting the oil market. A vast literature arose from Kilian's (2009) identification of fundamental oil supply and demand shocks that determine changes in real oil prices, using a structural vector autoregression (SVAR) framework. Kilian and Murphy (2014) extend this by adding oil inventories as another fundamental oil market variable, which Kim and Vera (2019) update. Baumeister and Hamilton (2019) extend Kilian and Murphy (2014) with Bayesian estimation of fundamental oil price shocks within an SVAR model. Kilian and Zhou (2022) study the link between oil prices, interest rates, and exchange rates.

Adding the nominal variables onto the Kilian (2009) model, Benk and Gillman (2023) first replicate the Kilian (2009) and Kim and Vera (2019) fundamental oil supply and demand price shocks without nominal factors. Then they add the US money supply growth rate and inflation expectations onto the Kilian (2009) SVAR model. Results show significant positive shocks from each nominal variable on real oil prices, with their historical decomposition of the real oil price changes showing that these monetary effects dominate in explaining most of the main oil price shock episodes since the 1970s during volatile times.

Despite MS-VAR models previously not being used for testing real oil price Granger predictability, a long-related history perhaps begins with Schwert (1989) who finds time-varying volatility associated with stock prices. Deschamps (2008) shows that MS-VAR models tend to be more appropriate than threshold models for capturing nonlinearity unless there is a priori exogeneity of variables that typically is lacking. Beckmann and Czudaj (2013) find that nominal exchange rates generally Granger-predict the oil prices using two volatility regimes. Kocaaslan (2013) uses MS-VAR methods to find that US energy consumption predicts output growth. Akgul et al. (2015) extend the MS-VAR model with Bayesian estimation of regimes that affect the relationship among oil, gold, and stock market prices. With an MS-VAR framework based on the Kilian (2009) and Kilian and Murphy (2014) oil price shocks, Basher et al., (2016, 2018) present evidence that the oil shocks help explain real exchange rates and excess stock returns (an equity premium) for oil exporting nations.

Less closely related, Chen et al. (2019) use MS-VAR evidence to show that the USD exchange rate, federal funds rate, financial speculation, and oil prices explain international copper price volatility. Abbas & Lan (2020) find MS-VAR evidence of commodity prices affecting inflation. With MS-VAR models Lien et al. (2022) find that policy uncertainty affects international financial markets more in high-volatility regimes than in low-volatility regimes. Alternatively, for policy uncertainty during crisis periods, Choi and Hammoudeh (2010) use GARCH estimation to find that financial and geopolitical crises induce time-varying volatility for oil prices and other asset prices, while another example is Roubaud and Arouri (2018) who estimate how policy uncertainty affects oil prices, the real US dollar exchange rate, and US stock market prices. On competition in the oil market Dibooglu and AlGhudea (2007) examine cheating in OPEC.

3 Motivating evidence: USD oil prices, US inflation, and US money supply

A way to preview data evidence is to see whether the percentage changes in the US CPI price inflation rate show any type of correspondence to the percentage change in real WTI oil prices, which our subsequent theory suggests. For this illustration, we present quarterly data beginning in November 1960 and ending in May 2009. During several episodes after May 2009 when the inflation rate is low, the fluctuations in the percentage change terms are so large that these dwarf the graph and blot the connection between the two data series in pre-2009 period, which is why Fig. 1 ends in 2009. The graph shows periods of striking comovement between the data series once the Bretton Woods gold standard breaks down fully in 1973. Our theory of the next Sect. 4 explains why such data series might move together, and our subsequent empirical analysis presents related results about Granger predictability of real oil prices.

4 Present value theory linking oil prices to money growth and inflation rates

The model presented here is a theoretical asset pricing model for oil prices from Gillman and Nakov (2009). It shows that the capital in the oil sector demands that the USD oil price follow changes in the discount factor which is the nominal interest rate. The model includes how the nominal interest rate can be written in terms of

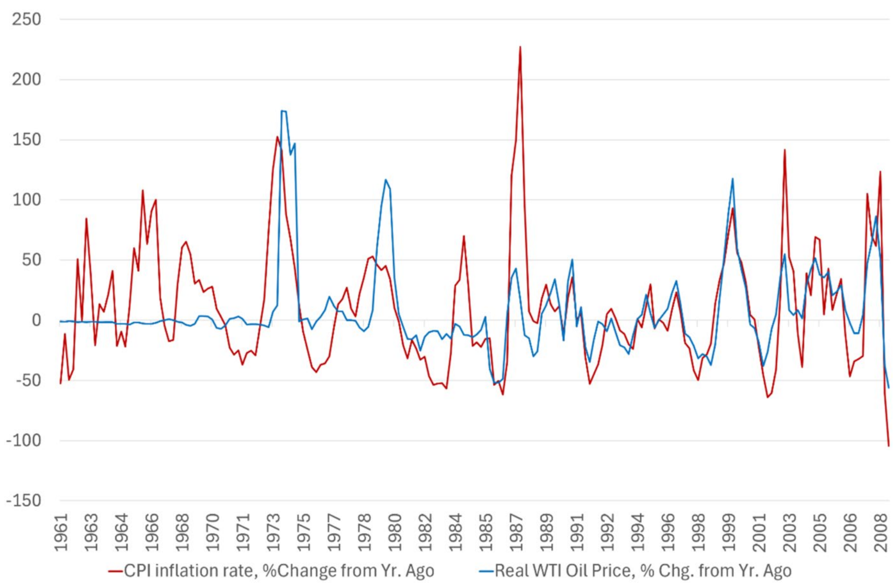

Fig. 1 Percentage change in real oil price (blue) and in the CPI inflation rate (red); May 1961–January 2009, quarterly

either the inflation rate or the money supply growth rate. This means that the theory shows why one would expect percentage changes in the USD oil price to follow percentage changes in the US inflation rate or money supply growth rate, which is what our empirical Granger predictability analysis estimates to provide evidence in support of or against this hypothesis.

In Gillman and Nakov (2009) oil is produced by the oil industry through a Cobb–Douglas function using labor, capital and a fixed factor of oil field reserves that grow exogenously at the balanced growth path rate g. The household buys shares in the oil industry that issues nominal dividends equal to the return to the fixed factor that by homotheticity implies a return of $\gamma P_{ot} o_t$, where $\gamma<1$, P_{ot} is the nominal oil price that is contracted for at time t, and o_t is the quantity of oil sold. Assuming that the oil supply also grows at the rate g, the present discounted value of an infinite stream of such nominal earnings, denoted by V_t and putting it in real terms by dividing by the nominal price level P_t, equals the end-of-period dividend flow $\gamma P_{ot} o_t (1+g)/P_t$ divided by the government debt nominal interest rate $R_t - g$:

$$\frac{V_t}{P_t} = \frac{\gamma \frac{P_{ot}}{P_t} o_t (1+g)}{R_t - g}. \tag{1}$$

Equation (1) means that the real price of oil needs to adjust to the discount factor, with R_t the focus, such that the real value of the oil stock asset remains constant with capital used in oil production still earning the competitive market real interest rate on capital. Note that the nominal interest rate can be written in terms of either the inflation rate or the money supply growth rate in such monetary dynamic general equilibrium (MDGE) models. This follows from the Fisher equation of interest rates by which the inflation rate affects R_t and by the cash-in-advance economy with log-utility in Gillman and Nakov (2009) in which the money supply growth rate directly changes R_t, as described in the footnote here.[1]

Equation (1) shows first that if no changes in the discount factor R_t occur, then the real price of oil can remain constant if the dollar oil price simply follows the aggregate price level change. But the nominal interest rate changes with regularity and dollar oil prices have to be set in this model so as to anticipate the changes in this discount rate. That means the USD oil price, and so the real oil price, has to jump if the nominal interest rate jumps. In this model, such jumps in the real oil price fundamentally come from jumps in the money supply growth rate and the ensuing inflation rate. The evidence in the last section shows graphically that the changes in the USD oil price follow changes in the rate of growth of the aggregate price level, the inflation rate, giving some credence to this theory. Further evidence can be found by

[1] From the cash-in-advance economy, given π as the inflation rate and θ as the money supply growth rate, then $$\left(1+\pi \right)\left(1+g\right)=1+\mathrm{\Theta}$$; from the Fisher equation with r the real interest rate, δ the depreciation rate, then $${1+R}_{t}=\left(1+{ r}_{t}-\delta \right)\left(1+{\pi }_{t}\right)$$; and with ρ the rate of time preference in the Euler equation for growth $$1+{g}_{t}=\frac{1+{r}_{t}\mathrm{ }-{\delta }_{k}}{1+\rho }$$; it results that $$1+{R}_{t}=\left(1+{\mathrm{\Theta}}_{t}\right)\left(1+\rho \right)$$, so that an increase in either the inflation rate π or the money supply growth rate θ directly impacts the nominal interest rate $${R}_{t}$$.

examining Granger predictability of the real oil price by both the US money supply growth rate and by the US inflation rate, using an MS-VAR model to capture different volatility regimes.

5 Methodology and data

Evidence suggests that oil prices exhibit regime-switching properties including regime dependence on monetary policy variables. Evidence also suggests that a Markov-switching VAR model may surpass the linear VAR model in one-quarter ahead projections for monetary aggregates in the United States. This indicates the utility of the MS-VAR model in analyzing the Granger (1969) predictive capacity of monetary aggregates on real oil prices.[2] The comprehensive Markov-switching model is detailed in Online Appendix A.

To verify whether the variables of interest exhibit regime-switching characteristics, a Markov-Switching specific linearity test must be utilized. There are several Markov-Switching-specific linearity tests in the literature that are computationally intensive.[3] Di Sanzo (2009) suggests a feasible test procedure for Markov-switching models based on a bootstrap resampling procedure and using Monte Carlo simulations. This bootstrap resampling demonstrates superior performance compared to the tests in Hansen (1992) and Carrasco et al. (2014), while also being computationally efficient.[4] In accordance with Di Sanzo (2009), the bootstrap-based likelihood ratio test is executed as follows: (1) Estimate the linear model and derive standardized residuals, (2) calculate the log-likelihood values for both the linear and Markov-switching models, (3) generate a bootstrap sample utilizing the estimated parameters and bootstrap residuals from the linear model, and (4) compute an LR* test statistic using the bootstrap sample, repeating steps 3 and 4 multiple times (e.g., 5000 iterations). Determine the distribution of the LR* statistic and compute the bootstrap p-value as the proportion of LR* values exceeding the observed value, LR.

To ascertain if an MS-VAR model is more suitable for the data compared to a linear model in elucidating real oil prices, one may utilize a standard likelihood ratio (LR) test. The LR test statistic is formulated as LR = 2[L(θ) − L(θ_r)], where L(θ) and L(θ_r) are the log-likelihood values for the Markov-switching model and the linear model, respectively, and r signifies the number of restrictions. This test follows an χ^2 distribution with r degrees of freedom. However, conventional testing methods regarding Markov-Switching are complicated because transition probabilities in

[2] See for example Zhang and Zhang (2015), Zhang and Wang (2015), Chai et al. (2018), and Yildirim et al. (2018). Regarding monetary policy, see Owyang and Ramey (2004), Neville and Owyang (2005), Assenmacher-Wesche (2006), and Anderson et al. (2014). See Elger et al. (2006) on MS-VAR; Baumeister et al. (2018) focus on forecasting oil prices in an alternative approach based on spreads between refined and crude prices.

[3] See Hansen (1992), Garcia (1998), Cho and White (2007), and Carrasco et al. (2014).

[4] Hamilton (1989) and Clements and Krolzig (1998) show an MS-VAR provides better forecast performance compared to linear models; Krolzig (1997) provides a multivariate generalization of Hamilton (1989) that is commonly used to analyze relationships among a set of variables.

such models are not defined in the linear model and hence the asymptotic distribution does not follow a standard χ^2-distribution. To address this issue, we use the alternative upper bound p-values proposed by Davies (1987).

For monetary data, the US monetary aggregates we consider include the monetary base (MB), M1, M2, Divisia M1 and Divisia M2. In addition, given the unusual buildup of excess reserves, which made the MB exceed M1 for the first time in US history after 2008, several variants of the typical aggregates are added used for testing. The main modification is to subtract Central Bank Liquidity Swaps, or simply Swaps (SWP), from the MB, M1 and M2. The reason for this is that these were temporary surges in money used to establish Federal Reserve Bank liquidity during the two bank-run crises in 2008 and 2020 that both occurred as oil prices crashed. These Swaps do not contribute to sustained money supply growth that causes inflation and have been shown to break up Granger predictability (Benk & Gillman, 2020). The Fed counts Swaps as part of reserves. During the liquidity crisis of 2008, the Federal Reserve System (Fed) reserves became negative. To keep reserves (including Swaps) positive during that crisis, the Fed borrowed short-term foreign currency in exchange for US dollars from other central banks and counted this foreign currency as reserves; they did it again during the 2020 bank run. The Swaps were rapidly unwound in both cases, rising from zero and falling back to zero from March 2008 to January 2010, and from March 2020 to October 2020. The other modified series that we consider is the addition of the MB and demand deposits (MB + DDEP).

For the US inflation rate data, we use the consumer price index for all urban consumers (CPI) and the CPI less energy prices (CPIE). Data for the expected inflation rate also is used, from the University of Michigan Inflation Expectation measure (EXPMich). All but the latter data series is monthly data sourced from the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis, as listed below by acronyms along with FRED designations and samples periods in parentheses. One major note is that the Fed defined M1 as currency plus demand deposits until 2020, after which money market funds were added. This caused M1 to suddenly increase threefold from \$4 trillion to \$12 trillion from March to May 2020, making M1 in magnitude nearly identical to M2. To get a consistent M1 definition (the original one), we thereby adjust the M1 series after March 2020 by subtracting back out the money market funds, but also use M2 that includes money market funds.

MB: money base (AMBSL, 1978m1–2024m6);
SWB: Central bank liquidity swaps (SWPT, 2003m1–2024m6);
DDep: demand deposits (DEMDEPSL, 1978m1–2024m6);
M1: M1 money stock (M1SL, 1978m1–2024m6)[5];
M2: M2 money stock (M2SL, 1978m1–2024m6);
CPIE: CPI less energy (CPILEGSL, 1978m1–2024m6);

[5] The FED redefined M1 in May 2020. To be consistent with earlier data, we calculate M1 for 2020m5-2024m6 by subtracting the estimated amount of the added deposits from the redefined M1, which eliminates a structural break in May 2020 of M1 due to the redefinition.

Table 1 ADF and PP unit root test results

Variables	Level		First differences	
	ADF	PP	ADF	PP
Real Oil Price	−3.171	−2.545	−10.807***	−15.973***
MB	−2.317	−2.032	−11.109***	−13.334***
MB-SWP	−2.316	−2.094	−5.634***	−17.907***
MB + DDep	−1.728	−1.451	−6.554***	−13.595***
MB-SWP + DDep	−1.796	−1.467	−6.224***	−18.804***
M1	−0.935	−0.438	−4.515***	−18.464***
M1-SWP	−1.008	−0.615	−6.18***	−16.94***
M2	−2.628	−1.973	−4.715***	−11.275***
M2-SWP	−2.575	−1.949	−4.757***	−11.989***
M1Divis	−2.805	−2.101	−4.831***	−17.731***
M1Divis-SWP	−2.652	−2.115	−6.049***	−16.778***
M2Divis	−3.076	−2.217	−6.719***	−11.474***
M2Divis-SWP	−3.083	−2.216	−4.746***	−12.614***
CPIE	−3.705**	−7.162***	−5.409***	−8.468***
CPI	−4.224***	−6.358***	−5.312***	−11.416***
EXPMich	−3.755**	−3.208	−6.533***	−31.001***

The optimal number of lags are selected according to the AIC. The tests in levels use an intercept and a time trend; the tests in first differences use just an intercept. (***) and (**) indicate a unit root can be rejected at the 1% and 5% significance level, respectively

CPI: CPI for all urban consumers (CPIAUCSL, 1978m1–2024m6);
WTI: spot crude oil price WTI (WTISPLC, 1978m1–2024m6);
M1Divis: monetary services index M1 (MSIM1P, 1978m1–2024m6)[6];
M2Divis: monetary services index M2 (MSIM2P, 1978m1–2024m6);
EXPMich: University of Michigan Inflation Expectation (MICH, 1978m1–2024m6).

5.1 Unit root tests

To find the order of integration, we first log linearize the variables and use the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests to look for unit roots. The test statistics for the real oil prices are shown in Table 1, along with the standard and adjusted monetary aggregates, the two measures of inflation (CPIE and CPI), a measure of inflation expectations (EXPMich), and finally the Divisia monetary aggregates. The table's results indicate that we can reject the null hypothesis of a unit root in levels for most of the variables. Since the test in levels contains a time trend, it seems CPI and EXPMich are trend-stationary per the ADF unit root test,

[6] We updated the M1Divis and M2Divis for 2014–2024 from the Center for Financial Stability.

whereas CPIE, CPI, and EXPMich are trend-stationary per the PP unit root test. For all series in first differences, the null hypothesis of a unit root is rejected at the 1% significance level. As the unit root tests indicate integration of order one in general, we use the first differences of the variables for regime-dependent Granger predictability tests.

5.2 Nonlinearity tests

Table 2 shows the results of the LR test suggested by Di Sanzo (2009). We can reject the null hypothesis of a linear model at the 1% significance level for all the variables. This implies a non-linear model provides a better fit for the data. Hence, to test the Granger-predictability hypotheses, we will use a non-linear, two-state bivariate Markov regime-switching model that finds low and high volatility regimes by looking at the standard error of regressions.

6 Results: MS-VAR Granger predictability of real oil prices and impulse response functions

We estimate a two-state 3-variable MS-VAR model of the real price of oil growth rate combined with a monetary aggregate growth rate and an inflation rate, selecting the lag length based on the Akaike information criterion. To select the optimal model specification, which includes the best explanatory variables, we construct a series of models as follows: Let $Y_i = [M_i, INF_i, ROIL]$ represent a vector, where M_i is the monetary aggregate, INF_i is the inflation measure, and ROIL is the real price of oil. We estimate three-variable MS-VAR models, systematically testing different combinations of M_i and INF_i. We consider seven different measures of the money supply and three different measures of inflation, resulting in a combination of 27 different MS-VAR models.

Table 3 provides the corresponding model fit statistics. These statistics help identify which model specification (linear vs. regime switching) and which combination

Table 2 Linearity test results

Variables	Di Sanzo *p*-value	Variables	Di Sanzo *p*-value
Real Oil	0.000	M1Divis-SWP	0.000
MB	0.000	M2	0.000
MB-SWP	0.000	M2-SWP	0.000
MB + DDep	0.000	M2Divis	0.000
MB-SWP + DDep	0.000	M2Divis-SWP	0.000
M1	0.000	CPIE	0.000
M1-SWP	0.000	CPI	0.000
M1Divis	0.000	EXPMich	0.000

Table 3 Model selection for real oil price model

3-variable MS-VAR model (asset price, monetary aggregate, inflation measure)	Lags	Log likelihood:MS-VAR model	AIC	HQ	BIC	Log likelihood: linear VAR (Null)	χ^2 *p*-value	Davies *p*-value
MB, CPI	2	5777.544	−20.618	−20.448	−20.182	5489.118	0.000	0.000
MB, CPIE	2	6045.757	−21.584	−2.414	−21.148	5708.847	0.000	0.000
MB, EXPMich	3	5395.873	−19.212	−18.987	−18.635	2566.135	0.000	0.000
MB-SWP, CPI	3	5792.498	−20.644	−20.419	−20.068	5446.956	0.000	0.000
MB-SWP, CPIE	3	6023.393	−21.960	−21.270	−20.919	5674.950	0.000	0.000
MB-SWP, EXPMich	2	5422.323	−19.338	−19.167	−18.902	2501.820	0.000	0.000
MB + DDep, CPI	4	5939.953	−21.149	−20.869	−20.432	5574.778	0.000	0.000
MB + DDep, CPIE	1	6103.103	−21.816	−21.701	−21.521	5613.075	0.000	0.000
MB + DDep, EXPMich	2	5517.348	−19.680	−19.510	−19.244	2621.845	0.000	0.000
M1, CPI	1	6083.341	−21.754	−21.630	−21.450	5762.755	0.000	0.000
M1, CPIE	2	6357.888	−22.709	−22.539	−22.273	6076.201	0.000	0.000
M1, EXPMich	2	5788.156	−20.656	−20.486	−20.220	2926.940	0.000	0.000
M1-SWP, CPI	2	6040.297	−21.565	−21.394	−21.129	5618.202	0.000	0.000
M1-SWP, CPIE	2	6279.179	−22.425	−22.255	−21.990	5827.816	0.000	0.000
M1-SWP, EXPMich	2	5706.272	−20.361	−20.191	−19.925	2679.548	0.000	0.000
M1Divis, CPI	1	6173.877	−22.071	−21.956	−21.776	5937.038	0.000	0.000
M1Divis, CPIE	2	6427.674	−22.961	−22.790	−22.525	6161.910	0.000	0.000
M1Divis, EXPMich	2	5861.484	−20.920	−20.750	−20.484	3014.144	0.000	0.000
M2, CPI	2	6623.934	−23.668	−23.498	−23.232	6387.684	0.000	0.000
M2, CPIE***	**2**	**6872.191**	**−24.562**	**−24.392**	**−24.127**	6612.654	0.000	0.000
M2, EXPMich	2	6312.754	−22.546	−22.376	−22.111	3464.654	0.000	0.000
M2-SWP, CPI	1	6579.657	−23.531	−23.415	−23.235	6367.280	0.000	0.000
M2-SWP, CPIE***	1	**6764.239**	**−24.195**	**−24.079**	**−23.899**	6436.839	0.000	0.000
M2-SWP, EXPMich	1	6277.089	−22.442	−22.327	−22.147	3435.449	0.000	0.000

Table 3 (continued)

3-variable MS-VAR model (asset price, monetary aggregate, inflation measure)	Lags	Log likelihood:MS-VAR model	AIC	HQ	BIC	Log likelihood: linear VAR (Null)	χ^2 *p*-value	Davies *p*-value
M2Divis, CPI	1	6548.906	−23.420	−23.305	−23.125	6253.414	0.000	0.000
M2Divis, CPIE* **	**1**	**6796.322**	**−24.310**	**−24.195**	**−24.015**	6413.786	0.000	0.000
M2Divis, EXPMich	1	6237.528	−22.300	−22.185	−22.005	3405.087	0.000	0.000

Log-L is log-likelihood of the model. AIC, HQ, and BIC are Akaike, Hannan-Quin and Schwarz Bayesian model information criteria respectively. *** indicates the models that have the best statistics that is the three models out of the 27 having the highest log-likelihood of monetary aggregates and inflation measures offers the best explanatory power for the real price of oil.

The last two columns of Table 3 indicate the p-values from the LR test when testing for the goodness of fit of a linear model against a regime switching alternative (MS-VAR). The Davies p-value results provide strong evidence in favor of the MS-VAR model, as the null hypothesis of a linear VAR model is rejected at less than 1% significance level in all cases. Utilizing a linear model may thus lead to misspecification; hence, we will use a MS-VAR model for testing for Granger predictability.

Table 3 also suggests that based on the log-likelihood of various model specifications, M2 and CPIE are the most suitable variables for fitting a model that explains changes in real oil prices. Moreover, the MS-VAR models incorporating M2-Swaps and M2 Divisia also exhibit strong model fit statistics. In conclusion, we identify CPI less energy as the most effective inflation variable, while M2, M2-Swaps, and M2 Divisia emerge as the key monetary variables in explaining real oil price dynamics.

Based on Table 3, the highest likelihood is for M2 and the CPIE combination with real oil prices that we set as our baseline Model 1. The next two highest likelihood statistics are for variants of MS, in particular M2-SWP and M2Divis, which we also consider for robustness as Models 2 and 3, respectively. These three MS-VAR models (in bold in Table 3) stand out in explaining changes in the real price of oil (ROIL). Therefore, regime-dependent Granger predictability and impulse-response analyses will be performed using these three model specifications, with comparison of the high volatility regimes of the three presented in Fig. 3 of the Appendix:

Model 1: [ROIL, M2, CPIE];
Model 2: [ROIL, M2-SWP, CPIE];
Model 3: [ROIL, M2Divis, CPIE].

Having chosen the baseline and the two next best models for robustness, we proceed by calculating the regime-dependent Granger-predictability between real oil prices and monetary factors in the US. Following Kanas (2005) and Cevik and Bugan (2018), we use the standard error of regression to identify the regimes.[7] If the standard deviation of the regression in the first regime is lower than that of the second regime, then we designate the first regime as the low-volatility regime and the second as the high-volatility regime.[8]

Table 4 presents Granger-predictability test results for low and high-volatility regimes. The null hypothesis is of no Granger-predictability; a *p*-value smaller than 0.10 indicates the rejection of the null hypothesis at the 10% significance level. The top value in each cell of the table gives the *p*-value for the null hypothesis of no

[7] See Hamilton and Susmel (1994) for an alternative approach that identifies regimes using the intercept of the conditional variance equation in MS-GARCH Models.

[8] We present the smoothed transition probabilities for the high volatility regime in Appendix B. The transition probabilities exhibit consistency across the three MS-VAR models, showing high correlations between different model specifications. This consistency reinforces the robustness of the regime classifications in capturing periods of heightened volatility.

Table 4 Granger predictability of real oil price

Model 1			Model 2			Model 3		
Regime	Low	High		Low	High		Low	High
M2	0.396 [0.966]	**0.015** **[0.032]**	**M2-SWP**	*0.110* [0.163]	**0.021** [**0.000**]	**M2Divis**	0.441 **[0.030]**	**0.018** [**0.060**]
CPIE	**0.055** [0.577]	0.203 [0.230]	**CPIE**	0.195 [0.609]	0.168 **[0.049]**	**CPIE**	0.182 [0.143]	*0.111* [**0.041**]

p values in bold indicate significant Granger-predictability from money and inflation to real oil prices at 10% significance level. Numbers in bold in square brackets indicate significant reverse predictability at 10% significance level

Granger-predictability from nominal variables to the real oil price and the value in the square brackets gives the *p*-value for reverse predictability.

Results indicate strong Granger predictability from all three models with variants of the M2 money supply growth rate to real oil prices in the high volatility regimes, with p-values consistently near 2%. Granger predictability by M2-SWP of real oil prices in Model 2 has a p-value of 0.11 for the low volatility regime, very close to a 10% level. For the baseline model, the CPIE inflation rate Granger predicts real oil prices in the low volatility regime. Testing of Granger predictability by the CPIE of real oil prices in the high volatility regime for Model 3 with M2Divis finds a p-value of 0.11, close to acceptance at the 10% level. There is reverse causality in various cases, of real oil prices to the three M2 aggregates in the high volatility regime and to the inflation rate in the high volatility regimes of Models 2 and 3.

The impulse response functions in Fig. 2 show the dynamic relationship between measures of monetary aggregates and inflation and real oil prices. Following the methodology of Ehrmann et al. (2003), we orthogonalize innovations by ranking the shocks to the monetary aggregate first. This regime-dependent impulse response analysis shows the direction and magnitude of the responses to unexpected shocks. The general response over time and the tightness of the bounds allows for inference.[9]

Given the selected three models from Table 3, we show here the impulse responses of the real oil prices to shocks in M2, M2-SWP, and M2 Divisia. We also consider the CPIE for inflation, and hence we show the response of real oil prices to a shock in the CPIE. The results for the two regimes of low and high volatility are presented in Fig. 2 for the three Models.

The impulse responses find for the baseline Model 1 a positive response of real oil prices to an unexpected M2 shock in the high volatility regime, after an initial fall, while showing a positive but insignificant response over time in the other two models also after initial significant declines. M2-SWP induces an unambiguous significant and positive response of real oil prices in the low volatility regime.

[9] These are the cumulative responses of the real oil price to a change in a nominal variable. As such, these are responses to permanent nominal shocks.

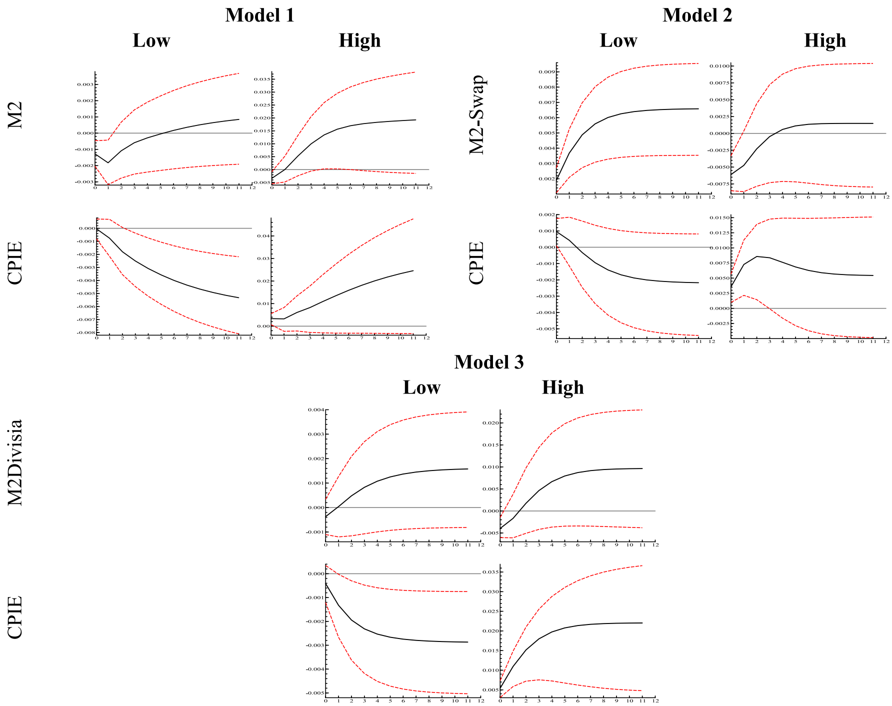

Fig. 2 Responses of real oil price to M2, M2-SWP, and M2Dvisia and to CPIE shocks

For the CPIE shocks, baseline Model 1 exhibits a positive but marginally insignificant response in the high volatility regime. In Models 2 and 3 for the high volatility regime, the CPIE impulse response is significantly positive for part of the time in Model 2 and the entire period in Model 3. In the low volatility regime the CPIE tends to have a negative effect, with significance in Models 1 and 3.

Removing swaps from M2 results in a distinct model with varying impulse responses. The real oil price's response to an unexpected M2-swap shock is consistently positive and statistically significant in the low volatility regime, while it has an initial negative response in the high volatility regime. The responses to an unexpected CPIE shock are positive and statistically significant only in the high volatility regime.

Using the M2 Divisia data to estimate the third model, we find that real oil prices react positively to an unexpected inflation shock, but not significantly different from zero over a longer horizon. However, in high volatility regimes, the immediate response is negative and statistically significant. Real oil prices react negatively to an unexpected CPIE shock in low volatility regimes, while reactions are positive and statistically significant in high volatility regimes.

Table 5 summarizes the Granger-predictability (GP) and impulse response (IR) findings. A check mark ✓ indicates significant Granger-predictability. A plus sign + indicates a positive impulse response; a negative sign − indicates a

Table 5 Summary of Granger predictability (GP) of real oil prices by alternative M2 growth rate variants and by CPIE growth rates, plus impulse responses (IP)

Model 1			Model 2			Model 3		
Regime	Low	High		Low	High		Low	High
M2 *GP*	(−)	✓	**M2-SWP***GP*	(✓)	✓	**M2Divis** *GP*		✓
IR		+	*IR*	+	(−)	*IR*		(−)
CPIE *GP*	✓	(+)	**CPIE** *GP*		+	**CPIE** *GP*	–	(✓)
IR	−		*IR*			*IR*		+

✓ for Granger predictability (GP). Impulse response (IR): a plus sign + to indicate a significant positive impulse response, a minus sign − for a significant negative response, and signs in parentheses marginally significance

negative shock effect; parentheses indicate marginal effects; and no mark indicates insignificance.

7 Discussion

Using model selection criteria across three variable joint regimes involving combinations of alternative monetary aggregates, alternative inflation rate aggregates and the real oil price, we find that M2 and its variants combined with the CPIE (CPI less energy prices) and the real oil price gives the best fitting set of regimes. Within these, all three variations of the M2 growth rate (M2, M2-SWP and M2Divisia) Granger predict real oil prices in the high volatility regime, and the CPIE so predicts in the low volatility regime for the baseline Model 1 with M2. The latter low volatility prediction could be viewed through Fig. 1 in which real oil prices historically change more closely in line with the changes in the inflation rate during less volatile times, even as large money supply accelerations (not shown in Fig. 1) can precede real oil price changes in the more volatile times.

Figure 3 of Appendix B provides the probabilities for the high volatility regime of these three joint variables of M2 or its variants along with the CPIE and the real oil price. It shows significant overlapping of the three alternative regimes so that one might consider these as showing a consistent view of the high volatility regime periods. These occur strongly during the late 1970s to the early 1980s and then sporadically in the mid to late 1980s as oil prices, inflation, and the money supply growth rate all dropped. The high volatility regimes include the 1990 and 2001 recessions, the surge in money, inflation and oil prices in the early 2000s, and then the turmoil starting in 2007–2008 and lasting up to 2015 after the fall in oil prices. With a brief surge in 2019, the last sustained high volatility period is after 2020 to the end of 2023.

That the M2 money supply growth rate and its variants should be found to Granger predict real oil prices during these high volatility periods stands as a key result of the paper. It demonstrates evidence that nominal factors, particularly the money supply growth rate, predicts oil prices in this Granger sense. Reverse predictability exists in all three cases. The latter non-trivial result seems natural in that major episodes of heightened real oil prices can lead the Federal Reserve to try to moderate the impact of the real price increase on the economy by accommodative monetary policy, as that literature finds.

Yet the essence of causality in neoclassical monetary models, in which the inflation tax exists to raise government revenue (unlike the canonical New Keynesian model), is that money creation results to cover deficits through the central bank creating bank reserves by buying Treasury debt. Such reserve creation in turn can accelerate inflation once the reserve money enters circulation (Gillman, 2023). We view the higher expected inflation rate from money supply acceleration during deficit financing by the central bank as getting built into asset prices such as oil, so that oil capital continues earning a competitive real rate of interest. In the model of real present value in Sect. 3, it appears that a change in real oil prices would be less likely to cause much of a change in the discount factor on the oil revenue stream. It seems more likely that a change in the discount factor, which occurs regularly as capital markets adjust to nominal factors such as the money supply growth rate and the inflation rate, would cause changes in real oil prices.

Our results find changes in the growth rates of both money and inflation Granger predict real oil prices in both regimes as consistent with the theory. Even though we find evidence of reverse causality, we make the case for why economic causality would be more from the nominal factors to real oil prices rather than the reverse. Arguably, the new evidence presented here as taken together with the theory supports a monetary explanation for why we experience episodes of high real oil prices. The historical decomposition of real oil price changes by fundamental oil market shocks plus money and inflation shocks in Gillman and Benk (2023) finds that three of the four major oil price episodes were caused mainly by monetary factors. Taking this evidence along with our new MS-VAR Granger predictability results reinforces a potentially significant yet overlooked cause of high oil prices: asset prices build in expectations of higher inflation rates that arise from accelerated money supply growth to keep earning a competitive return on capital.

As in numerous past studies, we also found robust Granger predictability of the various measures of inflation by the monetary aggregate growth rates (results not reported but available upon request). It supports the concept that ramped up acceleration of printing money to help finance accelerating government debt can lead to inflation episodes that coincide with major oil price episodes, both of which can have real negative effects on the economy. Exceptions to such negative economy-wide effects exist when the real oil price episodes enrichen nations dependent upon oil export revenue such as Russia and Iran. Their wealth increase combined with autocratic government aggression can induce the US to counter the aggression through accelerated spending financed with accelerated money creation that can in turn drive-up real oil prices in a vicious cycle.

8 Conclusion

We employ the MS-VAR approach to find Granger-predictability of real oil prices by US monetary aggregate growth rates and inflation rates. We choose low and high volatility regimes by testing the goodness of fit for a set of combinations in which each includes a monetary aggregate, an inflation rate variable and the real oil price. Using a set of alternative monetary aggregates growth rates and inflation rate measures, we find the highest likelihood for the M2 aggregate, along with two variations of M2, as combined with the CPI less energy prices (CPIE) and real oil prices. M2 minus Central bank liquidity swaps (M2-SWP) and M2 Divisia are the other two M2 variants that we find with the next highest goodness of fit. Results for these three models find that the monetary aggregate Granger predicts real oil prices in high volatility regimes for all three of the variations of M2, and in the low volatility regime for the CPIE in the baseline model with M2. This gives a new body of evidence that supports how monetary factors can predict real oil prices especially in high volatility times that our transition probability results show coincide with all four major oil price episodes since the late 1970s.

The intuition of the results is taken from the asset pricing theory that is presented in brief, whereby the real oil price needs to rise nearly proportionately to the changes in the discount rate on the present value of the stream of dividends of the oil flow producer. Because the discount rate can be expressed equivalently in terms of the inflation rate or the money supply growth rate, this suggests how changes in the latter nominal variables can lead to subsequent changes in the real oil price. The theory implies a causality from nominal factors to real oil prices in an economic modelling sense in which exogenous changes in the money supply growth rate cause changes in the inflation rate and subsequent changes in certain asset prices. Our evidence presents predictability by these nominal factors of real oil prices albeit without economic causality. Combined with the intuition from the model, the empirical results provides a contrarian view to the consensus that real oil prices are explained only by fundamental supply and demand in the oil market. Rather, we provide support for the hypothesis that monetary factors can play a significant role in causing deviations from fundamentals that ignite major real oil price episodes during volatile times.

Appendix A. MS-VAR model

For the identification of two Markov-switching regimes, we follow the literature by using the standard error of regression. This identifies the regimes based on standard error of regression where the lower value corresponds to the low volatility regime and the higher value to the high volatility regime. As in the single equation Markov-Switching model, the regimes can be defined according to the unobserved state variable that follows a Markov process in the MS-VAR model. Let $Y_t = (y_{1t}, y_{2t}, \ldots, y_{Kt})$,

$t = 1, 2, \ldots, T$ be a K-dimensional time series vector, where T is the sample size. Then, a *p-th* order and m-state MS-VAR model can be defined as:

$$Y_t = \begin{cases} v_1 + A_{11}Y_{t-1} + \cdots + A_{p1}Y_{t-p} + B_1 u_{t1} & if\ s_t = 1 \\ \vdots & \\ v_m + A_{1m}Y_{t-1} + \cdots + A_{pm}Y_{t-p} + B_m u_{tm} & if\ s_t = m \end{cases} \tag{2}$$

v_i are constant terms and $A_{1i}, \ldots, A_{pi}$ are autoregressive coefficient matrices for VAR parameters corresponding to states. The matrices $B_1 u_t$ are the reduced-form shocks, and u_t follows a multivariate normal distribution. N (0, I_K) and the regime-dependent variance–covariance matrix for the residuals can be formulated as follows:

$$\sum\nolimits_i = E\left(B_i u_t u_t' B_t'\right) = B_i E\left(u_t u'\right) B_i' = B_i I_K B_i' = B_i B_i' \tag{3}$$

The transition process of the Markov-Switching model is given by a first-order m state Markov stochastic process. Let p_{ij} be transition probability that state i in period t will be followed by state j in period $t+1$, which is defined as;

$$p_{ij} = P\left(s_{t+1} = j / s_{t+1} = i\right), \quad \sum_{j-1}^{m} p_{ij} = 1 \quad \forall i,j \in (1, \ldots, m) \tag{4}$$

In addition, all transition probabilities can be defined as an m x m transition matrix as follows:

$$\begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \tag{5}$$

The MS-VAR model is a nonlinear model in nature, hence, the regime or the state is unobservable and maximum likelihood methods are used to estimate the parameters. We use the Maximum Likelihood (ML) method based on the Expectation-Maximization (EM) algorithm to estimate the parameters. This iterative technique obtains both the estimates of the parameters and the transition probabilities governing the Markov chain of the unobserved states. The Likelihood ratio test statistic follows a χ^2 (k) distribution asymptotically where k is the number of restrictions.[10]

Calculating impulse-response functions in the MS-VAR model requires estimating the regime-dependent variance–covariance matrices. We use Cholesky decompositions to orthogonalize the shocks in the regime-dependent impulse-response

[10] Kanas and Ionnidis (2010) suggest that the predictability between variables in the MS-VAR model can be tested by a Likelihood Ratio (LR) test where the predictability is examined by imposing restrictions on the estimated autoregressive coefficients in each regime.

functions in order to illustrate dynamics between variables. Here we follow the methodology of Ehrmann et al. (2003). In addition, all transition probabilities can be defined as an *m x m* transition matrix as follows:

$$\begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \tag{6}$$

Appendix B. Smoothed probabilities for the high volatility regime

Figure 3 the probability of the high volatility regime from the tri-variate MS-VAR models consisting of the real oil price, an M2 measure of money (M2, M2-SWP, M2Divis), and a measure of inflation (CPI minus Energy denoted CPIE). The model using M2 is denoted Model 1, whereas Model 2 uses M2-SWP, and Model 3 uses M2Divis.

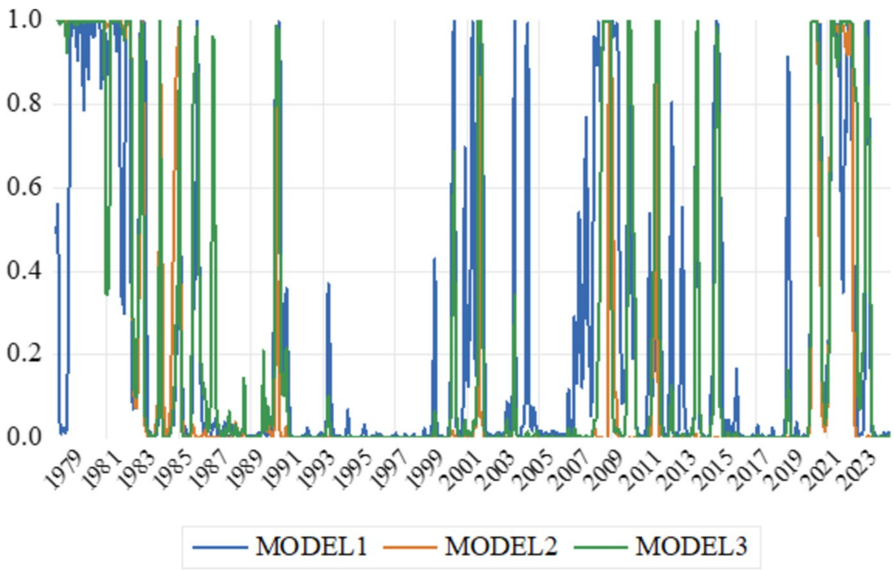

Fig. 3 Smoothed probabilities for the high volatility regime in model 1, model 2 and model 3

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Data availability Data is available from the author upon reasonable request.

Declarations

Conflict of ınterest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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