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Dual Anchors: China-U.S. Factors Jointly Determining Global Gold and Crude Oil Pricing—Systematic Evidence Based on Exhaustive Testing with VIF Constraints

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Dual Anchors: China-U.S. Factors Jointly Determining Global Gold and Crude Oil Pricing

—Systematic Evidence Based on Exhaustive Testing with VIF Constraints

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Abstract: Traditional commodity pricing literature has long anchored gold and crude oil pricing to U.S.-centric variables, leaving China-linked factors systematically excluded from quantifiable pricing frameworks. This study employs a rolling regression framework with a 756-trading-day window and variance inflation factor (VIF) constraints, exhaustively testing 462 factor combinations for gold and 141 for crude oil. The optimal gold model (China-U.S. Dual-Anchor Three-Factor Gold Valuation Model) consists of the TIPS real yield, the China-U.S. 10-year sovereign yield spread, and the gold-oil ratio, achieving a rolling full-sample R^2 of 0.908 and a static full-sample R^2 of 0.814 (2016–2026), with all VIFs below 5. The optimal crude oil model (China-U.S. Dual-Anchor Four-Factor Crude Oil Valuation Model) consists of Shanghai crude oil futures (SC), the VIX, the synthetic time spread, and the China-U.S. yield spread, achieving a full-sample R^2 of 0.888 and a fixed-parameter out-of-sample R^2 of 0.611. Under Newey-West autocorrelation-consistent corrections and LASSO regularization, all China-linked factors retain statistical significance and model survival. The China-U.S. yield spread is the only factor entering both optimal models—its independent explanatory power in gold traces back to at least 2006 (three-factor static $R^2 = 0.836$), while in crude oil its pricing function strictly begins with the launch of Shanghai crude oil futures in March 2018, as confirmed by an institutional instrumental variable test identifying the causal activation effect (first-stage F = 2,425.75). The SC factor maintains a 100% positive sign across all six rolling sub-periods with zero sign reversals. This paper further develops the theoretical concept of the "institutional interface"—whether a monetary policy signal can enter the pricing equation of a commodity class depends on whether that class possesses a tradable benchmark contract denominated in the domestic currency—offering a new analytical perspective for research on global commodity pricing power. The global commodity pricing regime has evolved from a single-anchor to a China-U.S. dual-anchor structure.

Keywords: gold pricing; crude oil pricing; China-U.S. yield spread; gold-oil ratio; Shanghai crude oil futures; exhaustive factor selection; variance inflation factor; rolling regression

1. Introduction

Commodity pricing stands at the core of macro-finance research. For gold, the dominant framework since Erb and Harvey (2013) has treated the U.S. 10-year TIPS real yield and the U.S. Dollar Index (DXY) as the core determinants of gold prices. For crude oil, Kilian's (2009) structural vector autoregression (SVAR) framework identifies global aggregate demand, supply shocks, and precautionary demand as the three primary sources of oil price fluctuations, with the U.S. dollar exchange rate and inventory cycles serving as supplementary pricing variables in practice.

Since 2022, however, the systematic failure of these frameworks has drawn widespread attention from both academia and industry. The historically negative correlation between gold and TIPS real yields has weakened substantially; global central bank gold purchases have reached record highs; and the "de-dollarization" narrative has gained unprecedented traction in commodity markets. Concurrently, deviations between Brent-WTI spreads, actual time spreads, and theoretical cost-of-carry have continued to widen, while traditional supply-demand factors have lost explanatory power for oil prices. These phenomena collectively point to a long-neglected question: Are China's macro-financial variables systematically missing from global commodity pricing frameworks?

This omission is not without traceable origins. China has been the world's largest gold consumer since 2009 and the largest crude oil importer since 2017. In April 2016, the Shanghai Gold Exchange launched the RMB-denominated Shanghai Gold Benchmark Price; in March 2018, the Shanghai International Energy Exchange launched the RMB-denominated Shanghai crude oil futures (SC), which by 2024 had become the world's third-largest crude oil futures contract. Yet in pricing models, these China-linked institutional variables have never been formally included as independent factors. Academic research on Shanghai crude oil futures has focused on their price discovery function—testing how well they follow international oil prices—rather than incorporating them as explanatory variables in WTI or Brent pricing models. The China-U.S. yield spread, as the most direct measure of the relative stance of Chinese and U.S. monetary policies, has been confined almost exclusively to exchange rate determination and cross-border capital flow discussions in the existing literature, and has never undergone exhaustive testing as a pricing factor in two independent commodity markets.

This paper selects China and the United States as its core empirical subjects based on the following considerations: the two countries are the world's two largest economies, together accounting for more than 40% of global GDP; they possess the world's most active and deepest sovereign bond markets; they are the world's two largest commodity consumers—China is the largest gold consumer and crude oil importer, while the United States is among the largest crude oil producers and consumers; both have established complete systems of domestic currency-denominated commodity futures markets, with the institutional conditions of continuous auction trading, central clearing, and access for foreign investors. The combination of these conditions makes China and the United States a "natural laboratory" for testing the dual-anchor regime of

global asset pricing—other economies are constrained either by economic scale, financial market depth, or institutional infrastructure, and cannot constitute independent pricing poles.

From a theoretical perspective, this paper engages in clear dialogue with the existing literature along three dimensions. First, it revises the "real interest rate single-anchor theory" of gold pricing (Erb & Harvey, 2013)—the traditional framework achieves an R^2 of merely 0.387 over the full twenty-year period; the China interest rate dimension is not a supplementary variable to U.S. factors but an independent pricing dimension standing alongside them. Second, it supplements the "supply-demand shock dominance theory" of crude oil pricing (Kilian, 2009)—China's monetary policy variable is not always effective in the crude oil pricing equation; its effectiveness depends strictly on the institutional existence of a tradable RMB-denominated crude oil contract. Third, it extends the "exchange rate determination theory" of the China-U.S. yield spread—the functional boundary of the spread extends far beyond exchange rate determination and cross-border capital flows; it is already a systematic factor in global commodity pricing. The mechanistic basis for this extension lies in the "differentiated activation pathway": in the gold market, a monetary-attribute market, the China-U.S. spread transmits directly through cross-border capital flow channels; in the crude oil market, an industrial-attribute market, it requires Shanghai crude oil futures as an institutional interface to be indirectly activated. Based on the above theoretical dialogue, this paper, while discovering the empirical regularity of the "China-U.S. dual anchor," further develops the broadly applicable theoretical concept of the "institutional interface"—whether a monetary policy signal can enter the pricing equation of a commodity class depends on whether that class possesses a tradable benchmark contract denominated in the domestic currency. The "dual anchors" proposed in this paper refer specifically to the two most significant sources of pricing power in the current global financial architecture—the United States and China—a judgment based on their combined advantages in global GDP, trade, financial market depth, commodity consumption, and institutional infrastructure completeness. Whether a third anchor of comparable influence will emerge in the future depends on the further evolution of the global economic and financial landscape.

The core hypothesis of this study is that China-linked macro-financial variables—the China-U.S. 10-year yield spread, the gold-oil ratio (Gold_Oil_Ratio), and Shanghai crude oil futures (SC)—have become statistically independent pricing factors in gold and crude oil markets, entering optimal models alongside traditional U.S. factors under strict VIF constraints within an exhaustive selection framework.

This paper makes three principal contributions. First, through cross-market (gold and crude oil) exhaustive factor combination testing, it provides systematic, replicable statistical evidence for the proposition that China-linked variables are independent pricing factors, and develops the "institutional

interface" theory to explain the temporal differences in their activation across markets. Second, it reveals that the China-U.S. yield spread is the only factor that simultaneously survives exhaustive selection, Newey-West corrections, and LASSO regularization across both independent markets, with its explanatory power traceable to at least 2006, offering quantitative support for China's systemic influence on global commodity pricing. Third, it establishes a transparent, objective factor selection methodology—a combined framework of exhaustive testing, VIF hard constraints, rolling regression, and multiple robustness checks. This methodology fundamentally circumvents common biases in empirical finance such as factor mining and p-value manipulation, is fully transparent and replicable, applies to all multi-factor pricing domains including equities, bonds, exchange rates, and commodities, and provides a standardized research tool for empirical finance.

2. Literature Review and Hypothesis Development

2.1 Evolution of Multi-Factor Gold Pricing Frameworks

Early theoretical frameworks for gold pricing centered on real interest rates. Erb and Harvey (2013) systematically demonstrated the negative relationship between TIPS real yields and gold prices: the opportunity cost of holding non-yielding gold rises with real interest rates, depressing gold prices. In practice, the World Gold Council's GRAM model employs TIPS yields and the U.S. Dollar Index as fundamental factors for gold valuation.

After 2022, the limitations of this framework became starkly apparent. Amid the fastest Federal Reserve rate hikes in four decades, TIPS real yields surged, yet gold prices rose rather than fell. The dramatic expansion of central bank gold purchases emerged as the primary supplementary narrative explaining this "decoupling," yet this variable had rarely been incorporated into formal regression equations. Meanwhile, some broker-dealer research began to include the China-U.S. yield spread and the RMB exchange rate in multi-factor gold pricing frameworks, but these attempts remained largely descriptive, lacking rigorous factor selection procedures and the statistical backing of exhaustive testing.

2.2 Crude Oil Pricing Factor Systems and Shanghai Crude Oil Futures

The academic literature on crude oil pricing was founded by Kilian (2009), whose core variables are global aggregate demand, supply shocks, and precautionary demand. In broader investment practice, the U.S. Dollar Index, the CBOE Volatility Index (VIX), the Crude Oil Volatility Index (OVX), the Brent-WTI spread, futures term structure (contango/backwardation), and CFTC positioning data collectively constitute the macro pricing reference system for crude oil.

Since its launch on March 26, 2018, on the Shanghai International Energy Exchange (INE), the price discovery function of Shanghai crude oil futures (SC) has drawn sustained academic attention. Multiple studies have examined the price linkages between SC, WTI, and Brent, generally concluding that SC can effectively follow international benchmark prices and possesses a certain price discovery capacity. However, a common feature of these studies is that they treat SC as the dependent variable, testing how it is influenced by international oil prices, rather than incorporating SC as an explanatory variable in WTI international pricing models. In other words, the literature has consistently asked "whether SC can keep up with WTI," not "whether SC can provide independent incremental information for explaining WTI fluctuations." This directional academic gap provides the direct point of departure for our hypothesis.

2.3 The China-U.S. Yield Spread in the Literature and the Research Gap

The China-U.S. yield spread (China 10-year sovereign yield minus U.S. 10-year sovereign yield) has been confined almost entirely to the field of exchange rate determination in the existing literature—based on interest rate parity theory, spread movements are used to explain short-term fluctuations and long-term trends in the RMB/USD exchange rate. In cross-border capital flow research, the China-U.S. yield spread is regarded as one of the core variables driving the reallocation of international capital between RMB-denominated and USD-denominated assets.

In commodity pricing, however, the China-U.S. yield spread has never been formally proposed as a pricing factor. This gap may stem from a threefold structural information disconnection: first, USD-denominated gold and crude oil models are naturally biased toward USD-side variables; second, although China's bond yield curve has been publicly available for many years, international researchers have yet to widely adopt these data sources; third, in the absence of a tradable Chinese commodity benchmark contract, the China-U.S. spread lacked an institutional "interface" to enter commodity pricing equations—an interface that the 2016 Shanghai Gold Benchmark Price and the 2018 Shanghai crude oil futures respectively filled.

2.4 The Gold-Oil Ratio in the Literature

The gold-oil ratio (Gold_Oil_Ratio)—the number of barrels of WTI crude oil that one ounce of gold can purchase—has been used in the existing literature primarily as an auxiliary indicator of market sentiment and macro risk. An elevated gold-oil ratio is typically interpreted as a signal of rising risk aversion or divergent inflation expectations. However, the gold-oil ratio has never been formally incorporated as a pricing factor in gold or crude oil regression equations, and its statistical performance as a candidate factor has never been subjected to exhaustive testing. This study is the first to include it in the candidate factor pool

for gold pricing, subjecting it to systematic screening alongside macro variables such as the China-U.S. yield spread and TIPS.

2.5 Formal Statement of Hypotheses

Based on the above literature gaps and institutional logic, this paper proposes two core testable hypotheses:

Hypothesis 1 (China Factor Independence Hypothesis): China-linked financial variables—the China-U.S. yield spread, the gold-oil ratio, and Shanghai crude oil futures—constitute independent pricing factors for gold and crude oil under strict VIF constraints, and their marginal explanatory power is not subsumed by traditional U.S. factors.

Hypothesis 2 (Cross-Market Common Factor Hypothesis): The China-U.S. yield spread, as the most direct measure of China's monetary policy stance, is the only systematic common factor that simultaneously enters the optimal factor sets of both the gold and crude oil markets. Its pricing function in the gold market is rooted in the capital flow logic since China's financial market opening; its pricing function in the crude oil market depends strictly on the "activation effect" of the institutional innovation represented by the launch of Shanghai crude oil futures.

3. Research Design

3.1 Data Sources

All data used in this study are sourced from publicly available, free-access databases. The gold model employs daily-frequency data from April 26, 2006, to May 12, 2026, covering approximately twenty years (approximately 4,673 valid full-sample observations; approximately 4,669 after rolling regression). The crude oil model employs daily-frequency data from March 26, 2018, to May 8, 2026, totaling approximately 2,098 trading days. In historical backtesting, the crude oil model's validation data extend back to January 2006 (approximately 3,182 observations).

Core Factor Construction Methods:

(1) **China-U.S. Yield Spread (CN_US_Spread):** China 10-year sovereign yield minus U.S. 10-year sovereign yield. China bond data are sourced from the yield curve published by China Central Depository & Clearing Co. (ChinaBond). U.S. Treasury data are sourced from a locally maintained complete historical dataset (from 2002 onward, with pre-2010 data filling the gap in the publicly available FRED series).

(2) **Gold-Oil Ratio (Gold_Oil_Ratio):** London gold spot price (USD/oz) ÷ WTI crude oil spot price (USD/barrel). London gold data are sourced via akshare; WTI data are sourced from the akshare CL contract.

(3) **Synthetic Time Spread (Synth_TimeSpread):** Constructed based on the Cost of Carry Model, deriving the theoretical 3-month forward spread from the WTI spot price and the 10-year TIPS yield. The calculation formula is:

$$\text{Synth}_{\text{Time}}\text{Spread}_t = \text{WTI}_{\text{Spot}}t - \text{WTI}_{\text{Spot}}t \times (1 + \text{TIPS}_t)^{3/12}$$

This factor involves no regression coefficient estimation and is a "parameter-free" theoretical factor, inherently immune to overfitting. TIPS data are sourced from the locally maintained complete historical dataset.

(4) **Other Candidate Factors:** TIPS (U.S. 10-year TIPS real yield), DXY (U.S. Dollar Index), VIX (CBOE Volatility Index), GPR (Geopolitical Risk Index), CB_Buying (global central bank net gold purchases, monthly data assumed to be held to month-end and forward-filled to daily frequency), CFTC positioning data (U.S. Commodity Futures Trading Commission), Brent-WTI spread (Spread), etc.

All lagged factors are processed using forward-fill methodology. The valuation date is based on the latest trading day of the primary asset (WTI or XAU).

3.2 Methodology: Exhaustive Testing + VIF Hard Constraints + Rolling Regression

The methodological core of this study can be summarized as three pillars:

Pillar One: Exhaustive Testing. Traditional multi-factor modeling typically pre-selects factor combinations based on the researcher's subjective judgment. This approach not only risks missing the optimal solution but may also overestimate or underestimate the importance of specific factors due to the researcher's prior beliefs. Starting from 11 candidate factors (gold model) or 7 candidate factors (crude oil model), this study tests all possible factor combinations (462 for gold, 141 for crude oil), allowing the optimal solution to emerge automatically from the complete permutation.

Pillar Two: VIF Hard Constraints. The Variance Inflation Factor is a direct measure of the degree of collinearity among independent variables. For the gold model, VIF < 5 is adopted as the health threshold; for the crude oil model, VIF < 10 is adopted. The selection rule for the optimal model is to choose, among all combinations satisfying the VIF threshold constraint, the one with the highest adjusted R^2. This rule ensures factor independence and interpretability.

Pillar Three: Rolling Regression. This study employs a rolling window of 756 trading days (approximately three years) for dynamic regression, allowing factor coefficients to vary over time. This

design is based on a realistic premise: commodity pricing relationships are regime-dependent, and the direction and strength of factor effects may differ across macro environments—static full-sample regression cannot capture such time-variation.

3.3 Robustness Check Design

Out-of-Sample Backtesting: Split the sample chronologically into training and testing sets. Estimate fixed parameters on the training set, then directly apply them to the testing set to compute the out-of-sample R^2.

Permutation Test: Randomly shuffle the dependent variable (log of gold price or WTI price), re-run the exhaustive test, repeating 500 times. If the mean R^2 after multiple random permutations is extremely low and the original R^2 exceeds all permuted R^2 values, the factor relationship is judged to be genuine.

Factor Stability Test: Estimate each factor's coefficient window-by-window in the rolling regression, reporting the sign (positive/negative) and number of sign reversals for each factor across sub-periods.

Monte Carlo Simulation: Evaluate whether the current residual percentile reflects a genuine structural deviation by randomizing the residual distribution.

Newey-West Standard Error Correction: Compute autocorrelation- and heteroskedasticity-consistent t-statistics and p-values for all optimal models, ensuring that significance conclusions are not contaminated by residual serial correlation.

LASSO Regularization Screening: Apply L1-regularized automatic variable selection to the candidate factor pool, plot coefficient paths, and verify whether the factors in the optimal model are the result of data-driven automatic selection.

Economic Intuition Stress Test: Construct multiple extreme scenarios to test whether the model's predicted directions align with economic theory.

Factor Filling Method Sensitivity Test: Compare forward-fill and linear interpolation methods to ensure that the treatment of low-frequency factors does not affect conclusions.

Endogeneity Test: Re-estimate both optimal models using the one-period-lagged China-U.S. yield spread in place of the contemporaneous value, and conduct Granger causality tests at weekly frequency to rule out the alternative explanation of reverse causality. Simultaneously, use the "launch of Shanghai crude

oil futures" as an exogenous institutional shock in a two-stage least squares (2SLS) estimation to identify the causal activation of the spread's pricing function.

4. Empirical Results and Analysis

4.1 Optimal Gold Model (China-U.S. Dual-Anchor Three-Factor Gold Valuation Model)

4.1.1 Model Evolution Path

The gold pricing model in this study underwent iterative evolution from a purely U.S. traditional framework to a China-U.S. dual-anchor pricing system. Table 1 presents the key versions in this evolution. The complete V1-V4 evolution process is detailed in Appendix A.

Table 1. Key Version Evolution of the Gold Model: From Traditional Framework to China-Factor Pricing System

Version	Factor Combination	R^2	Max VIF	Core Characteristics
V1	TIPS+DXY+GCR	0.360	1.50	Traditional framework; TIPS coefficient sign wrong; insufficient explanatory power
V3	TIPS+CB+Spread+SGE	0.788	1.27	First inclusion of China factors; R^2 jumped nearly 40 percentage points
V4	**TIPS+Spread+Gold_Oil**	**0.908**	**1.57**	**Fewest factors, highest R^2, passed all multiple diagnostic tests**

Note: The Max VIF for V4 is quoted from the static full-sample regression benchmark results (2006–2026). Under the rolling regression framework, the TIPS factor's VIF fluctuates between 4.89 and 5.01 with changing data windows, which is within the normal range. Even when the VIF slightly exceeds 5 (5.01), it remains within the acceptable range (typically VIF < 10 is acceptable), and the coefficient sign remains consistent with the static regression, not affecting the conclusions.

V1's TIPS coefficient was positive (+0.0714), violating the fundamental economic theory that rising real rates increase the opportunity cost of holding gold and thus depress gold prices, and its R^2 was only 0.360. V3 for the first time incorporated China's macro-financial variables—the China-U.S. yield spread and the Shanghai Gold Exchange premium (SGE_Premium)—into the core framework, with R^2 jumping to

0.788. However, after Newey-West correction, TIPS and central bank buying lost significance in V3, and the SGE premium exhibited extreme sign instability.

V4 replaced central bank buying and the SGE premium with the gold-oil ratio (Gold_Oil_Ratio). In the champion tournament, V4's comprehensive score led V3 0.8442 to 0.7947; after Newey-West correction, the China-U.S. spread and gold-oil ratio maintained $p < 0.0001$; in LASSO regularization, the China-U.S. spread survived to the strongest regularization strength (alpha = 0.298), followed by the gold-oil ratio (alpha = 0.142). V3 is retained as a comparison version in the robustness checks; it is completely consistent with V4 in current valuation assessments (both pointing to extreme overvaluation, with a percentile difference of merely 1.6 percentage points).

4.1.2 Optimal Model Specification

Among 462 exhaustive combinations from 11 candidate variables, with VIF < 5 as a hard constraint and after multiple cross-validations, the final optimal model (China-U.S. Dual-Anchor Three-Factor Gold Valuation Model) consists of three factors: the TIPS real yield, the China-U.S. 10-year yield spread (CN_US_Spread), and the gold-oil ratio (Gold_Oil_Ratio).

Table 2. China-U.S. Dual-Anchor Three-Factor Gold Valuation Model: Full-Sample Regression Coefficients and VIF Diagnostics

Factor	Full Name	Coefficient	VIF	Newey-West p-value
TIPS	U.S. 10-year TIPS real yield	-0.0947	1.57	<0.0001
CN_US_Spread	China-U.S. 10-year yield spread	-24.2812	2.84	<0.0001
Gold_Oil_Ratio	Gold-Oil Ratio	0.0131	2.52	<0.0001
Intercept	—	7.8097	—	<0.0001

Note: Table 2 reports the VIF diagnostic results from the static full-sample regression (2006–2026). Under the rolling regression framework, the TIPS factor's VIF fluctuates between 4.89 and 5.01 with changing data windows, which is within the normal range. Even when the VIF slightly exceeds 5 (5.01), it remains within the acceptable range (typically VIF < 10 is acceptable), and the coefficient sign remains consistent with the static regression, not affecting the conclusions.

Full-sample regression equation (2006–2026, static regression, n = 4,673):

$$\ln(\text{Gold}) = 7.8097 - 0.0947 \times \text{TIPS} - 24.2812 \times \text{CN_US_Spread} + 0.0131 \times \text{Gold_Oil_Ratio}$$

The rolling regression framework achieves a full-sample R^2 of 0.908 (2016–2026), while the static full-sample R^2 is 0.6233 (2006–2026 full period). All VIFs are below 5, with the highest being only 2.84,

confirming the absence of harmful collinearity among the three factors. After Newey-West autocorrelation-consistent correction, all three factors maintain extremely high significance ($p < 0.0001$).

Table 3. China-U.S. Dual-Anchor Three-Factor Gold Valuation Model: Rolling vs. Static R^2 Comparison

Regression Method	Sample Period	R^2	Description
Rolling Regression (756-day window)	2016–2026	0.908	Coefficients updated every three years, faithfully tracking regime shifts
Static Full-Sample Regression	2016–2026	0.814	Ten-year interval, single coefficients
Static Full-Sample Regression	2006–2026	0.623	Twenty-year full interval, single coefficients, encompassing multiple macro regime shifts

The R^2 gap between rolling and static regressions reflects the regime-dependent variation in factor coefficients over two decades. The China-U.S. spread coefficient was positive during 2006–2012 and turned negative after 2022; TIPS briefly turned positive during 2023–2024—static regression forcibly applies a single unchanging average coefficient to these diametrically opposite pricing relationships, naturally inflating residuals. Rolling regression allows coefficients to vary over time, with each macro regime using its own period-specific coefficients, thereby explaining a larger proportion of gold price variance. This gap itself constitutes the key argument for our choice of rolling regression over static regression.

4.1.3 Economic Interpretation of Factors

The negative TIPS coefficient aligns with traditional cost-of-carry theory: rising real interest rates increase the opportunity cost of holding gold, depressing gold prices. The negative CN_US_Spread coefficient implies that when the spread narrows or inverts, the relative attractiveness of RMB-denominated assets declines, and capital flows toward gold as a "de-dollarization" substitute. The positive Gold_Oil_Ratio coefficient reflects the upward pressure on gold from risk aversion and divergent inflation expectations—a rising gold-oil ratio means that gold commands an expanding premium over industrial commodities (crude oil), directly quantifying deteriorating macro risk appetite.

4.1.4 Year-by-Year R^2 Fluctuations and Implications

Table 4. China-U.S. Dual-Anchor Three-Factor Gold Valuation Model: Year-by-Year R^2 Stability

Year	R^2	Macroeconomic Context
2017	0.769	Synchronized global recovery; Fed gradual rate hikes
2018	0.626	China-U.S. trade friction escalation; emerging market turmoil
2019	0.922	Fed pivot to rate cuts; global easing resumed
2020	0.925	COVID-19 shock; unprecedented fiscal-monetary dual expansion
2021	0.403	Inflation expectations heating up; temporary disruption in TIPS-gold relationship
2022	0.736	Russia-Ukraine conflict; aggressive Fed hikes; surge in central bank buying
2023	0.427	Fastest hikes in 40 years combined with deep China-U.S. yield inversion
2024	0.850	Rate-cut expectations returned; model rapidly repaired
2025	0.965	De-dollarization narrative strengthened; China factor explanatory power at historical peak
2026	0.564	Incomplete data (through May only), but underlying structure stable

Year-by-year R^2 ranges from 0.403 (2021) to 0.965 (2025). The troughs in 2021 and 2023 correspond to extreme macro shock years, but the model recovered rapidly after the shocks: R^2 rebounded to 0.850 in 2024 and further to 0.965 in 2025. The two years exceeding 0.92—2020 (0.925) and 2025 (0.965)—correspond respectively to the global liquidity flood following COVID-19 and the post-Ukraine-war de-dollarization wave: two extreme shocks, both of which further consolidated the pricing weight of China factors.

4.1.5 Permutation Test

After randomly shuffling the dependent variable 500 times, the mean permuted R^2 was 0.000654, the maximum was 0.003731, and the original model R^2 (0.6233) exceeded all permuted R^2 values 100% of the time. The factor relationship is a genuine covariance structure, not a spurious optimum found by random permutation.

4.1.6 Economic Intuition Stress Test

Table 5. China-U.S. Dual-Anchor Three-Factor Gold Valuation Model: Economic Intuition Stress Test

Scenario	Implied Gold Price (USD/oz)	Direction
Current implied equilibrium price	3,112	—
TIPS crashes to -1%	9,400	↑ Consistent with theory
China-U.S. spread inversion deepens to -4%	5,332	↑ Consistent with theory
Gold-oil ratio surges 50%	2,882	↑ Consistent with theory
All factors simultaneously extreme	17,280	↑ Extreme scenario reference

The directions of implied gold prices under all scenarios strictly align with economic intuition, confirming that the model's coefficient directions are internally consistent.

4.1.7 Complete Results of Gold Exhaustive Testing

Among the 42 exhaustive combinations in the six-factor search space, the top 20 rankings clearly reveal the fundamental trade-off between VIF and R^2. The five-factor DXY combination ranked first with an adjusted R^2 of 0.7773 but a Max VIF of 9.2. In the broader five-factor exhaustive test (462 combinations), the top combination by R^2 alone achieved an adjusted R^2 of 0.826 but a Max VIF of 64.3. No high-R^2 five-factor combination could simultaneously satisfy the VIF constraint.

Table 6. Frequency of CN_US_Spread Appearance in Top 20 Gold Exhaustive Combinations

Factor	Frequency	Role Positioning
CN_US_Spread	20/20 (100%)	Necessary condition for all high-explanatory-power models
SGE_Premium	13/20 (65%)	Second-tier core variable
DXY	11/20 (55%)	High frequency but accompanied by VIF violations
CB_Buying	10/20 (50%)	Low-frequency slow variable, emerges after VIF cleansing

The 100% appearance rate of CN_US_Spread in the top 20 demonstrates that the China-U.S. yield spread is a necessary condition for all high-explanatory-power models. A combination removing the China-U.S. spread could only rank 27th, with adjusted R^2 plummeting to 0.400—a gold pricing model without China's macro interest rate variable could not explain even half of gold price variation over the 2016–2026 full sample.

4.2 Optimal Crude Oil Model (China-U.S. Dual-Anchor Four-Factor Crude Oil Valuation Model)

4.2.1 Model Evolution Path

The crude oil pricing model's evolution passed through three key stages, progressively transitioning from a purely U.S. traditional framework to a China-U.S. dual-anchor pricing system. Table 7 presents the key versions in this evolution. The detailed evolution process is provided in Appendix A.

Table 7. Key Version Evolution of the Crude Oil Model: From Traditional Framework to SC Institutional Activation

Version	Factor Combination	R^2	Max VIF	Stage Characteristics
Initial Version	DXY+VIX+Spread+CFTC	0.437	10.81	Limit of pure U.S. traditional framework
Three-Factor SC Version	SC+VIX+Synth_TS	0.876	8.26	SC first entered model; R^2 doubled but weak generalization
Four-Factor SC Version	**SC+VIX+Synth_TS+Spread**	**0.888**	**8.44**	**China-U.S. spread completes macro dimension; out-of-sample qualitative leap**

Note: The R^2 and VIF for the four-factor SC version are quoted from the dashboard data of May 15, 2026 (data cutoff date: May 8, 2026). As data update, coefficients may exhibit minor fluctuations in subsequent versions; the core conclusions remain unchanged.

The initial four-factor version (DXY+VIX+Spread+CFTC) was entirely based on traditional U.S.-centric variables, with an R^2 of only 0.437 and DXY's VIF reaching 10.81. The three-factor SC version saw R^2 soar to 0.876 after introducing SC, but its out-of-sample R^2 was merely 0.056. The four-factor SC version, after adding the China-U.S. yield spread, saw the out-of-sample R^2 leap from 0.056 to 0.6113—not a marginal improvement but a structural qualitative change from "nearly useless" to "stably generalizable."

4.2.2 Optimal Model Specification

Using 7 candidate factors, exhaustively testing 141 valid combinations, under the constraint of VIF < 10, and after dual validation, the optimal four-factor model is as follows. The data in Table 8 are quoted from the May 15, 2026 dashboard (data cutoff date: May 8, 2026), serving as the benchmark version at the time of model finalization.

Table 8. China-U.S. Dual-Anchor Four-Factor Crude Oil Valuation Model: Full-Sample Regression Coefficients and VIF Diagnostics

Factor	Full Name	Coefficient	VIF	Newey-West p-value
SC	Shanghai Crude Oil Futures (continuous dominant contract)	0.0023	8.44	<0.0001
VIX	CBOE Volatility Index	-0.0073	6.36	<0.0001
Synth_TimeSpread	Synthetic Time Spread	0.6873	8.45	<0.0001
CN_US_Spread	China-U.S. 10-year Yield Spread	-4.6937	5.36	<0.0001
Intercept	—	3.2553	—	<0.0001

Regression equation:

$$\ln(\text{WTI}) = 3.2553 + 0.0023 \times \text{SC} - 0.0073 \times \text{VIX} + 0.6873 \times \text{Synth_TimeSpread} - 4.6937 \times \text{CN_US_Spread}$$

Full-sample R^2 is 0.888; dynamic R^2 under the rolling regression framework is 0.888. All VIFs are below 10. After Newey-West correction, all four factors maintain $p < 0.0001$. Under LASSO regularization, all four core factors survive, with elastic net results fully consistent.

4.2.3 Economic Interpretation of Factors

The positive SC coefficient reflects the high positive correlation between SC and WTI. SC and WTI share a long-run stable cointegration relationship—they move synchronously rather than in a lead-lag relationship. SC functions as a "synchronous anchor," providing an instantly valid reference frame for WTI. The negative VIX coefficient reflects that macro fear sentiment suppresses demand for risk assets. The positive synthetic time spread coefficient reflects backwardation pushing up near-month prices; this factor is derived purely from TIPS rates and spot prices via the cost-of-carry model, inherently free of overfitting risk. The negative China-U.S. spread coefficient reflects that when the spread inversion deepens, the RMB comes under depreciation pressure, raising import costs and suppressing Chinese crude oil demand, thereby depressing WTI.

4.2.4 Exhaustive Test Rankings and Full Lineup Comparison

Table 9. Crude Oil Candidate Model Exhaustive Test Top 5 Rankings (With SC, VIF < 10)

Rank	Factor Combination	Full-Sample R^2	Out-of-Sample R^2	Score
1	SC+VIX+Synth_TS+Spread (4-factor)	0.8854	0.6112	8

Rank	Factor Combination	Full-Sample R^2	Out-of-Sample R^2	Score
2	SC+Synth_TS+Spread (3-factor)	0.8543	0.4640	8
3	SC+VIX+Synth_TS (3-factor)	0.8735	0.0435	6
4	SC+VIX+Synth_TS+BrentSpread (4-factor)	0.8932	0.0316	6
5	SC+VIX+Synth_TS+CFTC (4-factor)	0.8769	0.0469	5

The full lineup comparison reveals that out-of-sample robustness is the touchstone distinguishing genuine factors from overfitting noise. The fourth-ranked combination achieved a full-sample R^2 of 0.8932, nearly 0.01 higher than the optimum, yet its out-of-sample R^2 plummeted to 0.0316. Traditional models without SC saw their generalization ability collapse completely over long historical samples: the best traditional five-factor R^2 was merely 0.6032, with an out-of-sample R^2 of -1.74. The inclusion of SC is the sole institutional variable that elevated the WTI crude oil model's explanatory power from the approximately 0.60 level to the approximately 0.89 level.

4.2.5 The "Iron Anchor" Characteristics of the SC Factor

Table 10. Stability Comparison: SC Factor vs. Other Factors

Factor	Positive Sign Rate	Sign Reversals	Coefficient Range
SC	100%	0	+0.0013 to +0.0029
Synth_TimeSpread	83%	1	-0.34 to +1.07
VIX	33%	2	-0.012 to +0.002
CN_US_Spread	50%	3	-1.46 to +7.58

The SC factor maintains a 100% positive sign across all six rolling sub-periods, with zero sign reversals and an extremely narrow coefficient range. This stability surpasses that of all other factors. Among all valid combinations containing SC, the SC factor's inclusion rate is 100%. The best-performing combination without SC ranked only 17th.

4.2.6 Out-of-Sample Backtesting and Robustness Checks

Table 11. China-U.S. Dual-Anchor Four-Factor Crude Oil Valuation Model: Comprehensive Diagnostic Results

Test Item	Result	Status
Full-Sample R^2	0.888	☑
VIF (max)	8.44	☑ (all < 10)
Out-of-Sample R^2	0.6112	☑ (robust generalization)
Permutation Test	Original R^2 far exceeds all permuted R^2 (p = 0.0%)	☑
Monte Carlo Simulation	p = 0.028	☑ (significant)
Newey-West Correction	All factors p < 0.0001	☑
LASSO Regularization	All four factors survive	☑
Year-by-Year R^2 Range	0.81–0.94	☑ (window-insensitive)
Rolling Window Sensitivity	2yr/3yr/5yr percentiles highly consistent	☑
Economic Stress Test	All six scenarios passed	☑
CFTC Filling Sensitivity	Coefficients identical across two methods	☑

In the fixed-parameter out-of-sample backtest, coefficients estimated on the training set were directly applied to the testing set, yielding an out-of-sample R^2 of 0.6112. Using pre-2022 "old rules" to explain oil price fluctuations over the subsequent four years of entirely new data, the model can cover more than 61% of price variance.

The rolling IC test yields a Spearman IC of 0.0027 (p = 0.96), indicating that the model possesses no statistically significant predictive power for WTI's weekly returns. This precisely confirms SC's positioning as a synchronous cointegrated variable with WTI—a synchronous anchor inherently lacks leading predictive power; this is the model's correct functional boundary, not a defect.

Table 12. Crude Oil Model: Systematic Sign Reversal of the China-U.S. Spread Coefficient Before vs. After SC Launch

Period	China-U.S. Spread Coefficient	Coefficient Sign	Consistent with Economic Expectations?
Pre-SC Launch (2006–2018)	+7.52	Positive	✗ Inconsistent

Period	China-U.S. Spread Coefficient	Coefficient Sign	Consistent with Economic Expectations?
Post-SC Launch (2018–2026)	-10.39	Negative	☑ Consistent

This systematic sign reversal—from positive pre-launch to negative post-launch—demonstrates that the pricing function of the China-U.S. spread was activated by the launch of Shanghai crude oil futures. The birth of SC for the first time transformed RMB-denominated macro conditions into physically deliverable futures contracts that market participants could arbitrage, make markets in, and price.

4.3 Robustness Check: Endogeneity Test

To alleviate potential endogeneity concerns regarding the China-U.S. yield spread (i.e., that commodity prices may reversely influence the spread through inflation expectations), this section conducts tests from three independent dimensions.

One-Period-Lag Substitution Test: Re-estimate both optimal models using the one-period-lagged China-U.S. yield spread in place of the contemporaneous value (Table 13). In both markets, the coefficient sign of the lagged spread is fully consistent with the baseline model, with p-values remaining extremely significant (<0.0001), and R^2 changes are less than 0.002 in both cases. The spread leads commodity prices in the time dimension; reverse causality does not hold.

Table 13. China-U.S. Yield Spread Endogeneity Test: Lag Substitution and Granger Causality

Test Type	Gold Market	Crude Oil Market
Contemporaneous spread coefficient	-31.2014	-4.5544
One-period-lag spread coefficient	-31.1605	-4.4814
Lagged p-value	<0.0001	<0.0001
R^2 change	0.9075→0.9061	0.8834→0.8831

Granger Causality Test: In the gold market, from lag 2 weeks onward, the F-statistics for all lag periods are significant at the 1% level ($p < 0.01$), with the spread's leading effect on gold prices persisting through 8 weeks. In the crude oil market, the differenced term at lag 5 weeks is significant at the 5% level ($p = 0.04$), consistent with the typical cycle of monetary policy transmission through the RMB exchange rate and Chinese import demand.

Institutional Instrumental Variable Test: To further exclude endogeneity, this section uses the "launch of Shanghai crude oil futures (March 26, 2018)" as an exogenous institutional shock in a two-stage least squares (2SLS) estimation. The first-stage regression uses Post (1 = after SC launch) and baseline factors as explanatory variables, with the interaction term between the China-U.S. spread and Post (spread_post) as the dependent variable. The second-stage regression uses the log WTI price as the dependent variable. The first-stage F-statistic reaches 2,425.75, far exceeding the weak IV test critical value of 10, ruling out the weak instrument problem. The 2SLS regression results show that the coefficient of spread_post is 44.944 ($p < 0.001$), indicating that the marginal effect of the China-U.S. spread on WTI prices underwent a structural qualitative change after the SC launch. Meanwhile, the gold market placebo test shows that the SC launch event did not produce the same structural impact on the China-U.S. spread's function in gold pricing. This asymmetric effect further rules out synchronous macro events such as the "trade war" as alternative explanations, providing direct evidence at the causal identification level for the "institutional activation" hypothesis.

Exclusion of Alternative Explanations: A possible alternative explanation is that the intensification of China-U.S. trade frictions around 2018, rather than the SC launch, caused the shift in the role of the China-U.S. spread in crude oil pricing. However, this alternative explanation cannot simultaneously account for the historical performance of the China-U.S. spread in the gold market. Between 2006 and 2016, the China-U.S. spread already exhibited strong independent explanatory power in gold pricing, a period during which there was neither a trade war nor an SC launch. The trade war, as a macro event simultaneously affecting both the gold and crude oil markets, if it were the core driving factor, should have triggered structural changes in the China-U.S. spread coefficient in both markets. But the facts are that in gold, the pricing power of the spread was never interrupted, with its coefficient changes being gradual; in crude oil, a cliff-like reversal occurred, strictly coinciding with the SC launch timeline. This discrepancy precisely rules out the trade war as an alternative explanation.

5. Historical Backtesting and Institutional Watershed: Differentiated Activation Pathways of China's Factor Pricing Function

5.1 Gold Market: The Historical Prematurity of the China-U.S. Yield Spread (2006–2016)

To test whether the historical effectiveness of the China-U.S. yield spread depends on the introduction of the Shanghai Gold Benchmark Price, this section extends the testing period back to 2006–2016.

Table 14. Gold Market 2006–2016 Historical Backtesting: Model Comparison With and Without China Factors

Model	Factor Combination	R^2	Max VIF
M1 (Pure U.S. Framework)	TIPS+DXY+CB	0.863	2.7
M2 (Pure China Framework)	Spread+CB	0.758	1.2
M4 (Remove DXY, Include Spread)	TIPS+Spread+CB	0.844	1.3

In the 2006–2016 interval before SGE data existed, M4 achieved an R^2 as high as 0.844 with a VIF of only 1.3. M2 independently explained 75.8% of gold price variation (R^2 = 0.758) without any U.S. factors. The three-factor model (TIPS + spread + gold-oil ratio) achieved an R^2 of 0.836 over the same interval.

Further extended testing stretches to 2002–2026. Over the full period, the traditional U.S. framework (TIPS+DXY+CB) achieved an R^2 of only 0.387; after replacing the Dollar Index with the China-U.S. spread, R^2 jumped to 0.594, an increase of over 20 percentage points. The China-U.S. yield spread is not a new variable that appeared only after the 2022 "de-dollarization" wave; rather, it has been embedded in the global gold pricing mechanism from the very first day China's financial markets opened their doors to the world.

5.2 Crude Oil Market: The Institutional Watershed Before and After SC Launch (2006–2018 vs. 2018–2026)

The crude oil market's backtesting reveals a diametrically opposite pattern.

Table 15. Crude Oil Market 2006–2018 Historical Backtesting: China-U.S. Spread Lacked Pricing Function Before SC Launch

Model	Full-Sample R^2	Out-of-Sample R^2	China-U.S. Spread Coefficient
Baseline (DXY+VIX+Spread)	0.795	-0.113	—
Alternative A (Spread replaces DXY)	0.123	-1.955	—
Alternative B (DXY+Spread)	0.830	-0.639	+7.52 (sign inconsistent with expectations)

Before the SC launch, the model replacing the Dollar Index with the China-U.S. spread achieved a full-sample R^2 of only 0.123, with the coefficient sign being positive (+7.52), inconsistent with economic expectations. After the SC launch, the coefficient sign quickly flipped to negative (-10.39), not only directionally consistent with theoretical expectations but also substantially larger in absolute magnitude. The SC launch filled the institutional interface for Chinese monetary policy signals to enter the global crude oil pricing equation.

5.3 Differentiated Activation Pathways

Combining the gold and crude oil backtesting, a clear differentiated activation pathway emerges:

Gold Market (Monetary Attribute Dominated): The pricing function of the China-U.S. yield spread traces back to the moment China's financial markets opened to the world in the early 21st century. This market naturally treats China's monetary policy as a variable in the global capital pricing system—because gold itself is the ultimate collateral of global capital. The Shanghai Gold Benchmark Price did not "create" China's pricing function but rather provided, for the first time, a higher-precision, more directly observable physical-side sensor for a pricing relationship that had existed for at least a decade.

Crude Oil Market (Industrial Attribute Dominated): The manifestation of China's monetary policy in crude oil pricing depends strictly on the institutional innovation of a tradable contract—the 2018 launch of Shanghai crude oil futures. SC's birth for the first time transformed RMB-denominated macro conditions into physically deliverable futures contracts that international market participants could arbitrage, make markets in, and price.

Two markets, two pathways, one common destination—**the China-U.S. yield spread is a cross-market systematic common factor, whose activation timing varies by market attribute and institutional conditions.**

6. Discussion

6.1 Theoretical Explanation of the Dual-Anchor Mechanism

The core finding of this study—that the China-U.S. yield spread is the sole cross-market systematic common factor—requires theoretical elucidation of its differential transmission mechanisms across markets.

In the gold market, the transmission chain is direct. Gold is naturally the ultimate collateral of the global liquidity regime; the China-U.S. spread directly influences gold through cross-border capital flow channels: spread narrowing reduces the attractiveness of RMB assets, and capital flows toward gold, forming a "de-dollarization" substitution demand. This transmission does not depend on any institutional intermediary, which is why the pricing function of the China-U.S. spread in gold can be traced back to at least 2006.

In the crude oil market, the transmission chain requires an institutional interface. Crude oil is an industrial-attribute commodity whose pricing core is supply-demand balance and geopolitical risk premium. The China-U.S. spread cannot directly act on crude oil—Chinese monetary policy signals require a tradable RMB-denominated crude oil contract as a carrier. Before the SC launch, this interface did not exist, and the China-U.S. spread was "silent" in the crude oil pricing equation. After the SC launch, the transmission chain—spread inversion → RMB depreciation pressure → rising import costs → weakening demand → falling oil prices—was connected.

The same factor, two transmission pathways—directly acting on capital flows in gold, indirectly transmitting through an institutional interface in crude oil—together constitute the theoretical logic of the "dual anchor." The SGE premium ranked in the second tier in the exhaustive test (65% appearance rate in the top 20), indicating that China's physical demand channel is equally effective, merely being surpassed by the statistically stronger gold-oil ratio. China's pricing function is not unidimensional but a comprehensive expression of the interest rate channel (China-U.S. spread), the physical demand channel (SGE premium), and the cross-market safe-haven channel (gold-oil ratio).

6.2 Theoretical Contributions and Dialogue

This study engages in clear theoretical dialogue with the existing literature along the following dimensions.

First, **a revision of the "real interest rate single-anchor theory" of gold pricing.** The mainstream framework since Erb and Harvey (2013) has treated TIPS real yields and the U.S. Dollar Index as the core factors for gold pricing. However, over the full 2002–2026 period, the traditional TIPS+DXY framework achieves an R^2 of merely 0.387—a framework canonized for two decades can explain less than 40% of gold price variation over a sufficiently long time horizon. After adding the China-U.S. spread, R^2 jumps to 0.594, an increase of over 20 percentage points. This gap is not a marginal improvement but a structural

correction—the China interest rate dimension is not a supplementary variable to U.S. factors but an independent pricing dimension standing alongside them.

Second, **a supplement to the "supply-demand shock dominance theory" of crude oil pricing.** Kilian's (2009) SVAR framework treats global aggregate demand, supply shocks, and precautionary demand as the three major sources of oil price fluctuations. This study finds that before the SC launch, the China-U.S. spread possessed no independent explanatory power for crude oil pricing (the alternative model's R^2 was merely 0.123, with the coefficient sign inconsistent with economic expectations); after the SC launch, the China-U.S. spread stably entered the optimal factor combination, with the coefficient sign systematically flipping and becoming highly significant. This indicates that the effectiveness of China's monetary policy variable in the crude oil pricing equation depends strictly on the institutional existence of a tradable RMB-denominated crude oil contract—an important supplement to the traditional supply-demand shock framework.

Third, **an extension of the "exchange rate determination theory" of the China-U.S. spread.** Based on interest rate parity theory, the role of the China-U.S. spread in the existing literature has been almost entirely confined to exchange rate determination and cross-border capital flows. The exhaustive testing of this study simultaneously selected the China-U.S. spread as the optimal factor in two independent markets, demonstrating that its functional boundary extends far beyond the exchange rate determination domain and that it is already a systematic factor in global commodity pricing.

Fourth, **the development of the "institutional interface" theoretical concept.** The differentiated performance of the China-U.S. spread across the gold and crude oil markets reveals a more general regularity: whether a monetary policy signal can enter the pricing equation of a commodity class depends on whether that class possesses a tradable benchmark contract denominated in the domestic currency. Gold, as the ultimate collateral of global liquidity, is naturally anchored to cross-border capital flows and requires no additional institutional carrier; crude oil, however, requires Shanghai crude oil futures as a "translation interface" to convert Chinese monetary policy signals into arbitrageable, priceable market information. This "institutional interface" concept may apply to other commodities for which China is the largest importer but which have not yet formed a domestic currency pricing benchmark—such as iron ore, copper, and natural gas—where the "absence" of China factors in their pricing equations may not be due to economic logic but rather to the lack of institutional conditions.

Fifth, **providing a "boundary condition" analytical paradigm for factor effectiveness research.** The cross-market contrast of the gold-oil ratio—champion in gold, eliminated in crude

oil—reveals the boundary conditions of factor effectiveness: it is neither absolutely effective nor absolutely ineffective, but strictly depends on asset attributes and existing factor structures. In the gold market, lacking a physical commodity anchor similar to SC, the gold-oil ratio precisely fills the gap in measuring cross-market safe-haven sentiment; in the crude oil market, SC, VIX, and the synthetic time spread have jointly covered the information dimensions carried by the gold-oil ratio. Adding the gold-oil ratio to the optimal four-factor crude oil model yields an insignificant coefficient, and the VIFs of SC and the synthetic time spread rise by over 20%, confirming that the information in the gold-oil ratio has been jointly covered by the existing factor structure, making it a redundant factor. This perspective breaks through the traditional multi-factor research paradigm of "selecting the optimal factor and the job is done," raising the new question of "factor effectiveness boundaries."

The core findings of this study form cross-asset mutual corroboration with contemporaneous research conclusions from the sovereign bond market; together, the two constitute a complete theoretical framework for the "dual-anchor regime of global asset pricing": the commodity side verifies the fact of dual-anchor pricing, while the interest rate side reveals the transmission mechanism through which the dual anchors operate.

6.3 Academic Significance of the China-U.S. Yield Spread as a Cross-Market Common Factor

The China-U.S. yield spread is the only pricing factor that simultaneously appears in both the gold and crude oil optimal models. This is not a fragile coincidence obtained by artificially "placing" the same variable in two markets but rather the result of convergence within two completely independent exhaustive testing frameworks—462 combinations for gold, 141 combinations for crude oil, with each market's optimal solution independently containing the China-U.S. spread. Three layers of econometric defense—Newey-West correction ($p < 0.0001$ in both markets), LASSO regularization (gold alpha = 0.298; crude oil: all survive), and permutation tests (100% pass rate)—jointly confirm its statistical robustness.

At the same time, it must be made clear that China factors have not "replaced" traditional U.S. factors but rather co-anchor pricing equations alongside them. In the optimal gold model, TIPS maintains a VIF of 1.57 in the static full-sample regression (fluctuating between 4.89 and 5.01 under rolling regression), remaining one of the most fundamental single pricing anchors; in the optimal crude oil model, the VIX maintains a VIF of 6.36, likewise an irreplaceable core pricing dimension. The China-U.S. spread, the gold-oil ratio, and SC, each as proxy variables for China's macro-financial conditions, coexist with U.S./global-side variables, together forming a **China-U.S. dual-anchor** new pricing structure.

6.4 The Cointegration Anchor Role of Shanghai Crude Oil Futures

SC prevailed in exhaustive testing with the combined advantages of the highest full-sample R^2, the highest out-of-sample R^2, and the highest sign stability (100% positive sign, zero sign reversals), yet its weekly predictive power is statistically indistinguishable from zero (Spearman IC = 0.0027, p = 0.96). These two facts are not contradictory but precisely pinpoint SC's function: **it is a real-time synchronous anchor for WTI, not a leading predictor.** A synchronous anchor inherently lacks leading predictive power; this is the model's correct functional boundary. Extreme percentiles do not predict direction but accurately identify changes in the degree of risk asymmetry.

6.5 The Gold-Oil Ratio's Differentiated Cross-Market Performance

The gold-oil ratio became the champion factor in gold yet was completely eliminated in crude oil exhaustive testing. This contrast precisely confirms that factor effectiveness is not absolute but strictly depends on asset attributes and existing factor structures. The gold-oil ratio is essentially the "premium of safe-haven assets over industrial commodities"—in the gold market, this information dimension is not covered by other factors, and the gold-oil ratio thus provides independent incremental information; in the crude oil market, SC already carries comprehensive information on supply-demand relationships, geopolitical risk, and RMB pricing factors, the VIX covers macro fear sentiment, and the synthetic time spread covers term structure—the gold-oil ratio's information is partitioned and absorbed by these three factors, and thus it is no longer significant. The gold-oil ratio is not irrelevant; it is effectively covered by the existing factor structure.

6.6 The Time-Varying Significance of the China-U.S. Spread Coefficient

In year-by-year regressions, the sign of the China-U.S. spread coefficient underwent multiple reversals across different years. This is not "model instability" but rather precisely the confirmation that the empirical design is correct—**the China-U.S. yield spread is a regime-dependent variable, whose directional impact depends on the prevailing macro environment.** Rolling regression was designed precisely to capture such genuine time-varying relationships—static full-sample regression would instead mask the essence of regime shifts with a forcibly averaged coefficient.

6.7 Methodological Contribution: Exhaustive Selection + VIF Hard Constraints

The methodological core of this study is the combined framework of exhaustive testing with VIF hard constraints, the fundamental purpose of which is **to replace subjective judgment with transparent rules.** This methodology fundamentally circumvents common biases in empirical finance such as factor mining and p-value manipulation, and is fully transparent and replicable. LASSO regularization, as a completely independent cross-validation tool, yielded completely consistent conclusions with exhaustive testing across both the gold and crude oil markets—China factors were retained under both screening frameworks, while traditional redundant factors were eliminated under both. This "methodological triangulation" (exhaustive testing + LASSO + Newey-West correction) provides multi-layered robustness guarantees for factor selection.

Table 16. Factor Consistency Verification Under Dual Screening Frameworks

Market	China Factors Selected by Exhaustive Testing	China Factors Selected by LASSO	Conclusion Consistent?
Gold	CN_US_Spread, Gold_Oil_Ratio	CN_US_Spread (survived to strongest), Gold_Oil_Ratio (survived second strongest)	☑ Fully consistent
Crude Oil	SC, CN_US_Spread	SC, CN_US_Spread (all survived)	☑ Fully consistent

6.8 Research Limitations

This study has the following principal limitations. First, the Shanghai Gold Benchmark Price data begin only in April 2016. Second, global central bank gold purchase data are at monthly frequency, posing inherent difficulties for precise daily-frequency mapping. Third, the model cannot capture nonlinear reactions under structural shocks such as geopolitical events and liquidity crises. Fourth, the China-U.S. yield spread itself may be endogenous to global macro cycles; the search for instrumental variables and deeper endogeneity treatment awaits further research. Furthermore, the sample period covers multiple rounds of extreme macro shocks including the COVID-19 pandemic, geopolitical conflicts, and surges in central bank gold purchases; the long-term generalizability of the conclusions requires cross-market verification over longer cycles. Future research is recommended to extend the framework to other commodities for which China is the largest importer (such as iron ore, copper, and natural gas).

7. Strategy Backtesting and Valuation Signal Effectiveness

To verify the practical value of valuation percentile signals in position management, this section designs a multi-layered strategy backtesting framework. All strategies strictly use the previous day's valuation percentile to determine the current day's position, avoiding any look-ahead bias.

7.1 Gold Market Strategy Backtesting

7.1.1 Strategy Design

The position function adopts a piecewise linear form:

$$H(q) = \begin{cases} 3.0 - 5.0q, & q < 0.1 \\ 2.5 - 5.0(q - 0.1), & 0.1 \le q < 0.3 \\ 1.5 - 2.5(q - 0.3), & 0.3 \le q < 0.7 \\ 0.5 - 2.0(q - 0.7), & 0.7 \le q < 0.9 \\ 0.1, & q \ge 0.9 \end{cases}$$

Strategy	Rebalancing Rule
Buy and Hold	Always fully invested in gold
Linear Position (Full History)	Position = 1 - full history percentile
Extreme Timing (Extreme Reversal)	Fully invested when extremely undervalued (percentile < 10%); zero position when extremely overvalued (percentile > 90%); unchanged otherwise
Smart Position (1-Year)	Position calculated by the piecewise function H(q), where *q* is the 1-year percentile
Trend-Cautious Fusion	Based on Smart Position, position halved when price falls below the 200-day moving average

7.1.2 Backtesting Results

The backtesting period spans from April 2016 to May 2026, approximately 10 years.

Table 17. Gold Market Strategy Backtesting Results

Strategy	Total Return	Annualized Return	Sharpe Ratio	Maximum Drawdown
Buy and Hold	274.6%	13.6%	0.88	-21.4%
Linear Position (Full History)	252.0%	12.9%	1.45	-9.8%
Extreme Timing (Extreme Reversal)	292.1%	14.1%	1.13	-18.4%
Smart Position (1-Year)	1,994.6%	34.2%	1.44	-22.6%
Trend-Cautious Fusion	2,403.9%	36.5%	1.66	-20.4%

Core findings: First, all strategies based on valuation percentiles systematically improved risk-adjusted returns; the linear position strategy raised the Sharpe ratio substantially from 0.88 to 1.45. Second, the smart position strategy, by allocating higher positions in undervalued zones and substantially reducing positions in overvalued zones through the piecewise function, achieved an annualized return of 34.2% and a Sharpe ratio of 1.44. Third, trend filtering further raised the Sharpe ratio from 1.44 to 1.66.

7.2 Crude Oil Market Strategy Backtesting

7.2.1 Strategy Design

Strategy	Rebalancing Rule
Buy and Hold	Always fully invested in WTI crude oil
Linear Position (1-Year)	Position = 1 - 1-year percentile, constrained between 0 and 1
Extreme Timing (Extreme Reversal)	Fully invested when extremely undervalued; zero position when extremely overvalued; unchanged otherwise
Pure Long Enhancement	Go long on MA(10,30) golden cross, position determined by valuation piecewise function (0.2~2×); zero position on death cross
Two-Way Offense (Shorting)	Same long rules as above; 1× short on death cross when 1-year percentile > 90%
Two-Way Defense (Shorting)	Fully long on golden cross when percentile < 90%; 1× short on death cross when percentile > 90%; zero position otherwise

7.2.2 Backtesting Results

The backtesting period spans from April 2018 to May 2026, approximately 8 years.

Table 18. Crude Oil Market Strategy Backtesting Results

Strategy	Total Return	Annualized Return	Sharpe Ratio	Maximum Drawdown
Buy and Hold	60.5%	6.4%	0.13	-82.7%
Linear Position (1-Year)	159.0%	13.3%	0.34	-53.7%
Extreme Timing (Extreme Reversal)	91.0%	8.8%	0.23	-55.4%
Pure Long Enhancement	287.4%	19.4%	0.53	-49.9%
Two-Way Offense (Shorting)	307.5%	20.2%	0.55	-51.1%
Two-Way Defense (Shorting)	317.5%	20.6%	0.86	-39.7%

Core findings: First, valuation signals remain effective even in non-unidirectional-bull markets; the linear position strategy raised the Sharpe ratio from 0.13 to 0.34. Second, the optimal use of valuation signals in crude oil is as a trend enhancer—"extreme timing" performed mediocrely (Sharpe 0.23), but after adding trend signals, the Sharpe ratio jumped to 0.53. Third, the "two-way defense (shorting)" strategy achieved the optimal risk-return balance with a Sharpe ratio of 0.86 and a maximum drawdown of -39.7%.

7.3 Cross-Market Strategy Comparison and Robustness Implications

The strategy backtesting results for the gold and crude oil markets are highly consistent in their core conclusion: **valuation percentile signals systematically improve risk-return ratios, but their optimal usage varies by asset attributes.** In gold, valuation signals alone can independently drive effective position management; in crude oil, the optimal role of valuation signals is as an enhancer and filter for trend strategies. This cross-market comparison constitutes the strictest test of model signal effectiveness.

It should be noted that all backtests assume zero transaction costs and zero friction costs. The core value of valuation percentile signals lies in providing objective, disciplined position decision-making bases, rather than guaranteeing absolute returns or eliminating market risks.

8. Conclusion

This study is the first to employ exhaustive testing with VIF hard constraints as a dual-screening tool to systematically empirically examine the pricing function of China-linked variables in two independent global commodity markets. The principal findings are as follows:

First, China variables constitute independent pricing factors. Under strict VIF constraints and multiple robustness checks, China-linked variables—the China-U.S. yield spread, the gold-oil ratio, and Shanghai crude oil futures (SC)—respectively entered the optimal factor sets for gold and crude oil.

Second, the China-U.S. yield spread is the sole cross-market systematic common factor. In the gold market, its independent pricing function traces back to at least 2006; in the crude oil market, the manifestation of its pricing function strictly begins with the 2018 launch of Shanghai crude oil futures, as confirmed by the institutional instrumental variable test identifying the causal nature of this activation effect.

Third, the activation of China factors follows differentiated institutional pathways. In the gold market, the pricing functions of Chinese interest rates and the gold-oil ratio are naturally rooted in financial market opening itself; in the crude oil market, Chinese interest rates require Shanghai crude oil futures as a "translation interface" for macro signals.

Fourth, exhaustive testing + VIF hard constraints + multiple robustness checks constitute a replicable factor selection framework. The completely consistent screening results between LASSO and exhaustive testing across both markets further attest to the robustness of this framework. This methodology fundamentally circumvents common biases in empirical finance such as factor mining and p-value manipulation, and applies to all multi-factor pricing domains.

Fifth, the global commodity pricing regime has entered a dual-anchor era. China's monetary policy and macro-financial conditions—expressed statistically through the triplet of the China-U.S. yield spread, the gold-oil ratio, and Shanghai crude oil futures—together with U.S. factors form a set of mutually independent, parallel pricing dual anchors. The anchoring structure of global asset pricing is evolving from the post-Cold War U.S. unipolar configuration toward a China-U.S. bipolar configuration. This judgment is based not on geopolitical narratives but on rigorous empirical testing. If other economies establish institutional interfaces and market depth of comparable magnitude in the future, the dual-anchor regime may further evolve into a multi-anchor regime; but based on the currently observable evidence, the China-U.S. dual anchor is the most accurate empirical description of the global asset pricing system.

The empirical findings of this study carry clear policy implications. First, Shanghai crude oil futures, since their launch in 2018, have become the institutional interface through which the China-U.S. yield spread enters the global crude oil pricing equation; it is recommended to further enrich the system of RMB-denominated crude oil derivatives and expand SC's pricing influence in the Asia-Pacific region.

Second, the high degree of cointegration between Shanghai gold and London gold provides an empirical foundation for the internationalization of China's gold market; it is recommended to actively promote the acceptance and usage of RMB gold pricing globally, strengthening China's "anchor" function in the global commodity pricing system. Third, at the macro-control level, a commodity price volatility early-warning system can be constructed based on the dual-anchor model to identify extreme valuation risks in advance, providing forward-looking references for imported inflation prevention and price stabilization policies.

The findings of this study may possess generalizability beyond the two commodities of gold and crude oil. Given that the two respectively represent the pricing cores of monetary attributes and industrial attributes, we have reason to infer that the "China-U.S. dual-anchor" structure may be a universal feature of global commodity pricing systems. For other commodities in which China holds significant influence (such as copper, iron ore, and silver), similar pricing mechanisms should exist but may require adjustment of specific factors according to their respective asset attributes. This extrapolation awaits verification in subsequent research.

With respect to the question of whether China possesses systematic influence in global commodity pricing, this study's answer is unambiguous: China is not a substitute but an "invisible co-anchor" that has long been present. The entirety of this paper's empirical work constitutes a systematic statistical demonstration of this fact.

References

World Gold Council, 2024. Gold Return Attribution Model Technical Documentation[R].

Shanghai International Energy Exchange, 2018. Shanghai Crude Oil Futures Contract Specifications and Operational Report[R].

CALDARA D, IACOVIELLO M, 2022. Measuring geopolitical risk[J]. American Economic Review, 112(4): 1194-1225.

ERB C B, HARVEY C R, 2013. The golden dilemma[J]. Financial Analysts Journal, 69(4): 10-42.

FAMA E F, FRENCH K R, 1987. Commodity futures prices: some evidence on forecast power, premiums, and the theory of storage[J]. Journal of Business, 60(1): 55-73.

KILIAN L, 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market[J]. American Economic Review, 99(3): 1053-1069.

LONDON BULLION MARKET ASSOCIATION, 2023. Shanghai-London gold price dynamics research report[R].

NEWEY W K, WEST K D, 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix[J]. Econometrica, 55(3): 703-708.

TIBSHIRANI R, 1996. Regression shrinkage and selection via the lasso[J]. Journal of the Royal Statistical Society: Series B, 58(1): 267-288.

WORKING H, 1949. The theory of price of storage[J]. American Economic Review, 39(6): 1254-1262.

Appendix A: Detailed Model Evolution Process

Gold Model V1-V4 Complete Evolution:

V1 (TIPS+DXY+GCR): R^2 = 0.360, TIPS coefficient sign wrong (+0.0714), violating economic theory. V2 (V1+CB_Buying): R^2 = 0.395, DXY and GCR redundant, VIF > 10 in exhaustive testing. V3 (TIPS+CB+Spread+SGE): R^2 = 0.788, first inclusion of China factors, but TIPS and CB_Buying lost significance after Newey-West correction. V4 (TIPS+Spread+Gold_Oil): R^2 = 0.908, fewest factors, highest explanatory power, passed all multiple diagnostic tests.

Crude Oil Model Initial–Three-Factor SC–Four-Factor SC Complete Evolution:

Initial Version (DXY+VIX+Spread+CFTC): R^2 = 0.437, DXY VIF = 10.81, CFTC coefficient ≈ 0. Three-Factor SC Version (SC+VIX+Synth_TS): R^2 = 0.876, but out-of-sample R^2 merely 0.056. Four-Factor SC Version (SC+VIX+Synth_TS+Spread): R^2 = 0.888, out-of-sample R^2 = 0.6113, Monte Carlo p = 0.028.

Appendix B: Factor Data Timeliness

Table B1. Gold Model (China-U.S. Dual-Anchor Three-Factor Gold Valuation Model) Data Timeliness

Factor	Latest Data Date	Status
London Gold Spot (XAU)	2026-05-12	Real-time
TIPS (10-year)	2026-05-08	Lag 4 days
China 10-year Sovereign Bond	2026-05-08	Lag 4 days
U.S. 10-year Treasury	2026-05-08	Lag 4 days
Gold-Oil Ratio	2026-05-08	Lag 4 days

Table B2. Crude Oil Model (China-U.S. Dual-Anchor Four-Factor Crude Oil Valuation Model) Data Timeliness

Factor	Latest Data Date	Status
WTI Crude Oil	2026-05-08	Real-time
Brent Crude Oil	2026-05-08	Real-time
Shanghai Crude Oil Futures SC	2026-05-08	Real-time
VIX	2026-05-07	Lag 1 day

Factor	Latest Data Date	Status
U.S. 10-year Treasury	2026-05-07	Lag 1 day
China 10-year Sovereign Bond	2026-05-09	Real-time
OVX (auxiliary display)	2026-05-07	Lag 1 day
Real Time Spread (auxiliary display)	2026-05-08	Real-time

All lagged factors are processed using forward-fill methodology. The valuation date is based on the latest trading day of the primary asset (WTI or XAU).

Data Availability Statement: All data used in this study are sourced from publicly available databases, including locally maintained complete historical data, China Central Depository & Clearing Co. (ChinaBond), the Shanghai Gold Exchange, the Shanghai International Energy Exchange, the World Gold Council, and the U.S. Commodity Futures Trading Commission. The U.S. Treasury historical data fill the gap in the publicly available FRED data (which begins in 2010). The analysis code is written in Python (pandas, statsmodels, scikit-learn). The valuation models of this study are updated daily in the form of public dashboards; readers can view the latest valuation percentiles, factor structures, and strategy backtesting results via the following links: https://shuipingtang.github.io/gold_en.html (Gold) and https://shuipingtang.github.io/crude-oil_en.html (Crude Oil).

Model Naming Note: To facilitate future scholarly citation and discussion, this study names the optimal gold model the "China-U.S. Dual-Anchor Three-Factor Gold Valuation Model" and the optimal crude oil model the "China-U.S. Dual-Anchor Four-Factor Crude Oil Valuation Model." These names are proposed by the author.

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