Financial Econometrics Series

SWP 2012/02

Oil Price Uncertainty and Sovereign Risk: Evidence from Asian Economies

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Oil Price Uncertainty and Sovereign Risk: Evidence from Asian Economies

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ABSTRACT
In this paper, we test whether oil price uncertainty predicts CDS returns for eight Asian countries. We use the Westerlund and Narayan (2011, 2012) predictability test that takes into consideration persistency, endogeneity, and heteroskedasticity of the data. In-sample evidence reveals that oil price uncertainty can predict CDS returns for three Asian countries whereas the out-of-sample evidence suggests that oil price uncertainty can predict CDS returns for six countries.

Keywords: Oil price uncertainty; Predictability; Asian markets; CDS returns.
1. Introduction

The pioneering work of Black and Sholes (1973) and Merton (1974) paved way to a stream of empirical and theoretical work in the area of contingent claim analysis. Reduced form approach and structural-based approach are two popular methodologies employed to model credit sensitive instruments (see, *inter alia*, Jarrow and Turnbull, 1995; Longstaff and Schwartz, 1995; Jarrow *et al*., 1997; Duffee, 1999; Collin-Dufresne *et al*., 2001; Elton *et al*., 2001; Duffee *et al*., 2003; Remolona *et al*., 2008; Ericsson *et al*., 2009; Longstaff *et al*., 2011). Reduced form models assume an exogenous process for default and rely on market-based data, while structural models directly link financial and macroeconomic variables of first and second moments as predictor variables.

For example, Longstaff and Schwartz (1995) proposed (i) an asset factor represented by the changes in the stock index and (ii) an interest rate factor represented by the changes in short rate as the predictor variables in their two factor model. Collin-Dufresne *et al*., (2001), in addition to these two predictor variables, extended the list of predictor variables to include other macroeconomic and financial variables – (i) volatility represented by the changes in the VIX index\(^1\), (ii) jump magnitudes and probabilities represented by the changes in the slope of the smirk of implied volatilities of options on S&P 500 futures, (iii) firm leverage represented by the changes in the leverage ratio of the firm, (iv) slope of yield curve captured by the changes in the yield spread of 10-year and 2-year Treasury bonds and changes in the slope of the yield curve. Longstaff *et al*., (2011), examining the nature of sovereign credit risk across 26 countries used several local and global predictor variables to examine how sovereign CDS were related to these predictor variables. They included the following

\(^1\) VIX index is the weighted average of eight implied volatilities of near-the-money options on the OEX (S&P 100) index.
additional predictor variables: (i) exchange rates, (ii) foreign currency reserve, (iii) corporate yield spread, (iv) equity premium, (vi) term premium, (vii) bond and equity flows, (viii) regional and global sovereign CDS spreads (ix) percentage change in oil prices and Standard and Poors Goldman Sach Commodity Index. In a related work, Ericsson et al., (2009) used only three major determinants in their predictive regression model. (i) Leverage, (ii) volatility and (iii) riskless rate were the three variables to predict changes in CDS. They find these predictor variables statistically and economically significant in predicting changes in CDS premium.

Risk-based measures are central to the Merton (1974) approach and are some of the most popular predictor variables proposed by the structural theory of default literature. These measures are captured by the volatility of the equity market and the changes in the VIX index capturing the implied volatility of the publicly-traded options in the US market. There is strong empirical evidence supporting risk-based measures as the predictors of contingent claims, including credit derivatives. Given the pervasive nature of oil as the central commodity shaping fundamentals at the macro level across economies around the globe, we depart from the usual approach of examining the role of oil as the determinant of spread changes (see Longstaff et al., 2011 for more details) by explicitly modelling oil price uncertainty as the predictor variable of sovereign spreads.

Oil supply shocks result in the reduction of productive capacity as firms tend to reduce the demand for factors of production due to the rising energy price (see Rotemberg and Woodford, 1996). This leads to economic slowdown. Given the role equity markets play as a key determinant of both corporate spreads (see, for example, Collin-Dufresne et al., 2001)
and sovereign credit spreads (see Longstaff et al., 2011), the oil price rise would force
corporate or sovereign spreads to widen. In a sovereign context, the widening of spread
signals the negative impact of an oil price shock on the health of the economy due to the
dampening effect it creates on the productive capacity of the economy - and induces upward
pressure on the level of sovereign risk. As the level of uncertainty in oil prices increases, we
expect the sovereign spread to respond and incorporate the additional risk emanating from the
oil market to reflect the credit market assessment of the country’s ability to meet its debt
obligations. Although oil is central to levels of economic activity, Olson (1988) argues that
the cost of energy is too insignificant a component to explain the slowdown in productivity.
However, the sovereign risk premium is expected to gauge the impact of oil uncertainty on
economic growth efficiently and impound this information in a timely manner.

The role of an oil price shock in shaping the macroeconomic landscape gained momentum
when Hamilton (1983) established the nexus between oil price and the business cycle. Since
his seminal work, a stream of empirical and theoretical work has followed closely
scrutinising the oil-macro link (see, inter alia, Loungani, 1986; Gisser and Goodwin, 1986;
Hamilton, 1988, 2009; Kilian, 2009; Natal, 2009). It is highly likely for a net oil importing
county to have an inverse relationship between oil price movements and macroeconomic
performance. The shocks emanating from oil price movements are transmitted via established
channels creating a causal effect on output, prices and productivity in the wider spectrum of
the economy (see Barsky and Kilian, 2004). The channelling of these effects is manifested in
the form of the slowing down of productive capacity, in addition to inflationary conditions
being induced in the wider economy.
Barsky and Kilian (2002) clearly demonstrate that oil price shocks are inflationary and lead to stagflation following an oil shock. Longstaff et al. (2011) decompose the risk premium in sovereign CDS spread into distress risk premium and jump-at-event risk premium. David (2008) argues that since macroeconomic shocks embed risk premium, the expected distress premium would be more sensitive to changes in price of risk rather than credit spread. It would be interesting, therefore, to see how CDS spreads respond to changes in oil price volatility. Overall, any disruption in the oil market will have implications for the macro-fundamentals of a given economy. This stems from two angles – one is the change in oil price and the other is the change in oil price volatility (see Ferderer 1996). Given the inability of credit risk models to adequately explain the properties of credit spreads, this paper examines whether oil price uncertainty predicts CDS spread returns.

Our empirical investigation is based on eight Asian countries, namely, China, Indonesia, Japan, Malaysia, the Philippines, South Korea, Thailand, and Vietnam. We use daily time series data, which mostly spans the period 11 March 2002 to 30 March 2012. Briefly, the in-sample evidence reveals that oil price uncertainty can predict CDS returns for three Asian countries (namely, Indonesia, South Korea, and Vietnam). On the other hand, the out-of-sample evidence suggests that oil price uncertainty can predict CDS returns for six countries (namely, Indonesia, Japan, Malaysia, the Philippines, South Korea, and Vietnam).

The rest of the paper is organised as follows. In the next section, we discuss the data and the methodology. In Section 3, we provide a detailed discussion of the results. In the final section, we provide concluding remarks.
2. Data and Methodology

2.1. Data

This paper is based on a five-day daily data set that includes eight Asian countries, namely China, Indonesia, Japan, Malaysia, the Philippines, South Korea, Thailand, and Vietnam. We consider only these eight countries because historical CDS return data for other Asian countries are unavailable. For example, for Hong Kong CDS data are available from 22 November 2005 to 30 March 2012. However, Hong Kong’s CDS data does not have much variation due to thin trading. Therefore, when we computed the log return of CDS, most of the values turned out to be zero. A note on sample size is in order. For six countries (Malaysia, China, Japan, the Philippines, South Korea, and Thailand) in our sample the data covers the period 11 March 2002 to 30 March 2012. Therefore, for these six countries we have no fewer than 2317 observations. For Indonesia and Vietnam, data covers the period 27 September 2005 to 21 December 2011 and 10 May 2006 to 17 November 2011, respectively, which consist a total of 16271 and 1441 observations, respectively. The specific dates of data for each country are reported in the first column of Table 1. The world crude oil index and daily CDS spread are obtained from the Bloomberg.

2.2. Methodology

Our empirical model is of the following form:

\[ CR_t = \alpha + \beta OU_{t-1} + \epsilon_{CR,t} \] (1)

Here, \( CR \) is the CDS return and \( OU \) is the oil price uncertainty. We used one-year rolling variance of oil returns as a proxy for oil price uncertainty. The \( \epsilon \) is characterised by a mean zero and variance \( \sigma^2 \). The null hypothesis of no predictability amounts to setting \( H_0: \beta = 0 \). In Equation (1), it is possible that oil price uncertainty is both endogenous and persistent. To
account for a persistent predictor variable we use the Westerlund and Narayan (2012) test and model the oil price uncertainty as follows:

\[ OU_t = \varphi(1 - \delta) + \delta OU_{t-1} + \mu_{OU,t} \]  

Equation (2) specifically enables us to avoid any small-sample bias originating as a result of persistency of the predictor variable (see Lewellen, 2004 and Stanbaugh, 1999).

If the error terms, \( \varepsilon_{CR,t} \) and \( \mu_{OU,t} \), are correlated, oil price uncertainty is said to be endogenous. Thus, we assume that \( \rho \), the correlation between the error terms from Equations (1) and (2) is statistically significant. This can be tested based on the following regression:

\[ \varepsilon_{CR,t} = \rho \mu_{OU,t} + \pi_t \]  

where \( \pi_t \) is iid and symmetric with mean zero and with variance \( \sigma_{\pi}^2 \).

2.2.1. The Westerlund and Narayan estimator

We use the bias-adjusted generalised least squares (GLS) estimator of \( \beta \) which is proposed by Westerlund and Narayan (2011, 2012). The bias-adjusted GLS estimator is based on making Equation (1) conditional on Equation (2), which removes the effect of endogeneity and has the following form:

\[ CR_t = \alpha - \rho \varphi(1 - \delta) + \beta^{adj} OU_{t-1} + \rho \Delta OU_t + \varepsilon_t \]  

where \( \beta^{adj} = \beta - \rho(\delta - 1) \). The estimator proposed by Westerlund and Narayan (2012) accounts for potential conditional heteroskedasticity in \( \varepsilon_t \). They assume that \( \delta = 1 + \frac{d}{T} \), where \( d \leq 0 \) is a drift parameter that measures the degree of persistency in the OU. This implies that if \( d = 0 \), then OU has an exact unit root; whereas, if \( d < 0 \) then the OU is stationary in the sense that \( \delta \) approaches one from below as \( T \) increases. Thus, Westerlund
and Narayan (2012) assumed that $\pi_t$ has the following autoregressive conditional heteroskedastic (ARCH) structure:

$$\sigma_{\pi_t}^2 = \theta_t + \sum_{j=1}^{q} \theta_j \pi_{t-j}^2$$

(5)

where $\sigma_{\pi_t}^2 = var(\pi_t | I_{t-1})$ and $I_t$ is the information available at time $t$. Importantly, Westerlund and Narayan (2011) show that the GLS-based test that exploits the information contained in the ARCH is more powerful than the OLS-based test that ignored ARCH. They show that the conditional variance of $\varepsilon_t$ is:

$$var((\varepsilon_t | I_{t-1}) = \sigma_{\varepsilon_t}^2 = \rho^2 \sigma_{\pi_t}^2 = \sigma_{\pi_t}^2$$

(6)

and the GLS t-statistics has the following form:

$$t_{GLS} = \frac{\hat{\beta}_{GLS}}{1/ \sqrt{\sum_{j=2}^{T} \omega_j^2 (OU_{t-1}^b)^2}}$$

(7)

where, $\omega_j$ is the GLS weight, $\hat{\beta}_{GLS}$ is the GLS estimator of $\beta$ from Equation (2), and $OU_{t}^b = OU_t - \sum_{k=2}^{T} OU_k / T$, where $T$ is the sample size.

3. RESULTS

3.1. Preliminary results

The Westerlund and Narayan (2012) predictability test works best when our data set is characterised by persistent and endogenous predictors and when the innovations of the predictive regression model are heteroskedastic. In this section, we begin by documenting these features of our data set. Before we begin, it is worthwhile discussing the common descriptive statistics of CDS returns of the eight Asian countries. The CDS returns are
computed as \( \log(CDS_t/CDS_{t-1}) \). In columns 4 and 5 of Table 1, we report the mean and standard deviation of CDS returns and oil price uncertainty, respectively. The average daily CDS returns are in the \(-0.04 – 0.1\) range. The highest mean CDS return is recorded for Vietnam and the lowest are observed for the Philippines and Indonesia. This suggests that the sovereign risk is highest for Vietnam and lowest for the Philippines and Indonesia. The standard deviation reveals that Japan’s (5.65) CDS return is the most volatile, followed by South Korea (5.55), China (4.86), and Thailand (4.64). The standard deviation for the rest of the countries is recorded at less than 4.5. In addition, oil price uncertainty is just one series for all eight countries, but the mean and standard deviations per country differ due to different sample sizes.

**INSERT TABLE 1**

We begin by testing for unit roots in our dependent and predictor variables and report the results in column 3 of Table 1. We have used the common augmented Dickey-Fuller (ADF, 1981) unit root test, which in the case of oil price uncertainty, includes a time trend and an intercept, while, in the case of CDS returns, it includes only an intercept. Schwarz Information Criterion (SIC) is used to obtain the optimal lag length, which is reported in square brackets and appear beside the ADF test statistic. In applying the SIC, we begin with eight lags. The probability (p-value) is also reported below the test statistic. One can comfortably take a decision on the null hypothesis based on the p-value. We find that the unit root null is rejected for the CDS returns series of all eight Asian countries. This implies that CDS returns of all eight countries are stationary series. The oil price uncertainty is just the one series for all eight countries. The ADF test statistic differs across the countries because of the different sample size for each country. We do not reject the null hypothesis of a unit root for the oil price uncertainty variable for any of the eight countries, implying that our predictor
variable is a unit root. In addition, we also report the first-order autoregressive coefficient of oil price uncertainty variable in Panel A of Table 2. We find that for all eight countries for which the null of unit root is not rejected, the AR coefficient is very close to one, implying that the oil price uncertainty variable is highly persistent.

**INSERT TABLE 2**

Next, we turn to the issue of endogeneity of the predictor variable. The results are reported in Panel B of Table 2. Unlike the strong evidence that oil price uncertainty is persistent, we find that the oil price uncertainty variable is endogenous for only three countries, namely, Indonesia, Japan, and South Korea.

Furthermore, variables in the predictive regression model are likely to be heteroskedastic. This is a common feature of high frequency financial data; therefore, it needs to be modelled appropriately (see Westerlund and Narayan, 2012). We use the Ljung-Box (LB) Q-statistics to examine the null hypothesis of no autocorrelation at a lag length of 24. We report the Q-statistic for oil price uncertainty and CDS returns, and squared oil price uncertainty and CDS returns in Panel C of Table 2. The results reveal that the null hypothesis of no autocorrelation is rejected for both the first and second moments of oil price uncertainty and CDS returns at the 1% level for all eight Asian countries. The presence of autocorrelation in the second order of data is indicative of ARCH effects in the variables. We also use a Lagrange multiplier (LM) test for hetroskedasticity. We proceed as follows. We run an OLS-based AR model of oil price uncertainty and CDS returns separately. In both models we include 24 lags. Then we extract the residuals from this AR model and examine the null hypothesis that there is “no ARCH” in the residuals. The null is again tested at 24 lags, and we report the results in Panel
D of Table 2. We reject the null hypothesis of no ARCH in the oil price uncertainty and CDS returns for all eight countries at 1% level. This suggests that both the dependent and predictor variables in our predictive regression model are heteroskedastic. This holds for all eight countries.

In summary, the main message emerging from the preliminary analysis is that, while the predictor variable (oil price uncertainty) is strongly persistent and heteroskedastic, we find strong evidence of endogeneity for only three countries. The main implication is that we need to model these features of the data, and we do. These features of the data, in particular, the heteroskedastic nature of the variables in our study motivates us to use the Westerlund and Narayan (2012) GLS estimator.

3.2. Results on predictability

The results based on an in-sample predictability test are reported in Panel A of Table 3. We report the coefficient of the FGLS test and the p-value associated with the null hypothesis of no predictability in columns 1 and 2 (see Panel A), respectively. The p-value is less than 0.1 in the case of two countries, South Korea and Vietnam; and, for Indonesia, the p-value is reported less than 0.05. This suggests that we reject the null hypothesis of no predictability at the 10% level in the case of South Korea and Vietnam and at the 5% level for Indonesia. Therefore, we conclude that for three out of eight countries, oil price uncertainty can predict CDS returns.

INSERT TABLE 3
Next, we move to the out-of-sample forecasting estimation. We use 50% of the sample to generate the first forecast. Using the in-sample of 50%, we generate estimates of the model by which we forecast CDS returns for the next day. We repeat this exercise of forecasting until the entire sample size is exhausted. We compute out-of-sample forecasts based on Equation (1). We call this the unrestricted model. Then we set $\beta = 0$ to restrict Equation (1). This generates forecasts from a restricted model (constant CDS return model) which has the following form:

\[
CR_{t+1} = \alpha + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim N(0, \sigma^2)
\]  

(8)

The results are reported in Panel B of Table 3. We begin by discussing the relative Theil $U$ statistic. The relative Theil U statistic is the ratio of the Theil $U$ from the unrestricted model (oil price uncertainty-based predictive regression model) to the restricted (constant) model. The implication of relative theil U statistic is that if the relative theil U is less than the value one, the unrestricted model outperforms the restricted model. In other words, this means that the forecasts from the unrestricted model are better than the forecasts from the restricted model. Our results reveal that for six countries, namely, Indonesia, Japan, Malaysia, the Philippines, South Korea, and Vietnam the relative Thiel U is recoded at less than the value one. This implies that the oil price uncertainty-based forecasting model is superior to the constant-based forecasting model. For China and Thailand, we find that the relative Theil U is equal to value one.

In addition, we consider the Campbell and Thompson (2008) measure of forecasting performance, namely, the out-of-sample $R^2$ (OOS$R^2$) statistic. The OOS$R^2$ statistic is computed as $OOSR^2 = 1 - (MSE^{UR} - MSE^R)$. The $MSE^{UR}$ and $MSE^R$ are the mean square
errors (MSE) of the out-of-sample forecasts from the unrestricted (oil price uncertainty-based) and restricted (constant-based) models, respectively. The implication of $OOSR^2$ is that, if $OOSR^2 > 0$, the oil-uncertainty-based model has a lower forecasting error than the constant-based model. This suggests that the unrestricted model outperforms the restricted model. The result for the $OOSR^2$ statistic is reported in Panel B of Table 3. The results suggest that $OOSR^2$ is greater than zero for five countries. These countries are Indonesia, Japan, the Philippines, South Korea, and Vietnam. The $OOSR^2$ statistic based results are consistent with relative Theil $U$, except in the case of Malaysia. Again, for China and Thailand, we report negative $OOSR^2$, which means that the unrestricted model could not outperform the restricted model.

4. CONCLUDING REMARKS

In this paper, we undertake an extensive test of CDS return predictability by using the oil price uncertainty as the predictor variable. We have a dataset covering eight Asian countries, and we use daily time series data. We use a recently proposed GLS-based test for CDS return predictability that accounts for three main statistical features of the data, namely, persistency, endogeneity, and in particular, heteroskedasticity. There is greater evidence of out-of-sample predictability compared to in-sample predictability. We discover that for three countries (Indonesia, South Korea, and Vietnam) oil price uncertainty predicts CDS returns. When we used $OOSR^2$ and relative Theil $U$ out-of-sample predictability tests, we find that for at least six countries (Indonesia, Japan, Malaysia, the Philippines, South Korea, and Vietnam) there is strong evidence of out-of-sample predictability.
References:


Table 1: Descriptive statistics and unit root test results

This table reports sample size of time series daily data for each country (column 2) and the mean (column 4) and standard deviation (column 5) of CDS returns (CDSR) and oil price uncertainty (OU). In column 3, we report results based on ADF unit root test. The ADF test examines the null hypothesis of unit root. The null hypothesis of unit root is tested for both variables. The optimal lag length, chosen using the Schwarz Information Criterion, is reported in the square brackets. The optimal lag length is selected by starting with a maximum of eight lags. The p-values, used to test the unit root null, are reported in parentheses.

<table>
<thead>
<tr>
<th>Country</th>
<th>Date</th>
<th>ADF test</th>
<th>Mean</th>
<th>Standard deviation</th>
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<td></td>
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<td>OU</td>
<td>CDSR</td>
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<tr>
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<td>0.0249</td>
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<td></td>
<td></td>
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<td>(0.7508)</td>
<td></td>
</tr>
<tr>
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<td>-0.0134</td>
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<td>(0.8154)</td>
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<td></td>
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<td>(0.7544)</td>
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</table>
### Table 2: Preliminary test results

This table reports a number of preliminary tests of the data. In Panel A, we report the autoregressive coefficient of the oil price uncertainty. These coefficients are used to judge the degree of persistency in a predictor variable. Panel B reports the endogeneity test results. This test is based on regressing the error term from the predictive regression model on the error term from the predictor variable; the coefficient, t-statistics, and p-value are reported. In panel C, we report results from a test of autocorrelation. We square both variables and test for autocorrelation at lags of 24. We report the resulting autocorrelation coefficient and use p-value to test the null hypothesis of no autocorrelation. In Panel D, we report results on heteroskedasticity of the CDS return and oil price uncertainty variables. Essentially, we run an autoregressive model for each variable with 24 lags and test for the null hypothesis of ‘no ARCH’ in the residuals of the model. The null is tested at lags of 24. The LM test statistic is reported together with the p-value. *, (**) , and (***) denotes statistical significance at the 1%, 5%, and 10% levels.

<table>
<thead>
<tr>
<th>Country</th>
<th>Panel A: AR</th>
<th>Panel B: Endogeneity</th>
<th>Panel C: Ljung-Box Q-statistic</th>
<th>Panel D: ARCH</th>
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<td>t-stat</td>
<td>p-value</td>
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<td>112.44*</td>
<td>54647*</td>
<td>617.16*</td>
<td>54637*</td>
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<tr>
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<td>97.96*</td>
<td>55017*</td>
<td>1104.2*</td>
<td>54996*</td>
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<tr>
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<td>81.358*</td>
<td>34170*</td>
<td>269.31*</td>
<td>34062*</td>
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</table>
Table 3: In-sample and out-of-sample forecasting evaluation

In Panel A of this table, we report the results from the time series predictive regression model proposed by Westerlund and Narayan (2011, 2012). The regression model regresses the CDS return on the one-period lagged oil price uncertainty variable. The null hypothesis is that the oil price uncertainty does not predict CDS returns. The predictor variable, oil price uncertainty, is proxied by one-year rolling variance of oil price returns. For each country’s predictive regression model we report the coefficient on the one-period lagged premium (predictor) variable and its p-value. In Panel B, we report the out-of-sample predictability for each of the eight Asian countries. We set the out-of-sample period equivalent to 50% of the sample size. In columns 4-5 we report two of the commonly-used metrics, namely, the relative Theil $U$ statistic (RTU) and the out-of-sample $R^2$, which we denote as $OOSR^2$. These tests are used as measures of the out-of-sample forecasting performance of our oil price uncertainty model relative to a constant model, which is typically used in the return predictability literature as a benchmark model. (***) and (****) denotes statistical significance at the 5% and 10% levels.

<table>
<thead>
<tr>
<th>Country</th>
<th>In-sample: FGLS</th>
<th>Out-of-sample</th>
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<th></th>
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<tr>
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<td>Coefficient</td>
<td>p-value</td>
<td>RTU</td>
<td>$OOSR^2$</td>
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<td>-0.0002</td>
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<td>0.0285</td>
<td>0.8971</td>
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<td>0.9960</td>
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<td>0.9907</td>
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<td>0.9747</td>
<td>0.0043</td>
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