Journal of Business Administration Online
ATU ARKANSAS TECH UNIVERSITY College of Business HTTPS://JBAO.ATU.EDU

Fall 2023, Vol. 17 No. 2

Forecasting Oil Price Changes with the Flexible Least Squares Approach

Ling T. He, University of Central Arkansas

Abstract

Flexible Least Squares (FLS) method allows time variation to reduce measurement error and generates time-varying coefficient estimates. The FLS coefficients in this study demonstrate remarkable power in forecasting WTI price changes. For example, FLS one- and three-month ahead forecasts can reduce the RMSE by at least 34% and 56%, respectively, compared to forecasts generated by more traditional approaches, such as Autoregression, VAR, and VEC.

The FLS estimation is a tradeoff process between minimizing dynamic error and measurement error. As a result, the FLS forecasts have lower volatility and more likely to be under predicted, they also tend to lag or trial the actual WTI price changes. In order to partially overcome the lagging problem, the use of higher frequency data, for example, weekly or daily data, may be productive.

Keywords: forecasting, time-varying coefficients, flexible least squares, Oil prices

JEL: C53

Introduction and Literature Review

The causal relationship, reflected in predicting power, between oil prices and exchange rates has been a widely researched topic in recent decades. However, the research results are not conclusive. Many researchers find that multiple shocks can be sources of real exchange rate variability (Lastrapes, 1992; Clarida and Gali, 1994) and particularly, oil prices can exert great influence on changes in exchange rates (Zhou, 1995; Amano and Norden, 1998a, b). Chen and Chen (2007) provide evidence that real oil prices may be “the dominant source” of fluctuations of exchange rates and have significant forecasting power. However, according to Breitenfellner and Cuaresma (2008), studies on the impact of oil prices on exchange rates, for example, Akram (2004) and Hebib and Kalamova (2007), typically focus on “exchange rates of currencies other than U.S. dollar.”

Different results are also reported in the literature. In their study of determining the extent of commodity driven by currencies or vice versa, Clements and Fry-McKibbin (2006) find more supporting evidence of the former. Results of Krichene (2005) suggest that the nominal effective exchange rate of the U.S. dollar can negatively influence crude oil prices. In addition, Yousefi and Wirjanto (2005) find that the OPEC member countries tend to adjust oil prices in response to changes in the exchange rate of the US dollar. Cashin, et al. (2004) report that the long-run relationship between real exchange rate and real commodity prices are time-varying. The significant influence of exchange rates on commodities suggests that currency markets may be more efficient and forward-looking than commodity markets. Results of Chen, Rogoff and Rossi (2010) demonstrate the "surprisingly robust power" of exchange rates in predicting global commodity prices and the reverse relationship is "notably less robust." The results suggest exchange rates are strongly forward-looking, whereas changes in commodity prices typically reflect short-term demand imbalances.

The purpose of this study is to use the Dollar/Euro exchange rate or Dollar index and other long- and short-term variables to forecast oil prices with the Flexible Least Squares (FLS) approach. FLS has several advantages in forecasting oil price changes compared with other statistical methods. Unlike many other statistical methods, such as Kalman Filtering, FLS does not require probability distribution assumption (Kalaba and Tesfatsion, 1990), it makes FLS more adaptable to different types of data sets. For example, FLS has been applied to assess asset management (Berzins, et al., 2013), identify critical shifts in risk sensitivities of stocks in different industries (He, 2001, 2005, Chen, et al., 2016), and even analyze the time-varying effect of public approval (Bond, et al., 2003). Because of the release of the restriction of time variation in the OLS, FLS is able to trace or generate the time-varying coefficient estimates in a linear regression. Alptekin, et al. (2019) find the rolling regression method, compared with FLS, fails to obtain accurate time-varying coefficients in their study of energy demand function. The capture of accurate time-varying coefficients is a key factor in quality forecasting. In his study of industrial stocks, He (2005) reports superior out-of-sample forecasts based on FLS coefficients to that of OLS rolling regressions, exponentially weighted rolling regressions, and Cusum and Cusum of Squares method. The ability of generating accurate time-varying coefficients makes FLS a more effective method to forecast volatile oil prices. For example, FLS forecasts of oil prices of this study (Table 1) are far more accurate than the Autoregression (AR)-, Vector Autoregression (VAR)- and Vector Error-Correction (VEC)-based forecasts (Breitenfellner and Cuaresma, 2008).

With the improved accuracy, FLS forecasting of oil prices can benefit different kinds of institutions in oil-related industries. For example, oil producers and distributors can use oil price forecasts in their operation management; government agencies can use them in the crude oil and petroleum reserve management. This study introduces a unique statistical method to oil price forecasting field. The robust results may be interesting to many researchers in the field.

The FLS Method and Data

The most important benefit offered by the FLS method is to trace variations of coefficient estimates over time by recursively estimate a general regression model, $Y_t = X_t b_t + e_t, t = 1, \ldots, T,$ to minimize the incompatibility cost, in terms of measurement error and dynamic error (Kalaba and Tesfatsion, 1988, 1989, and 1990), $\epsilon = \frac{1}{1-\mu}[(1-\mu)r_M^2 + \mu r_D^2]$,

Where $r_M^2 = \sum(\mathrm{y} - \bar{y})^2$

$$r_D^2 = \sum(b_{t+1} - b_t)^T (b_{t+1} - b_t)$$

The smoothing weight, μ, can adjust the squared residual dynamic error, r_D^2, by taking a value between 0 and 1. As it comes to zero, the squared residual dynamic error tends to increase and the squared residual measurement error reduces to zero. On the other hand, when μ moves toward 1, the mean of each FLS coefficient converges to a constant, the OLS solution. According to Tesfatsion and Veitch (1990), allowing a small time variation in the coefficients can result in “large decreases in measurement error.” The choice of μ essentially decides how much of the restriction of time constant imposed by the OLS should be released, in order to achieve the best result of minimizing the incompatibility cost.

This study applies the FLS method to estimate the single- and multi-factor regression models and then uses the time varying FLS coefficient estimates to generate the out-of-sample forecasts of WTI price changes.

This study uses the following time series data:

WTI monthly prices - St. Louis Fed.

Monthly Dollar index and Dollar/Euro exchange rate – St. Louise Fed. Both Dollar index and Dollar/Euro exchange rate are identified as the most influential factors in determining and forecasting oil prices in many studies.

10-year U.S. bond yield (monthly) – St. Louise Fed. The variable reflects the market expectations of future inflation and economic prospects in the long-run and has potential influence on forecasting of WTI price changes. In fact, not only exchange rates but also oil prices are sensitive to changes in interest rates (Frankel, 2006). Krichene (2005) reports that both interest rates and the exchange rate of U.S. dollar inversely affect oil prices.

Monthly current U.S. stock of crude oil and petroleum – U.S. Energy Information Administration (EIA). The variable can cause and catch up the short-term dynamics of demand and supply of crude oil and petroleum, therefore, may possess important power in determining WTI prices. Baumeister, Guerin and Kilian (2015) report that cumulative changes in U.S. crude oil inventory can significantly improve forecasting accuracy.

All variables are in percentage changes. The data set covers a 40-year period, January 1979 – December 2018. The Covid-19 pandemic completely disrupted the world economy, financial markets, and supply chain. Oil prices experienced historical volatility. For example, on April 20, 2020, WTI futures prices dropped by 300%, traded around -$37 per barrel. In addition to the data variability, the purpose of excluding the extreme impacts of Covid-19 on oil price volatility dictates the sample period in this study.

Empirical Results

The purpose of this study is to use the time varying FLS coefficient estimates to make out-of-sample forecasts for oil prices. Results are robust in comparison with forecasts generated by more traditional methods, such as Autoregression, VAR, and VEC. In their exercise of oil forecasting, Breitenfellner and Cuaresma (2008) report that one- and three-month leading forecasts by VAR have smaller RMSE than those by AR and VEC. The reductions are about 0.003 to 0.025 and significant at the 10% (Table 1). Results of this study indicate that the FLS forecasts are far more accurate than VAR forecasts.

The RMSE of FLS one- and three-month ahead forecasts are 0.0532 and 0.0656, respectively and represent reductions of 34% and 56%, compared with the VAR forecasts, and significant at the 0.01% (Table 1).

Table 1. Root Mean Squared Error (RMSE) of WTI Prices forecasts with Dollar/Euro Rates: Jan 83- Dec 07

	AR	VAR	VEC	FLS	FLS vs VAR t-statistic
1-month	0.084	0.081*	0.084	0.053271	-31.74***
3-month	0.164	0.151*	0.176	0.065556	-59.97***
6-month	0.242	0.219	0.280	0.067036	-100.13***
9-month	0.307	0.291	0.365	0.065575	-170.58***

All forecasts are out-of-sample and based on a single-factor model, WTI=a+b$/Euro+u.

Results of AR, VAR and VEC models are reported by Breitenfellner and Cuaresma (2008). The authors indicate that RMSE for VAR (1- and 3-month) are significantly lower that of AR and VEC at the 10% level (Diebold & Mariano Test).

FLS estimation is based on a smoothing weight of 0.5.

**** indicates results of the equal mean test with unequal variance assumption are significant at the 0.01% level.*

As an important world-wide traded commodity, oil prices are volatile and the changes are subject to several factors. The most influential factor is the most widely used world reserve currencies. Results of Table 2 clearly indicate that the two top reserve currencies, U.S. dollar and euro, have almost identical potential to forecast changes in the WTI prices by applying the FLS method. The result justifies the dollar can be used as a single proxy for the reserve currency in this study.

The OLS results in Table 3 show that the independent variable, Dollar, has a sizable coefficient of -1.28 and a t-value significant at the 1% level, and itself can explain up to 4% variations in the WTI prices. Furthermore, WTI demonstrates significant, at the 1% level, correlations with percentage changes not only in the dollar index (Dollar), but also in the 10-year U.S. bond yields (Bond) and the stock of oil petroleum with one-month lag (Stock, Table 3). When the three variables are used to explain changes in WTI in an OLS model, the overall explanatory power of the model jumped from 4% to 13.8%, and all three coefficients are sizable and significant at the 1% level (Table 3). Both Dollar and Stock have negative impacts on WTI. A stronger dollar makes weaker demand for dollar-priced oil and a high stock of oil also lowers oil demand. On the other hand, changes in the U.S. bond yield reflect investors' expectations of future economic growth and price level, therefore, significantly positively affect WTI prices. The strong influence of the three variables on WTI prices warrants a further examination of their forecasting power.

Table 2. Absolute Forecast Error of FLS Forecasts with U.S. Dollar or Dollar/Euro Rates: Jan 79- Dec 18

	#of Forecasts	U.S. Dollar	Dollar/Euro	t-statistic
1-month	479	0.0518	0.0514	0.125
3-month	477	0.0668	0.0666	0.057
6-month	474	0.0688	0.0686	0.057
9-month	471	0.0669	0.0669	-0.015

FLS estimation is based on a smoothing weight of 0.5.

Table 3. Descriptive Statistics and Regression Coefficients of WTI Prices: Jan 79-Dec 18

	N	Mean	St. Deviation	Coefficients of Correlation			
WTI	480	0.0059	0.0821	1.0000			
Dollar	480	0.0005	0.0128	-0.2000 (-4.46)***	1.0000		
Stock	480	0.0009	0.0132	-0.1084 (-2.38)***	-0.0513 (-1.12)	1.0000	
Bond	480	-0.0009	0.0549	0.2583 (5.85)***	0.1480 (3.27)***	-0.0201	1.0000
				WTI	Dollar	Stock	Bond

This study uses eight different smoothing weights, ranging from 0.5 to 0.9, in the FLS estimation of the three-factor model. The three coefficients multiply with three variables in the next month, in addition to the constant term, to get a one-month leading forecast. Table 4 presents different forecasts, absolute forecasting errors and their standard deviations. The results are very stable, there are no noticeable changes. Nevertheless, the smoothing weight of 0.675 is chosen in forecasting of WTI, because it has the lowest absolute forecasting error and standard deviations of forecasts and forecasting errors.

Table 4. Continuous OLS Coefficients of WTI

Dollar	Stock	Bond	Constant	R^2
-1.2859 (-4.462)***			0.0065 (1.760)*	0.04
-1.6027 (-5.786)***	-0.7165 (-2.705)***	0.4380 (6.806)***	0.0077 (2.185)**	0.138

WTI= Percentage changes in OK WTI Cushing Spot Price FOB (Dollars per Barrel).

Dollar= Percentage changes in the dollar index.

Stock= Percentage changes in the stock of oil petroleum with one-month lag.

Bond= Percentage changes in the 10-year U.S. bond yields.

t-values are in parentheses.

*, **, *** *represent the 10%, 5%, and 1% significant level, respectively.*

Table 5. One-Month Leading FLS Forecasts of WTI Prices: Jan 79- Dec 18

	Forecast	St. Dev. of Forecast	Absolute Forecasting Error(e)	St. Dev. of e
U=0.5	0.0061	0.0556	0.0482	0.0428
U=0.6	0.0061	0.0519	0.0472	0.0423
U=0.7	0.0061	0.0482	0.0470	0.0420
U=0.8	0.0060	0.0441	0.0477	0.0425
U=0.9	0.0060	0.0392	0.0493	0.0445
U=0.65	0.0061	0.0501	0.0470	0.0421
U=0.675	0.0060	0.0492	0.0470	0.0421
U=0.75	0.0060	0.0462	0.0473	0.0422

U= smoothing weights used the FLS estimations.

Summary statistics of the FLS coefficient estimates with a smoothing weight of 0.675 in Table 5 suggest the FLS mean is very close to the OLS estimate for all three variables. Dollar indicates the long-term variability evidenced by the highest standard deviation of its coefficients. Clearly, with the lowest standard deviation, Stock is most stable in the long-run.

Table 6. Long-Term FLS Forecasts of WTI Prices with a Smoothing Weight of 0.675: Jan 79- Dec 18

	Forecast	Absolute Forecasting Error(e)	1-month vs others t-statistic	3-month vs others t-statistic	6-month vs others t-statistic	9-month vs others t-statistic
1-month	0.0060 (0.0492)	0.0470 (0.0421)				
3-month	0.0062 (0.0467)	0.0580 (0.0557)	-3.466***			
6-month	0.0063 (0.0463)	0.0625 (0.0607)	-4.603***	-1.207		
9-month	0.0062 (0.0462)	0.0605 (0.0553)	-4.305***	-0.765	0.405	
12-month	0.0062 (0.0453)	0.0607 (0.0560)	-4.283***	-0.821	0.416	0.007

Standard deviations are in parentheses.

**** indicates results of the equal mean test with unequal variance assumption for absolute forecasting errors are significant at the 1% significant level.*

Figure 1 shows the time variation paths of the three FLS coefficients from January 1979 to December 2018. The continuous decline in the dollar index is striking, especially, after 2000. Figure 2 presents both changes in WTI prices and FLS one-month leading forecasts over the sample period. Obviously, volatility of forecasts is smaller than that of WTI. It is the result of a smoothing weight applied in the FLS estimation, which is a compromise process between minimizing dynamic error and measurement error. The less volatile forecasts may lead to the phenomenon that under-forecasts, forecasts less than actual WTI changes, are more frequent than over-forecasts. The figure also shows that forecasts slightly trail the changes in WTI prices. However, the lag seems narrowing since 2008.

When the FLS coefficients are used to forecast longer-term changes in WTI prices, results are less promising. Compared with the one-month leading forecasts, the three-, six-, nine-, and 12-month forecasts have slightly higher forecast means and much higher absolute forecast errors that are significant at the 1% level (Table 6). On the other hand, all longer-term forecasts share the similar accuracy or inaccuracy, there are no meaningful differences among them.

Figure 1. Time Varying FLS Coefficient Estimates

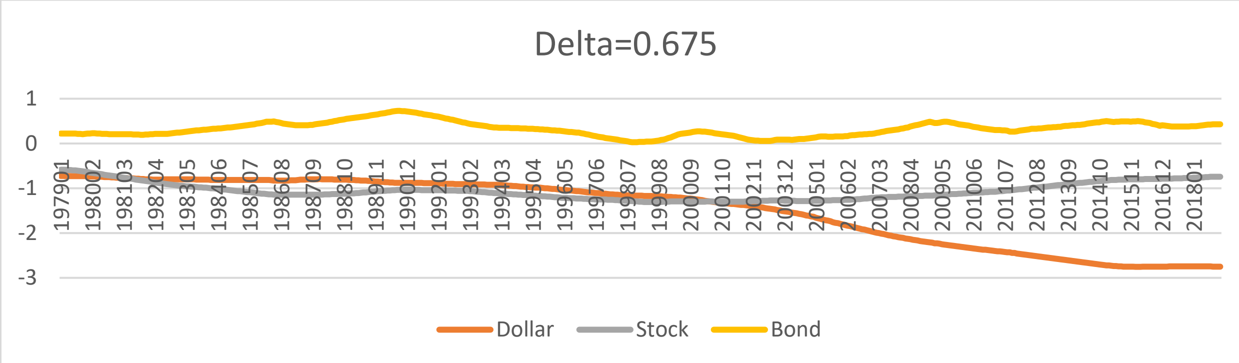
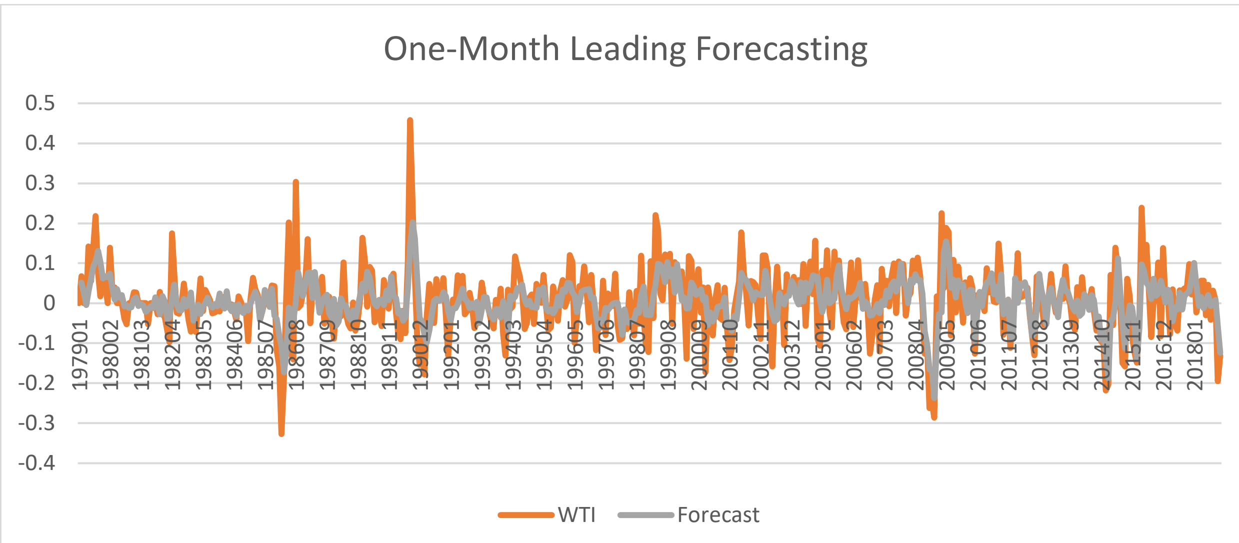


Figure 2. FLS One-Month Leading Forecasting



Concluding Comments

Results of this study suggest the following:

1. Results of a single-factor (Dollar/Euro exchange rate) model indicate that the FLS forecasts are much more robust and accurate than that developed from more traditional methods, such AR, VAR, and VEC.
2. The FLS coefficient estimates of the dollar index, the 10-year U.S. bond yields, and the one-month lagged stock of oil petroleum can capture meaningful time variation relationships with WTI prices. The FLS forecasts produce encouraging results. Therefore, the FLS approach may be an effective forecasting tool.
3. Results of this study indicate one-month leading forecast is more accurate than longer-term forecasts.
4. The FLS forecasts tend to more often under predict the actual WTI price changes, due to the nature of the FLS estimation process.

Limitations of FLS Forecasting

There are two limitations of FLS forecasting. The FLS coefficient estimation is essentially a smoothing process by using a smoothing weight to minimize the incompatibility cost, in terms of measurement error and dynamic error, as a result, the time-varying coefficient estimates are always smoother than the volatility of oil prices. This is the major reason why FLS forecasts are more likely to be under predicted. The lagging or trailing the actual WTI changes may be another limitation for the FLS forecasts.

In order to partially overcome the under prediction and lagging problems in future FLS forecasting of oil prices, the use of higher-frequency data may be productive.

References

Alptekin, A., Broadstock, D., Chen, X. and Wang, D. "Time-Varying Parameter Energy Demand Functions: Bench-marking State-Space Methods against Rolling Regressions," *Energy Economics* 82, 2019, pp. 26-41.

Amano, R. and Norden, S. “Oil Prices and the Rise and Fall of the US Real Exchange Rate,” *Journal of International Money and Finance* 17 (2), 1998a, pp. 299-316.

Amano, R. and Norden, S. “Exchange Rates and Oil Prices,” *Review of International Economics* 6 (4), 1998b, pp. 683-694.

Baumeister, C., Guerin, P. and Kilian, L. “Do High-Frequency Financial Data Help forecast Oil Prices? The MIDAS Touch at Work,” *International Journal of Forecasting* 31 (2), 2015, pp. 238-252.

Berzins, J., Liu, C. and Trzcinka, C. “Asset Management and Investment Banking,” *Journal of Financial Economics* 110 (1), 2013, pp. 215-231.

Bond, J., Fleisher, R. and Wood, B. “The Marginal and Time-Varying Effect of Public Approval on Presidential Success in Congress,” *The Journal of Politics* 65 (1), pp.92-110.

Breitenfellner, A. and Cuaresma, J. “Crude Oil Prices and the USD/EUR Exchange Rate,” *Monetary Policy & The Economy* 4, 2008, pp. 102-121.

Cashin, P., Cespedes, L. and Sahay, R. “Commodity Currencies and the Real Exchange Rate,” *Journal of Development Economics* 75 (1), 2004, pp. 239-268.

Chen, S. and Chen, H. “Oil Prices and Real Exchange Rates,” *Energy Economics* 29, 2007, pp. 390-404.

Chen, K., He, L.T. and Lenin, R.B. “Time Variation Paths of Risk Sensitivities of Bank Stocks in the Past Two Decades,” *Journal of Risk Finance* 17 (4), 2016, pp. 446-455.

Chen, Y., Rogoff, K. and Rossi, B. “Can Exchange Rates Forecast Commodity Prices?” *The Quarterly Journal of Economics* 125 (3), 2010, pp. 1145-97.

Clarida, R. and Gali, J. “Sources of Real Exchange Rate Fluctuations: How Important Are Nominal Shock?” *Carnegie-Rochester Conference Series on Public Policy* 41, 1994, pp.1-56.

Clements, K. and Fry-McKibbin, R. “Commodity Currencies and Currency Commodities,” CAMA Working Paper No. 07, 2006, pp. 1-65.

Frankel, J. “Commodity Prices, Monetary Policy, and Currency Regimes,” *NBER Working Paper* No. C0011, 2006, pp.1-45.

He, L.T. “Time Variation Paths of International Transmission of Stock Volatility – U.S. vs. Hong Kong and South Korea,” *Global Finance Journal* 12 (1), 2001, pp. 79-93.

He, L.T. “Instability and Predictability of Factor Betas of Industrial Stocks: The Flexible Least Squares Solutions,” *Quarterly Review of Economics and Finance* 45, 2005, pp. 619–640.

Kalaba, R. and Testfatsion, L. “The Flexible Least Squares Approach to Time-Varying Linear Regression,” *Journal of Dynamics and Control* 12, 1988, pp. 43-48.

Kalaba, R. and Testfatsion, L. “Time-Varying Linear Regression via Flexible Least Squares,” *Computers and Mathematics with Applications* 17, 1989, pp. 1215-1245.

Kalaba, R. and Testfatsion, L. “Flexible Least Squares for Approximately Linear Systems,” *IEEE Transactions, Man and Cybernetics SMC* 20, 1990, pp. 978-989.

Krichene, N. “A Simultaneous Equations Model for World Crude Oil and Natural Gas Markets,” *IMF Working Paper* No. 032, 2005, PP. 1-24.

Lastrape, W. “Sources of Fluctuations in Real and Nominal Exchange rate,” Review of Economics and Statistics 74 (3), 1992, pp. 530-539.

Yousefi, A. and Wirjanto, T. “A Stylized Exchange Rate Pass-Through Model of Crude Oil Price Formation,” OPEC Review 29 (3), 2005, pp. 177-197.