Spillovers between Exchange Rate Pressure and CDS Bid-Ask Spreads, Reserve Assets and Oil Prices Using the Quantile ARDL Model

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Abstract

Purpose – This paper examines the quantile relationships between the Saudi Riyal (SAR) exchange rate pressure, CDS spreads, total reserve assets, and oil prices.

Design/methodology/approach – This study applied the error correction model and the relatively novel the quantile ARDL (QARDL) model.

Findings – the results show a negative and significant relationship between the long-run coefficient of the SAR exchange rate pressure and the long run coefficients of both the CDS and the oil price. However, the long run coefficient of the foreign reserves is statistically insignificant, thus indicating that exchange rate pressure, CDS spread and oil price variables are cointegrated. As for the short-run coefficients, we find that the lag SAR pressure affects the current pressure. Moreover, the short-run coefficient of the foreign reserves affects negatively the SAR pressure. Using the quantile ARDL (QARDL) model, we find a significant relationship particularly in the extreme quantiles, regardless of the level or the log level series. Under the long-run coefficients, the positive (negative) relationship characterizes the nexus of the reserves-pressure and the oil-pressure (oil pressure). As for the short-run coefficients, we find that an increase in the lag SAR pressures contributes to the current pressure across all quantiles, whereas an increase in the reserves reduces the pressure in the extreme quantiles. These results have important implications for policy makers.

Originality/value – There is generally a lack of understanding on the spillovers between exchange rate pressure and CDS bid-ask spreads, reserve assets and oil prices. This is, as far as the authors knows, the first study to apply the quantile ARDL to examine the spillovers between exchange rate pressure and CDS Bid-Ask spreads, reserve assets and oil prices. Our findings have important implications for governments and policy makers.

Keywords Exchange Rate Pressure; CDS Bid-Ask Spreads; Reserve Assets; Oil Prices; Quantile ARDL Model.

Paper type Research paper

1. Introduction

The study by Girton and Roper (1977) is the first to develop the concept of exchange market pressure (EMP). This concept assesses the total pressure on a currency rate, which has been resisted through foreign exchange intervention or relieved through exchange rate changes by the monetary authority (Patnaik et al., 2017). Oil is a strategic commodity for the large oil-exporter and is priced in US dollar. Oil prices had steadily declined since summer 2014 and persisted until Febraury 2016. The decline had accelerated in that year as a result of Saudi Arabia's decision to open the oil spigot to chock off shale oil producers in the United States. Those prices finally collapsed to $26/barrel in February 2016 as a result of the shale producers' flexibility to reduce production costs and increase efficiency.

As a result, Saudi Arabia and other GCC countries have been suffering from decreasing oil revenues, increasing fiscal budget deficits and dwindling foreign exchange reserves due to these countries' inability to increase oil prices or pursue a fiscal policy austerity which is politically unpopular. Dwindling foreign reserves in the oil-exporting countries, including the GCC countries, have also caught the attention of speculators which have exerted upward pressures on the spreads of the credit default swaps (CDS) of Saudi Arabia and the other GCC countries. The pressure on CDSs has in turn wielded further downward pressures on those countries' exchange rates which are usually stable because of their pegs with an anchor aided by usually strong foreign reserves. The Kingdom has kept its peg with the dollar at $3.75 since 1986.

Saudi Arabia had $742 billion of foreign reserves in summer 2014. However, those reserves dwindled to $493.7 billion (about 33.46%) in April 2019, standing at 62% of GDP, which translates on average to more than a $5 billion drop per month. If the current situation continues, Saudi Arabia will deplete its foreign reserves, currently standing at 14 months of imports, in a short period of time, given the continuing relatively low oil prices, the procurement of expensive weapons and the war in Yemen. If such an outcome materializes in an environment of persistently low oil prices, Saudi Arabia will be forced to relinquish its dollar-riyal peg or replace it by a basket of currencies, and its CDS spread will go through the roof. This will also have incredible political and economic consequences for the Kingdom, and its neighbors as the contagious credit risk spreads.

However, the recent Saudi Arabia's "Vision 2030" including the National Transformation Plan has renewed the debate on the pressure of the Saudi dollar-riyal exchange rate. The objective of this study is to set the stage for an un-precedent research that examines the pressure on the Saudi dollar-riyal exchange rate due to changes in the explanatory factors that include the Saudi foreign exchange reserves, foreign reserves months of imports, Saudi CDS spreads and oil prices among other factors, with a concertation on extreme tail dependence which carries much more risk than the other quantiles. Since the riyal is pegged to the dollar, the pressure on the riyal will be represented by dividing the exchange rate over the fiscal budget as a percentage of GDP, as explained below, which is a novel concept and has never been tested before. The interdependence between these variables is also studied in the current paper. The CDS contracts are important derivatives for investors, regulators and dealers as they process risk in the financial sector and the whole economy. CDS's are used by different economic agents as a financial instrument to transmit risk exposures among themselves to avoid the potential default risk of sovereign and corporate bonds (Mensi et al., 2019).

To this end, we use the Quantile Autoregressive Distributed Lag model (QARDL) developed by Cho et al. (2015). This model is an extension of the standard or linear ARDL, which materializes by combining the ARDL model of Pesaran and Shin (1999) that relies on relations in the short- and long run, with the quantile regression methodology of Koenker and Bassett (1978) that captures the relationships across the quantiles (or different states or conditions of the markets). The QARDL model framework has at least three advantages over the standard approaches that rely on the estimation of the cointegration relationship in Engle and Granger (1987) or the quantile cointegration relationship in Xiao (2009). First, the QARDL model estimation enables one to examine the long-run and short-run relationships between Y_t and $\boldsymbol{X}_t$ specific to the quantile level and also their interrelationships across multiple quantile levels. Second, the simulations in Cho et al. (2015) show that the QARDL estimation and inference deliver better results than those obtained by estimating the quantile cointegration relationship directly. Third, despite these advantages, researchers can still interpret the estimated parameters in the framework of the error correction model in Engle and Granger (1987) by allowing for the presence of both $I(1)$ and $I(0)$ variables. This aspect is substantially different from the quantile regression in Koenker and Bassett (1978) and its extensions which assume that the economic variables of interest are $I(1)$ variables.

These advantages fit our proposal which examines the pressure on the Saudi dollar-real exchange rate in the tail distributions due to experiencing declining oil prices, growing fiscal budget deficits, dwindling foreign reserves which have been the pillars that have supported the stability of this exchange rate, and rising own CDS spreads. The QARDL model allows thus to simultaneously examine the long-run relationship with their related short-run movements over a range of quantiles. This model provides a full information not only of the mean level but also of the entire conditional distributions; the short- and long-term relationships between the macro variables. This methodology, which to our knowledge is novel and has not been applied to emerging markets, can also be implemented to other GCC countries that are also facing the same exchange rate pressure situation which Saudi Arabia is facing now.

The results show from the DOLS estimation, the long-run coefficient of the foreign reserve (*rsrv*), turn out not to be significant, whereas the coefficients of the CDS (*cds*) and the oil price (*oilp*) are both significant, thereby indicating that the exchange rate pressure (*pres*), *cds* and *oilp* are cointegrated. In addition, the pressure *pres* is negatively associated with *cds* and *oilp* as desired. Moreover, we show that the long-run coefficient of the oil price crash increases the pressure on the exchange rate. The long run CDS's and the oil prices decreases contribute to the pressure on the exchange rate.

Using the quantile ARDL model for the level (without log) series, we observe that the adjustment coefficient shows that the cointegration is a stable system. The results also indicate that the long-run relationship detected by the error correction model estimation is driven by the quantile cointegration relationships at extremely low and high quantile levels. More precisely, the long-run coefficients for the foreign reserves and CDS variables are positively related to the SAR pressure in the extreme lowest and highest quantile levels (if τ is 0.020 or 0.980). In contrast, the long-run coefficient of the oil prices affects negatively the SAR pressure under extreme quantiles. On the other hand, the short coefficient for the one-lag (third-lags) SAR pressure affects positively (negatively) the current exchange pressure. The short-run coefficient of the lagged foreign reserve variables influences negatively the SAR pressure in the extreme quantiles, indicating that a decrease in those reserves increases the SAR exchange pressure. The results using the logarithm of the level series are closely similar to those of the level series as a long-run cointegration between the current pressure and both the CDS and oil prices under the extreme quantiles. The short-run coefficients are statistically significant for the foreign reserves and the oil price.

The remainder of the paper is organized as follows. Section 2 presents the methodology. Section 3 presents the data and a preliminary analysis, while Section 4 discusses the findings. Section

5 concludes with some implications.

2. Empirical QARDL Analysis of the Pressure on the SA Exchange Rate

In this section, we empirically examine the long-run relationship between the pressure on the SA exchange rate and other macro-variables in Saudi Arabia, using the quantile regression approach. The model we desire to explore is the QARDL model in Cho, Kim, and Shin (2015) which extends the ARDL relationship between nonstationary variables. Specifically, if we suppose that $(Y_t, \boldsymbol{X}_t')'$ is an $I(1)$ process, the quantile version of the ARDL relationship is given as follows. For each $\tau \in (0, 1)$, we have

$$Y_t = \alpha_*(\tau) + \sum_{j=1}^{p} \phi_{j*}(\tau) Y_{t-j} + \sum_{j=0}^{q} \boldsymbol{\theta}_{j*}(\tau)' \boldsymbol{X}_{t-j} + U_t(\tau), \tag{1}$$

which can be rewritten as

$$Y_t = \alpha_*(\tau) + \boldsymbol{\gamma}_*(\tau)' \boldsymbol{X}_t + \sum_{j=1}^{p} \phi_{j*}(\tau) Y_{t-j} + \sum_{j=0}^{q-1} \boldsymbol{\delta}_{j*}(\tau)' \Delta X_{t-j} + U_t(\tau),$$

where $\boldsymbol{\delta}_{j*}(\tau) \coloneqq -\sum_{i=j+1}^{q} \boldsymbol{\theta}_{i*}(\tau)$. The error correction form in Eq. (1) is also given as

$$\begin{aligned} \Delta Y_t &= \alpha_*(\tau) + \zeta_*(\tau)(Y_{t-1} - \boldsymbol{\beta}_*(\tau)' \boldsymbol{X}_{t-1}) \\ &\quad + \sum_{j=1}^{p-1} \phi_j^*(\tau) \Delta Y_{t-j} + \sum_{j=1}^{q-1} \boldsymbol{\theta}_j^{*\prime} \Delta \boldsymbol{X}_{t-j} + U_t(\tau) \end{aligned} \tag{2}$$

with

$$\boldsymbol{\beta}_*(\tau) \coloneqq \boldsymbol{\gamma}_*(\tau)\left(1 - \sum_{i=1}^{p} \phi_{i*}(\tau)\right)^{-1}, \qquad \boldsymbol{\gamma}_*(\tau) \coloneqq \sum_{j=0}^{q} \boldsymbol{\theta}_{j*}(\tau),$$

$$\zeta_*(\tau) \coloneqq \sum_{i=1}^{p} \phi_{i*}(\tau) - 1, \qquad \boldsymbol{\theta}_0^*(\tau) \coloneqq \boldsymbol{\theta}_{0*}(\tau),$$

and for i=1, 2, …, p-1,

$$\phi_j^*(\tau) \coloneqq -\sum_{h=j+1}^{p} \phi_{h*}(\tau), \text{ and } \boldsymbol{\theta}_j^*(\tau) \coloneqq -\sum_{h=j+1}^{p} \boldsymbol{\theta}_{j*}(\tau).$$

Here, the long-run quantile relationship between Y_t and $\boldsymbol{X}_t$ is captured by $\boldsymbol{\beta}_*(\tau)$. The other parameters in Eq. (2) characterize the short-run interrelationship between Y_t and $\boldsymbol{X}_t$. Cho, Kim, and Shin (2015) provide a consistent estimator for the set of the parameters in Eq. (1) and define a long-run parameter estimator using the estimators and show that it is consistent at the speed of the sample size (i.e., super-consistent) and is further normally distributed, so that an inference on the long-run parameter can be conducted using the conventional Wald (1943) test's principle.

For the purpose of this section, we construct our data set to contain the main features of the pressure on the SA exchange rate and other macro-variables. We first define the pressure on the exchange rate (*pres*) by the following formula:

(*Saudi riyal dollar exchange rate*) / (*1 + Budget Surplus or Deficit / GDP*)

Using the two data sets of the level and log level series, we separately estimate the parameters in model (2). We specifically follow the two-step estimation plan that applies the estimation of the long-run parameter in Cho, Kim and Shin (2015). For each quantile level $\tau \in (0, 1)$, we first estimate the long-run parameter $\boldsymbol{\beta}_*(\tau)$ by estimating the parameters in Eq. (1) as in Cho, Kim and Shin (2015) and then estimate the short-run parameters in Eq. (2). Here, the lag orders p and q are estimated by the SIC procedure as in Pesaran and Shin (1998). For the second-step estimation, we specifically let $\hat{u}_t(\tau) \coloneqq Y_t - \widehat{\boldsymbol{\beta}}_n(\tau)'\boldsymbol{X}_t$, where $\widehat{\boldsymbol{\beta}}_n(\tau)$ denotes the long-run parameter estimator obtained from the first step, and we next estimate the short-run parameters by the quantile regression by regressing ΔY_t against $(1, \hat{u}_{t-1}(\tau), \Delta Y_{t-1}, \dots, \Delta Y_{t-p+1}, \Delta \boldsymbol{X}'_{t-1}, \dots, \Delta \boldsymbol{X}'_{t-q+1})'$. As $\widehat{\boldsymbol{\beta}}_n(\tau)$ is super-consistent, we can treat it as a known parameter in estimating the short-run parameters, and the large sample distribution of $\widehat{\boldsymbol{\beta}}_n(\tau)$ does not affect the limit distribution of the short-run parameters. In particular, when obtaining the p-values of the t-test statistics, we assume the sandwich-form asymptotic covariance matrix for the robust standard errors. In the case when the assumed covariance matrix is not properly estimated, we bootstrap the residuals to obtain the standard error of the estimate. When estimating the asymptotic covariance matrix, we also use the Hall and Sheather (1988) bandwidth so that we can consistently estimate the density function associated with the standard error by the Epanechnikov (1969) kernel function.

The quantile levels are selected by our empirical data analysis. We tried many quantile levels for the QARDL analysis of our data and let the quantile τ belong to $T := \{0.020, 0.125, 0.250$ $0.375, 0.500, 0.625, 0.750, 0.875, 0.980\}$. As it will be clear soon, all the quantile levels in (0.00, 1.00) are not relevant to the QARDL process. When τ is located around 0.500, the estimated parameters turn out to be insignificant. On the contrary, as the quantile level τ approaches 0.00 or 1.00, it turns out that the estimated parameters are significant. We therefore added 0.020 and 0.980 to the quantile levels as extreme end points of T.

When applying the two-step estimation, we also estimate model variations. First, we estimate the error correction model as in Engle and Granger (1987) to compare the model estimations. For this purpose, we first estimate the long-run parameters by the dynamic OLS (DOLS) estimation developed by Stock and Watson (1993) and next estimate the short-run parameters by least squares method. The DOLS estimator is also super-consistent as for the least squares estimator, but the associated t-test statistics are asymptotically normal under the null hypothesis. Due to its straightforward application, we rely on the DOLS estimation for the long-run parameters using the same lag orders as above. Next, we extend the QARDL analysis by adding exogenous variables to the right side. Specifically, all $I(1)$ variables under consideration are not cointegrated as it turns out. Instead of removing the non-cointegrated variables from the system of the model in Eq. (3), we treat them as exogenous variables. That is, we extend the models in Eq. (1) into the following:

$$Y_t = \alpha_*(\tau) + \boldsymbol{\gamma}_*(\tau)'\boldsymbol{X}_t$$
$$+ \sum_{j=1}^{p} \phi_{j*}(\tau)Y_{t-j} + \sum_{j=0}^{q-1} \boldsymbol{\delta}_{j*}(\tau)'\Delta X_{t-j} + \sum_{j=0}^{q-1} \boldsymbol{W}_{t-j}\boldsymbol{\delta}_{j*}(\tau) + U_t(\tau), \quad (3)$$

and

$$\Delta Y_t = \alpha_*(\tau) + \zeta_*(\tau)(Y_{t-1} - \boldsymbol{\beta}_*(\tau)'\boldsymbol{X}_{t-1})$$
$$+ \sum_{j=1}^{p-1} \phi_j^*(\tau)\Delta Y_{t-j} + \sum_{j=1}^{q-1} \boldsymbol{\theta}_j^{*\prime}\Delta \boldsymbol{X}_{t-j} + \sum_{j=0}^{q-1} \boldsymbol{W}_{t-j}\boldsymbol{\delta}_{j*}(\tau) + U_t(\tau), \quad (4)$$

respectively, to estimate the unknown parameters by the two-step estimation procedure, where $\boldsymbol{X}$ and $\boldsymbol{W}$ are redefined as the cointegrated and differenced non-cointegrated variables, respectively. The other parameters and Y are the same as before. For example, if *rsrv* turns out to be non-cointegrated with the other variables, we let $\boldsymbol{X}_t$ and W_t be ($pres_t$, cds_t, $oilp_t$) and $\Delta rsrv_t$, respectively, so that we can estimate the influence of *rsvs* on the error correction system constructed by *pres*, *cds*, and *oilp*. The estimation procedure is parallel to the estimation of the parameters in Eqs. (1) and (2). We first estimate the long-run parameter $\boldsymbol{\beta}_*(\tau)$ by extending the estimation method in Cho, Kim and Shin (2015), and next estimate the short-run parameters in Eq. (4) by the quantile regression. For reference purposes, we also call the models in Eqs. (1) and (2) the benchmark models, and the models in Eqs. (3) and (4) the extensive-form models.

3. Data and descriptive statistics

This study uses monthly data for The SAR pressure (*pres*). Note that Saudi Arabia has a fixed exchange rate regimes pegged to the US Dollar. The exchange rate has been 3.75 SAR/USD since June 1986. Here, the monthly frequency data are unavailable for the budget deficit or surplus and GDP in Saudi Arabia, although annual observations are available. We therefore converted the yearly budget surplus or deficit and GDP observations to monthly observations using the cubic spline method. Specifically, it assigns each value in the annual series to the January and December observations and places all intermediate points by a cubic polynomial. We next let the other variables be the oil price (*oilp*) measured by the Arabian light crude oil Asia spot price, the Saudi Arabia total reserve assets (*rsrv*) which are measured in 10,000 Saudi riyals, and the credit default swap (CDS) bid-ask spread of Saudi Arabia (*cds*). All these variables are monthly observable. The data are extracted from Bloomberg.

Table 1 provides the unit root testing results for these variables. We first applied the augmented Dickey and Fuller (1979, ADF) test statistic to all available observations of *pres*, *rsrv*, *cds*, and *oilp*. When applying the ADF test statistic, the autoregressive lag of each variable was selected by the Schwarz (1978) information criterion (SIC). As each variable has a different sample size, we first applied the ADF test to the whole samples. For example, *rsrv* has available observations from Jan. of 2001 to Dec. of 2018, and as a result, we could not find evidence that *rsrv* is a stationary process. Likewise, for the other variables *pres*, *cds*, and *oilp*, we obtain the inference results that they are all nonstationary processes. In addition to this inference, we apply the ADF test to the log of the variables, i.e., log(*pres*), log(*rsrv*), log(*cds*), and log(*oilp*), and infer from this application that the logs are also nonstationary processes. Next, we restrict the sample period to the shortest sample period displayed by *cds*, which has the shortest sample period among the variables of consideration. As a result, we could obtain the same conclusion as before. That is, there is no evidence for the variables that they are stationary processes. Irrespective of whether they are level or log observations, they are all nonstationary processes.

The inference results in Table 1 enable us to specify the variables to fit to the model framework. We construct two data sets to estimate the unknown parameters using the level and log observations separately. For constructing the first data set, we let *pres* be the target variable Y to comply with the goal of this study and let $\boldsymbol{X}$ be the other variables, viz., *rsrv*, *cds*, and *oilp*. We next construct the second data set by taking the log to the variables. That is, we let Y and $\boldsymbol{X}$ be log(*pres*) and (log(*rsrv*), log(*cds*), log(*oilp*)), respectively. These two data sets start from Aug. of 2008 and ends at Dec. of 2018.

Before discussing the parameter estimation, we first examine the descriptive statistics. Table 2 provides the estimated descriptive statistics using the full sample observations and those restricted to the sample period from Aug. of 2008 to Dec. of 2018. As we see from the comparisons, there is no big change in the estimates for $\Delta pres$, $\Delta rsvs$, and Δcds. Their sample means, medians, and standard deviations are more or less similar irrespective of whether the full or restricted observations are examined. This aspect implies that there was no sizable structural change for the variables. On the contrary, the standard deviation of $\Delta oilp$ has substantially increased from 4.7519 to 7.0353, which implies that $\Delta oilp$ has become more volatile since 2008. We suppose that $\Delta oilp$ has been stationary since Aug. of 2008 from the fact the ADF test does not detect nonstationarity for $\Delta oilp$ and then estimate the long-run and short-run parameters.

[Insert Tables 1&2 here]

4. Results and Discussions

4.1 Model Estimation Using Level Observations

In this subsection, we discuss estimating the long-run and short-run parameters in the quantile models (1), (2), (3), and (4) using the level observations. We first estimate the benchmark error correction model and contain the estimated parameters in the second column of Table 3 along their p-values. If the p-values are less than 5%, we mark them by the boldface font. As shown in this table, we report the long-run parameter estimation in panel (a).[1] From the DOLS estimation, the long-run coefficient of *rsrv* turns out not to be significant, whereas the coefficients of *cds* and *oilp* are significant. This fact implies that *pres*, *cds* and *oilp* are cointegrated, but *rsrv* is not, so that it can be more appropriate to treat *rsrv* as an exogenous variable. As we see from the estimates, *pres* is negatively associated with *cds* and *oilp* as desired. In the long term, we show that an oil price plunge increases the pressure on the exchange rate. An inverse long run relationship exists between CDS and the pressure on the exchange rate. Second, panel (b) provides the estimated short-run parameters, along with their *p*-values. Note that the adjustment parameter (i.e., the coefficient of the lagged cointegration error) is negatively valued and significant, implying that the current cointegration is a stable system. We further note that the coefficients of the lagged *pres* are statistically significant up to the third lag, and that of $\Delta rsrv_{t-1}$ is also statistically significant, although *rsrv* is not cointegrated with *pres*, *cds* and *oilp*. This aspect implies that it can be more appropriate to treat *rsrv* as an exogenous variable for the error correction model.

We next estimate the quantile error correction model in Eq. (2) and report the estimated parameters in the same table. From the third column of Table 3 to the last, we report the long-run and short-run parameter estimates for each $\tau \in T$. The results show that, first, for most $\tau \in T$, particularly for τ in the middle of 0 and 1, the long-run coefficients are not significant, whereas the long-run coefficients are significant for the extremely small or large quantile levels. That is, if τ is 0.020 or 0.980, the long-run coefficients are significantly different from zero. For the other quantile levels, the long-run coefficients are not statistically significant. From this, we can infer that the long-run relationship detected by the error correction model estimation is driven by the quantile cointegration relationships at the extremely low and high quantile levels. Second, although *rsrv* is not cointegrated

[1] By the SIC procedure, we estimated p and q to be equal to 4 and 2, respectively.

with other variables by the error correction model estimation, it turns out that *rsrv* is cointegrated with the others for $\tau = 0.020$, but they are not cointegrated for the other τ's. This fact implies that the cointegration relationship among the variables is not the same for all τ's, and it can be different even from that of the error correction model. For $\tau = 0.20$, *rsrv* should be treated as an endogenous variable, but for the other *tau*'s, it can be treated as exogenous. Third, the signs of the estimated coefficients are not necessarily equal to each other across the quantile levels. For example, the long-run coefficient of *oilp* is positively valued for $\tau = 0.02$, whereas the same coefficient is negatively valued for $\tau = 0.98$. On the contrary, the signs of the long-run coefficient for *cds* are same for both $\tau = 0.02$ and 0.98. This aspect implies that the long-run relationship between *pres* and *oilp* need to be understood differently for low and high τ's. Fourth, we now examine the short-run parameter estimation. Note that the adjustment parameter of each quantile model is negatively valued and significant across all quantile levels, implying that the quantile cointegration displays a stable system for each quantile level. Furthermore, for $\tau = 0.020$, in which *rsrv* can be treated as a cointegrated variable, the coefficient of $\Delta rsrv_{t-1}$ is not significant any more, which is a different aspect from that of error correction model.

In summary, from this estimation, we mainly obtain the following result: the long-run relationship among *pres*, *rsrv*, *cds*, and *oilp* is driven by the extremely low or high quantile levels, and the long-run relationship between *pres* and *oilp* are different across different quantile levels.

We next extend the model scope by letting $\Delta rsrv_t$ be exogenous and estimate the extensive-form models, viz., Eqs. (3) and (4). As for the analysis in Table 3, we first estimate the error correction and quantile error correction models across different quantile levels and next contain the long-run and short-run parameter estimators, along with their *p*-values in panels (a) and (b) of Table 4, respectively.

The error correction model estimation results are reported in the second column of Table 4 and can be summarized as follows. First, we estimated p and q to be 3 and 2, respectively by the SIC procedure, and the DOLS estimation in panel (a) yields similar coefficients as the estimates in the error correction model in Table 3. Their signs are the same, and the coefficient values are more or less similar to each other. Second, the short-run parameter estimates in panel (b) of Table 4 are also more or less similar to those in panel (b) of Table 3. The signs are the same between the corresponding coefficients, and their values are not quite different from each other. The only different part is that the coefficient of $\Delta pres_{t-2}$ is significant, whereas that of Table 3 is not. Instead, the coefficient of $\Delta pres_{t-3}$ in Table 3 was significantly estimated, whereas it was not estimated in Table 4 by the order estimation of the SIC procedure.

Overall, the error correction model estimation in Table 4 reinforces the model estimation results in Table 3. The long-run relationship between *pres* and (*cds*, *oilp*) is negatively associated, and $\Delta rsrvt{-}1$ significantly alleviates the serial correlation in the error term of the short-run equation.

The quantile error correction model estimation results are reported from the third column to the last of Table 4. As discussed above, if $\tau = 0.02$, *rsrv* is cointegrated with other variables. Although we estimate the parameters in the extensive-form models without including *rsrv* in the long-run equation for the same quantile level, the estimation results should be referred to only for reference. We summarize the estimation results as follows. First, as before, the long-run quantile parameter estimates are only significant when τ is extremely low or high. Note that when $\tau = 0.020$, the long-run coefficients of *cds* and *oilp* are significant, whereas only the long-run quantile coefficient of *cds* is significant for $\tau = 0.980$. For the other quantile levels in T, the long-run coefficients are not significant. Although we do not report in Table 4, we also let τ be 0.999 and estimated the long-run quantile coefficients and could observe that the long-run parameters are significant for both *cds* and *oilp*. This aspect implies that the long-run quantile relationship holds for low and high τ's and that the long-run relationship captured by the error correction model estimation is driven by the quantile long-run relationships attained at the extremely low and high quantile levels. This aspect is the same observation as for the model estimation given in Table 3.

Second, for τ = 0.980, the long-run quantile coefficients display the same signs as the corresponding parameters in Table 3, although the coefficient of *oilp* is not significant. Nevertheless, if we further increase the level of τ, the long-run quantile coefficient of *oilp* becomes significant. When τ = 0.999, the estimated coefficients of *cds* and *oilp* are 0.0298 and -0.0030, respectively, and their *p*-values are 0.0000, implying that the same conclusion can be inferred as in Table 3. If τ is extremely high, *pres* is positively and negatively associated with *cds* and *oilp*, respectively in the long run. On the contrary, for τ = 0.02, *pres* is positively associated with *rsrv*, *cds* and *oilp* in the long run as the third column of Table 3 displayed. The negative coefficients of *cds* and *oilp* given in Table 4 for τ = 0.02 must be different from the signs in Table 3 as the cointegrated variable *rsrv* was omitted from the long-run quantile equation.

Third, the short-run parameter estimates are provided in panel (b). Note that across different quantile levels, the coefficients of the cointegration errors are negatively valued, so that the cointegration system must be a stable one, although some of them are close to zero and may not be distinguishable from zero. When the quantile level is close to 0.5, the adjustment coefficient is not significant.

Finally, when τ = 0.980, we also note that the estimated quantile short-run coefficients are more or less similar to the corresponding ones in Table 3. Only the coefficients of $\Delta pres_{t-1}$ and $\Delta rsrv_{t-1}$ are significant and their signs are the same as in Table 3.

In short, we obtain the same conclusion as those obtained from Table 3. The cointegration relationship exhibited by the error correction model is mainly driven by the long-run relationships attained at the low and high quantile levels, and the long-run relationship between *pres* and *oilp* are differently signed across the low and high quantile levels.

To sum up this section, we obtain that the cointegration relationship displayed by the error correction model is driven mainly by the long-run relationships attained at the extremely low and high quantile levels. Furthermore, *pres* is positively cointegrated with *cds* at both low and high quantile levels, but *pres* is positively and negatively cointegrated with *oilp* at the low and high quantile levels, respectively, although the error correction model estimation implies that *pres* is negatively cointegrated with *cds* and *oilp* but not with *rsrv*.

[Insert Tables 3&4 here]

4 .2 Model Estimation Using Log Observations

In this subsection, we examine the long-run and short-run quantile equations using the log observations and make sure which empirical findings obtained from the level observations are effective even for the log observations.

We proceed our estimation in parallel to the estimations using the level observations. We first estimate the error correction model using the benchmark model. As before, the long-run parameters are estimated by the DOLS estimation and the short-run parameters are estimated by the least squares. The second column of Table 5 reports the estimation outputs. We summarize the estimation results as follows. First, the SIC procedure estimates the lag orders for p and q *to* be 4 and 2, respectively, which is the same lag orders as in Table 3. Using the estimated lag orders, we report the estimated long-run coefficients in panel (a) of Table 5, from which we observe that the long-run coefficient of log($rsrv$) is not significant but the long-run coefficients of log(cds) and log($oilp$) are negatively valued and significant, implying that log($pres$) is negatively cointegrated with log(cds) and log($oilp$), but Δ log($rsrv$) can be treated as an exogenous variable. This is the same observation as for the level examination. Second, we report the estimated short-run coefficients in panel (b) of Table 5. The qualitative results are more or less similar to the level observation case. That is, the adjustment coefficient is negatively valued, so that the error correction system must be a stable one, and the coefficients of $\Delta\log(pres_{t-1})$ and $\Delta\log(pres_{t-3})$ are significant, maintaining the same signs as for the level observation case. The only different aspect from the level observation case is that the coefficient of $\Delta\log(oilp_{t-1})$ becomes significant, whereas the $\Delta\log(rsrv_{t-1})$ is insignificant.

We next estimate the quantile error correction model in Eq. (2) using the log observations and report the estimated parameters in Table 5. From the third to the last column of Table 3, we report the long-run and short-run parameter estimates across different τ's. We summarize the estimation results as follows.

First, for most $\tau \in T$, particularly for τ in the middle of 0 and 1, the long-run coefficients are not significant, whereas the long-run quantile coefficients are significant only for $\tau = 0.980$, which is different from the level observation case as the long-run quantile coefficients were significant for $\tau = 0.020$ in Table 3. We therefore let $\tau = 0.010$ and estimated the long-run parameter and could observe that the long-run coefficients of log(cds) and log($oilp$) are -0.1246 and 0.0245, respectively, and their p-values are 0.0000. On the contrary, the long-run quantile coefficient of log($rsrv$) is 0.1364 and its p-value is 0.2825. From this observation, we conclude that the long-run relationship detected by the error correction model estimation must be driven by the quantile cointegration relationship among log($pres$), log(cds) and log($oilp$) at extremely low and high quantile levels as for the level observation case. By the log transformation, more extreme quantile levels are required to detect the long-run quantile relationship among the log observations.

Second, as before, the signs of the estimated coefficients are not equal across different quantile levels. In particular, the long-run quantile coefficients of log(*cds*) are negatively observed across different quantile levels, which holds even when $\tau = 0.980$. Note that this observation is different from the level observation case in which the long-run quantile coefficients of *cds* are positively valued for $\tau = 0.02$ and 0.980. By the log transformation, the long-run quantile coefficients of *cds* are reversed to negative from positive values. On the contrary, the quantile long-run coefficients of log(*oilp*) maintain the same signs as for the level observation case. That is, when τ is extremely low (i.e., $\tau = 0.01$), the coefficient of log(*oilp*) is positively valued and significant; if τ is extremely high (i.e., $\tau = 0.980$), the same coefficient is negatively valued and significant. This aspect implies that the long-run relationship between log(*pres*) and log(*oilp*) need to be differently understood for low and high τ's.

Third, we further examine the quantile long-run relationship by further increasing the level of τ. We let τ be 0.999 and could observe that log(*pres*), log(*cds*), log(*oilp*), and log(*rsrv*) are cointegrated. Although the estimates are not reported in Table 5, the estimated coefficients of log(*cds*), log(*oilp*), and log(*rsrv*) are -0.5832, -0.8366, and -0.3011, respectively, and all of their *p*-values are 0.0000. This is a different result from the earlier estimates owing to the fact that even log(*rsrv*) is cointegrated with log(*pres*) as well as log(*cds*) and log(*oilp*). Therefore, if τ is extremely high, Δlog(*rsrv*) may not be treated as exogenous.

Finally, we examine the short-run quantile parameter estimation. Note that the adjustment parameter of each quantile model is negatively valued and significant across all quantile levels except for $\tau = 0.750$, implying that the quantile cointegration displays a stable system for each quantile level. Furthermore, for $\tau = 0.020$, in which *rsrv* can be treated as a cointegrated variable, the coefficient of $\Delta\log(rsrv_{t-1})$ is significant, which is different from estimating the error correction model. If $\tau = 0.980$, the coefficients of $\Delta\log(rsrv_{t-1})$ and $\Delta\log(rsrv_{t-3})$ are significant, whose aspect is also observed even when $\tau = 0.999$.

Overall, the estimations in Table 5 are qualitatively similar to those in Table 3. The long-run relationship among log(*pres*), log(*cds*) and log(*oilp*) is driven by the those in the low and high quantile levels, but log(*rsrv*) is not cointegrated with the other variables for any quantile level of consideration, which is one of the two different aspects from Table 3. Another different aspect is that the long-run quantile coefficients of log(*cds*) are negatively valued for significant cases, whereas the corresponding coefficients in Table 3 are positively valued if they are significant.

Next, we estimate the extensive-form model, viz., Eqs. (3) and (4) by letting $\Delta\log(rsrv_t)$ be exogenous. As before, we first estimate the error correction and quantile error correction models across different quantile levels and next report the long and short-run parameter estimators, along with their *p*-values in panels (a) and of Table 6, respectively.

The error correction estimation results are reported in the second column of Table 6. We summarize the results as follows. First, *p* and *q* are estimated to be equal to 3 and 2, respectively by the SIC procedure as for Table 4, and the DOLS estimation in panel (a) produces similar coefficients as the estimates in the error correction model in Table 5. Their signs are the same, and their coefficient values are similar. Second, even the short-run parameter estimates in panel (b) of Table 6 are similarly obtained to those in panel (b) of Table 5. The signs of corresponding coefficients are the same, and their values are not quite different from each other. The only difference is that the coefficient of $\Delta\log(pres_{t-2})$ is now significant as for the level observation case, whereas that of Table 5 is not. Instead, the coefficient of $\Delta\log(pres_{t-3})$ in Table 5 was significantly estimated, which was not estimated in Table 6 by the SIC procedure. In short, the error correction model estimation in Table 6 validates the error correction model estimation in Table 5. The long-run relationship between log(*pres*) and (log(*cds*), log(*oilp*)) is negatively associated, and Δlog($oilp_{t-1}$) significantly alleviates the serial correlation in the error term of the short-run equation.

Finally, we report the quantile error correction model estimation results from the third column to the last of Table 6. We summarize the estimation results as follows. First, the long-run parameter estimates are provided in panel (a). For each $\tau \in T$, none of the long-run quantile coefficients is significant. We therefore further increase or decrease the level of τ. Although it was not reported in Table 6, if $\tau = 0.999$, the long-run quantile coefficients are significant. Specifically, the long-run coefficients of log(*cds*) and log(*oilp*) are estimated as 0.9851 and 0.3516, respectively with *p*-values equal to 0.0000. Likewise, if τ is 0.001, the long-run coefficients of log(*cds*) and log(*oilp*) are estimated as -0.0872 and -0.0167, respectively, and their *p*-values are 0.0000 and 0.0101, respectively. This aspect implies that the long-run relationship between among log(*pres*), log(*cds*), and log(*oilp*)) is driven by the extremely high and low quantile levels. More extreme quantile levels are required to obtain the long-run quantile cointegration than estimating the benchmark model. Second, although the long-run quantile coefficients display the significant coefficient values for τ = 0.999, the estimation results using the benchmark model imply that log(*rsrv*) should be included in the long-run equation. Therefore, we refer to the estimation results with $\tau = 0.999$ only for reference purposes. Note that the estimated coefficients of log(*rsrv*), log(*cds*) and log(*oilp*) are negatively valued as discussed above, but the coefficients of log(*cds*) and log(*oilp*) are now reversed to positive. On the contrary, if we let $\tau = 0.010$, as we discussed above, Δlog($rsrv_{t-1}$) can be treated as an exogenous variable, and the extensive-form model estimation in Table 6 shows that the coefficient of log(*cds*) is significantly negative, but that of log(*oilp*) is negatively valued and close to zero, which is a consistent result to what is delivered by the benchmark model. Finally, the short-run parameter estimates are provided in panel (b). Note that across different quantile levels, the coefficients of the cointegration errors are negatively valued, so that the cointegration system must be a stable one, although some of them are close to zero and may not be distinguishable from zero. When the quantile level is 0.500 or 0.625, the adjustment coefficient is not significant.

Overall, the estimations in Table 6 are qualitatively similar to those in Table 5. The long-run relationship among log(*pres*), log(*cds*) and log(*oilp*) is driven by the those in the low and high quantile levels, and the cointegration coefficients have different signs and/or values across different quantile levels.

To sum this section, the cointegration relationship exhibited by the error correction model is driven mainly by the long-run relationships attained at extremely low and high quantile levels. Furthermore, as for the error correction model, log(*pres*) is negatively cointegrated with log(*cds*) at both low and high quantile levels, but log(*pres*) is negatively and positively cointegrated with log(*rsrv*) and and log(*oilp*) at the high and low quantile levels, respectively, which is different from the error correction model estimation: log(*pres*) is negatively cointegrated with log(*cds*) and log(*oilp*) but not with log(*rsrv*).

[Insert Tables 5&6 here]

5. Concluding Remarks

Budget deficit is an economic challenge of economies particularly those they are oil-dependent. Saudi Arabia, the largest oil producer in the world, is one of the countries that suffer from this deficit in the recent years. The foreign exchange rates pressure, budget deficit, the oil price plunge and the CDS spread continue to be a concern of the economic policy makers of Saudi Arabia. The aim of this paper is to examine the quantile relationship between the SAR foreign exchange rates pressure, budget reserve, the oil price and the CDS spread which is desirable due to the high volatility in the oil market. To this end, the quantile ARDL model along with the error correction model is applied to a monthly level and log level data ranging from August 2008 to December 2018.

By using the fully-modified ordinary least squares estimation,[2] we find evidence of an insignificant relationship between the long-run coefficient of the foreign reserves and the SAR pressure. Moreover, the long-run coefficients of CDS and oil prices are negatively associated with pressure, indicating evidence of cointegration between the SAR pressure, CDS spread and oil prices. In addition, the SAR pressure is negatively related with the CDS and oil prices. A decrease in the long-run coefficients of CDS and the oil prices contributes to the pressure on the exchange rate.

Using the quantile ARDL model, we find for the level series that the adjustment coefficient value shows that the cointegration is a stable system, indicating that the long-run relationship detected by the error correction model estimation is driven by the extreme quantile cointegration relationships. The long-run coefficients for the foreign reserves and CDS variables contribute to the SAR pressure, whereas the long-run coefficient of oil prices affects negatively the pressure for extreme lower and upper quantiles. As for the short coefficient for one-lag (third-lags) pressure, the result shows that it affects positively (negatively) the current SAR exchange pressure. The short-run coefficient of the lag reserve influences negatively the pressure for the extreme quantiles, thereby indicating that a decrease in the foreign reserves increases the SAR exchange pressure.

Using the logarithm level series, we find the same results as for the level series where the findings indicate a long-run cointegration between the current pressure and both the CDS and oil prices under the extreme quantiles. The short-run coefficients are statistically significant for the foreign reserves and the oil price. The reaction of the Saudi dollar-riyal exchange rate to pressures on the

[2] We estimated the same model by the fully-modified OLS estimation developed by Phillips and Hansen (1990) and obtained similar estimates to the DOLS estimates.

foreign reserves, CDS spreads and oil prices depends on the tail distributions.

The results have important implications for policy makers in the Kingdom. The Saudi government must seriously seek ways to reduce the budget deficit in order to avoid inflation recession problem related to threats to the exchange rate by adopting proper monetary and financial policies and careful budgeting plan to achieve a balanced budget. The policy makers should consider the evolving relationship among the considered variables across extreme quantiles (or market scenarios). The Saud leading role in OPEC has implications for its exchange rates. Unwise and drastic measures such as flooding the oil market may threaten its peg.

References

CHO, J.S., KIM, T.-H., and SHIN, Y. (2015): "Quantile Cointegration in the Autoregressive Distributed Lag Modeling Framework," *Journal of Econometrics*, 188, 281–300.

CHO, J.S., GREENWOOD-NIMMO, M., AND SHIN, Y. (2015): "Consistent Two-Step Estimation of the Nonlinear Autoregressive Distributed Lag Model: Theory and Application," Discussion Paper, School of Economics, Yonsei University.

DEJONG, R. M. and DAVIDSON, J. (2000): "The Functional Central Limit Theorem and Weak Convergence to Stochastic Integrals I: Weakly Dependent Processes," *Econometric Theory*, 16, 621–642.

DICKEY, D. A. and FULLER, W. A. (1979): "Distribution of the Estimators for Autoregressive Time Series with a Unit Root," *Journal of the American Statistical Association*, 74, 427–431.

ENGLE, R. and GRANGER, C. (1987): "Co-integration and Error Correction: Representation, Estimation and Testing," *Econometrica*, 55, 251–276.

EPANECHINKOV, V.A. (1969)" "Non-parametric Estimation of a Multivariate Probability Density," *Theory of Probability and Its Applications*, 14, 153–158.

GIRTON, L., and ROPER. D, (1977): “A monetary model of exchange market pressure applied to the postwar Canadian experience,” *American Economic Review*, 67, 537–548.

HALL, P., and S. SHEATHER. (1988): “On the Distribution of a Studentized Quantile,” *Journal of the Royal Statistical Society, B*, 50, 381–391.

KOENKER, R. and BASSETT, G. (1978): “Regression Quantiles,” *Econometrica*, 46, 33–50.

MENSI, W., SHAHZAD, S.J.H., HAMMOUDEH, S., HKIRI, B., and Al-YAHYAEE, K.H. (2019): “Long-run relationships between US financial credit markets and risk factors: Evidence from the Quantile ARDL approach,” *Finance Research Letters*, 29, 101–110.

NEWEY, W. K. and WEST, K. D. (1987): “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix,” *Econometrica*, 55, 703–708.

PATNAIK, I., FELMAN, J., and SHAH, A. (2017): “An exchange market pressure measure for cross country analysis,” *Journal of International Money and Finance*, 73, Part A, 62–77.

PESARAN, M.H. and SHIN, Y. (1998): “An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis,” in S. Strøm, (Ed.), *Econometrics and economic theory in the twentieth century: the Ragnar Frisch centennial symposium*, Cambridge University Press, Cambridge, UK, 371–413.

PESARAN, M. H., and SHIN Y. (1999): “An autoregressive distributed lag modeling approach o cointegration analysis,” In S. Strom, (ed) Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium, Cambridge University Press, Cambridge.

PESARAN, M.H., SHIN, Y., and SMITH, R. (2001): “Bound Testing Approaches to the Analysis of Level Relationship,” *Journal of Applied Econometrics*, 16, 289–326.

PHILLIPS, P. C. B. and HANSEN, B. E. (1990): “Statistical Inference in Instrumental Variable Regression with *I*(1) Processes,” *Review of Economic Studies*, 57, 99–125.

SCHWARZ, G. (1978): “Estimating the Dimension of a Model,” *Annals of Statistics*, 2, 461–464.

SHIN, Y., YU, B., and GREENWOOD-NIMMO, M. (2014): "Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework," in Horrace, W., and Sickles, R. (Eds.), *Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications*, 281–314. New York: Springer Science & Business Media.

STOCK, J. and WATSON, M. (1993): "A simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems," *Econometrica*, 61, 783-820.

WALD, A. (1943): "Tests of Statistical Hypotheses Concerning Several Parameters When the Number of Observations is Large," *Transactions of American Mathematical Society*, 54, 426–482.

XIAO, Z., (2009): "Quantile Cointegrating Regression," *Journal of Econometrics*, 150, 248–260.

	pres	*rsrv*	*cds*	*oilp*	log(*pres*)	log(*rsrv*)	log(*cds*)	log(*oilp*)
sample period	07/1986 12/2018	01/2001 12/2018	06/2008 12/2018	07/1986 12/2018	07/1986 12/2018	01/2001 12/2018	06/2008 12/2018	07/1986 12/2018
ADF test	-1.9890	-1.3981	-2.4146	-2.0565	-1.7909	-1.8414	-2.7890	-1.7089
p-value	(0.2917)	(0.5828)	(0.1399)	(0.2627)	(0.3849)	(0.3507)	(0.0627)	(0.4260)
sample period	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018
ADF test	-2.0982	-1.0647	-2.4143	-2.2540	-2.0472	-1.0047	-2.7891	-2.1429
p-value	(0.2458)	(0.7282)	(0.1399)	(0.1887)	(0.2666)	(0.7503)	(0.0627)	(0.2285)

Table 1: THE AUGMENTED DICKEY AND FULLER (1979) TEST STATISTICS FOR THE VARIABLES. This table shows the ADF test results for the variables used in this study. The first panel shows the testing results using the whole sample observations of each variable. The second panel shows the testing results using the samples from 08/2008 to 12/2018. As a result, we cannot reject the unit-root hypothesis for all variables of consideration. None of the *p*-values is less than 5%.

	$\Delta pres$	$\Delta rsrv$	Δcds	$\Delta oilp$	Δ log(*pres*)	Δ log(*rsrv*)	Δ log(*cds*)	Δ log(*oilp*)
sample period	07/1986 12/2018	01/2001 12/2018	06/2008 12/2018	07/1986 12/2018	07/1986 12/2018	01/2001 12/2018	06/2008 12/2018	07/1986 12/2018
Mean	-0.0012	0.2061	-0.0161	0.1173	-0.0002	0.0105	-0.0032	0.0047
Median	-0.0074	0.1719	0.0000	0.2000	-0.0019	0.0062	0.0000	0.0116
Maximum	0.1217	2.3756	17.000	17.860	0.0342	0.0963	1.2039	0.4872
Minimum	-0.0649	-2.0214	-16.900	-34.250	-0.0195	-0.0482	-0.9545	-0.4495
Std. Dev.	0.0300	0.7286	4.4562	4.7519	0.0089	0.0250	0.3410	0.1015
Obs.	389	216	124	389	389	216	124	389
sample period	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018	08/2008 12/2018
Mean	0.0083	0.0610	-0.0161	-0.4527	0.0024	0.0013	-0.0032	-0.0057
Median	-0.0028	0.0879	0.0000	-0.0350	-0.0008	0.0018	0.0000	-0.0005
Maximum	0.1217	1.6967	17.000	15.130	0.0342	0.0402	1.2039	0.2645
Minimum	-0.0649	-2.0214	-16.900	-34.250	-0.0173	-0.0305	-0.9545	-0.4495
Std. Dev.	0.0389	0.7977	4.4562	7.0353	0.0107	0.0143	0.3410	0.1013
Obs.	124	124	124	124	124	124	124	124

Table 2: DESCRIPTIVE STATISTICS OF THE DIFFERENCED LEVEL AND LOG OF LEVEL OBSERVATIONS. This table shows the descriptive statistics of the variables of consideration, using the whole sample period of each variable and the restricted sample period from August 2008 to December 2018.

τ	ECM	0.020	0.125	0.250	0.375	0.500	0.625	0.750	0.875	0.980
panel (a): long-run parameters										
$rsrv_t$	-0.0017	0.0299	0.0116	0.0141	0.0219	0.0228	0.0411	0.0163	0.0148	0.0156
p-value	0.6396	**0.0000**	0.8415	0.9630	0.9803	0.9809	0.9792	0.9535	0.9197	0.0694
cds_t	-0.0329	0.0208	-0.0127	-0.0085	0.0104	0.0188	0.0511	0.0013	0.0239	0.0493
p-value	**0.0000**	**0.0017**	0.8130	0.9759	0.9900	0.9831	0.9722	0.9959	0.8608	**0.0000**
$oilp_t$	-0.0128	0.0052	-0.0124	-0.0126	-0.0107	-0.0130	-0.0152	-0.0140	-0.0113	-0.0051
p-value	**0.0000**	**0.0017**	0.8130	0.9759	0.9900	0.9831	0.9722	0.9959	0.8608	**0.0000**
panel (b): short-run parameters										
$cnst$	0.0285	0.0116	0.0440	0.0266	0.0121	0.0114	0.0056	0.0283	0.0256	0.0386
p-value	0.1407	**0.0247**	**0.0387**	**0.0001**	**0.0001**	**0.0002**	**0.0005**	**0.0033**	**0.0000**	**0.0014**
$coint.\ error_{t-1}$	-0.0054	-0.0133	-0.0107	-0.0066	-0.0037	-0.0033	-0.0021	-0.0067	-0.0061	-0.0102
p-value	0.1473	**0.0007**	**0.0352**	**0.0000**	**0.0000**	**0.0002**	**0.0010**	**0.0042**	**0.0000**	**0.0061**
$\Delta pres_{t-1}$	1.3615	1.1799	1.2771	1.3343	1.3551	1.3439	1.3114	1.2267	1.0801	1.2412
p-value	**0.0000**	**0.0010**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
$\Delta pres_{t-2}$	-0.0368	-0.3780	-0.0983	-0.1029	-0.0880	-0.0646	0.0047	0.1378	0.2318	-0.0281
p-value	0.8020	0.5312	0.6457	0.3699	0.4587	0.6606	0.9596	0.2529	**0.0259**	0.9478
$\Delta pres_{t-3}$	-0.3808	-0.0178	-0.2439	-0.2860	-0.3200	-0.3272	-0.3629	-0.4183	-0.3819	-0.3345
p-value	**0.0000**	0.9533	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	0.1346
$\Delta rsrv_{t-1}$	-0.0016	-0.0019	-0.0008	-0.0001	-0.0002	0.0000	-0.0002	-0.0008	-0.0016	-0.0041
p-value	**0.0104**	0.4400	0.4014	0.6262	0.4110	0.8774	0.5991	0.1595	**0.0002**	**0.0057**
Δcds_{t-1}	0.0001	-0.0004	0.0000	0.0000	0.0000	0.0000	-0.0001	-0.0001	-0.0001	-0.0001
p-value	0.5786	0.1651	0.7725	0.9786	0.8272	0.9954	0.1821	0.3527	0.3785	0.8044
$\Delta oilp_{t-1}$	0.0001	-0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0003
p-value	0.1957	0.4889	0.1130	0.2533	0.8860	0.3177	0.7885	0.0856	0.7484	0.0809
Sample period	08/2008	~ 12/2018								
Estimated order of p	4									
Estimated order of q	2									

Table 3: ESTIMATION OF THE BENCHMARK MODEL USING LEVEL OBSERVATIONS. This table shows the two-step estimation results using the benchmark model and the error correction model. Each column in panel (a) shows the long-run parameter estimators in the error correction model and the quantile model for each quantile level in T. The long-run parameters in the error correction model are estimated by Stock and Watson's (1993) DOLS estimation, while those in the quantile model are estimated by the QARDL estimation as in Cho, Kim and Shin (2015). The columns in panel (b) show the short-run parameter estimators. The short-run parameters in the error correction model are estimated by the OLS estimation, and those in the quantile model are estimated by the quantile regression. The p-values less than 0.05 are marked by the boldface font.

τ	ECM	0.020	0.125	0.250	0.375	0.500	0.625	0.750	0.875	0.980
panel (a): long-run parameters										
cds_t	-0.0307	-0.0229	-0.0209	-0.0210	-0.0122	-0.0016	-0.0077	-0.0082	0.0033	0.0343
p-value	**0.0000**	**0.0000**	0.5367	0.8865	0.9757	0.9981	0.9810	0.9709	0.9681	**0.0000**
$oilp_t$	-0.0141	-0.0069	-0.0102	-0.0088	-0.0103	-0.0062	-0.0088	-0.0068	-0.0046	-0.0018
p-value	**0.0000**	**0.0000**	0.6423	0.9269	0.9687	0.9892	0.9664	0.9630	0.9320	0.6586
panel (b): short-run parameters										
$cnst$	0.0601	0.1308	0.0660	0.0426	0.0215	0.0188	0.0370	0.0430	0.0426	0.0496
p-value	**0.0050**	**0.0181**	**0.0275**	0.0760	0.0810	**0.0250**	0.1433	**0.0008**	**0.0006**	**0.0002**
$coint.\ error_{t-1}$	-0.0115	-0.0305	-0.0144	-0.0094	-0.0046	-0.0043	-0.0079	-0.0092	-0.0093	-0.0104
p-value	**0.0054**	**0.0126**	**0.0228**	0.0682	0.0761	**0.0246**	0.1446	**0.0011**	**0.0012**	**0.0013**
$\Delta pres_{t-1}$	1.5922	1.4275	1.5525	1.6362	1.7081	1.6819	1.5305	1.4463	1.2283	1.3707
p-value	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0001**
$\Delta pres_{t-2}$	-0.6325	-0.5550	-0.6071	-0.6735	-0.7349	-0.7046	-0.5435	-0.4745	-0.2885	-0.5180
p-value	**0.0000**	**0.0125**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	0.1065	**0.0000**	0.1671	0.1621
$\Delta rsrv_t$	0.0010	0.0005	0.0012	0.0003	0.0002	-0.0003	-0.0003	-0.0015	-0.0023	-0.0018
p-value	0.2365	0.7879	0.1635	0.6747	0.6654	0.4711	0.5586	0.0914	**0.0008**	0.4414
$\Delta rsrv_{t-1}$	-0.0018	-0.0046	-0.0009	-0.0006	-0.0003	-0.0006	-0.0009	-0.0015	-0.0020	-0.0053
p-value	**0.0324**	0.1318	0.3913	0.4149	0.3761	0.1077	0.1379	**0.0474**	**0.0025**	**0.0120**
Δcds_{t-1}	0.0002	0.0000	-0.0001	0.0000	0.0000	0.0001	0.0001	0.0001	-0.0001	-0.0003
p-value	0.2564	0.9699	0.7030	0.9163	0.8394	0.3493	0.3408	0.6856	0.4002	0.3115
$\Delta oilp_{t-1}$	0.0001	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002
p-value	0.2208	0.2385	0.9556	0.6512	0.5390	0.4138	0.4303	0.4944	0.5328	0.2374
Sample period	08/2008 $\sim$ 12/2018									
Estimated order of p	3									
Estimated order of q	2									

Table 4: ESTIMATION OF THE EXTENSIVE-FORM MODEL USING LEVEL OBSERVATIONS. This table shows the two-step estimation results, using the benchmark model and the error correction model. Each column in panel (a) shows the long-run parameter estimators in the error correction model and the quantile model for each quantile level in T. The long-run parameters in the error correction model are estimated by Stock and Watson's (1993) DOLS estimation, and those in the quantile model are estimated by the QARDL estimation as in Cho, Kim and Shin (2015). The columns in panel (b) show the short-run parameter estimators. The short-run parameters in the error correction model are estimated by the OLS estimation, and those in the quantile model were estimated by the quantile regression. The p-values less than 0.05 are marked by the boldface font.

τ	ECM	0.020	0.125	0.250	0.375	0.500	0.625	0.750	0.875	0.980
panel (a): long-run parameters										
$\log(rsrv_t)$	0.0877	0.1329	0.1405	0.1794	0.1893	0.1557	0.4292	0.1816	0.1198	-0.8056
p-value	0.2223	0.6664	0.9680	0.9876	0.9939	0.9965	0.9949	0.9899	0.9713	0.5423
$\log(cds_t)$	-0.0930	-0.1237	-0.0621	-0.0414	-0.0334	-0.0223	0.0519	0.0046	-0.0322	-0.8379
p-value	**0.0000**	0.1524	0.9495	0.9897	0.9962	0.9982	0.9978	0.9991	0.9725	**0.0237**
$\log(oilp_t)$	-0.4225	0.0242	-0.1205	-0.1581	-0.1803	-0.1701	-0.1751	-0.2257	-0.2273	-0.1507
p-value	**0.0000**	0.1524	0.9495	0.9897	0.9962	0.9982	0.9978	0.9991	0.9725	**0.0237**
panel (b): short-run parameters										
$Cnst$	0.0041	0.0102	0.0149	0.0091	0.0074	0.0071	0.0008	0.0089	0.0218	-0.0203
p-value	0.4279	**0.0001**	**0.0000**	**0.0078**	**0.0008**	**0.0014**	**0.0000**	0.0675	**0.0000**	**0.0038**
$coint.\ error_{t-1}$	-0.0013	-0.0128	-0.0110	-0.0067	-0.0053	-0.0048	-0.0023	-0.0054	-0.0111	0.0033
p-value	0.4424	**0.0000**	**0.0000**	**0.0070**	**0.0007**	**0.0015**	**0.0001**	0.0732	**0.0000**	**0.0024**
$\Delta\log(pres_{t-1})$	1.4018	1.5192	1.2915	1.3118	1.3348	1.3176	1.3242	1.2282	1.2166	1.0561
p-value	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
$\Delta\log(pres_{t-2})$	-0.0980	-0.4703	-0.2189	-0.0940	-0.0835	-0.0414	0.0119	0.0910	-0.0276	0.3907
p-value	0.5017	0.1831	0.0715	0.5610	0.5572	0.8169	0.9400	0.6339	0.7754	0.2304
$\Delta\log(pres_{t-3})$	-0.3619	-0.1086	-0.1272	-0.2625	-0.2990	-0.3146	-0.3804	-0.3723	-0.2516	-0.5901
p-value	**0.0000**	0.5017	0.0832	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0053**	**0.0000**	**0.0015**
$\Delta\log(rsrv_{t-1})$	-0.0160	-0.0847	-0.0344	-0.0149	-0.0080	-0.0093	-0.0101	-0.0175	-0.0234	-0.0013
p-value	0.1341	**0.0111**	**0.0088**	0.1178	0.1372	0.1165	0.0967	0.2044	**0.0026**	0.9626
$\Delta\log(cds_{t-1})$	-0.0001	0.0009	0.0001	0.0000	0.0000	0.0000	-0.0002	-0.0002	-0.0003	-0.0012
p-value	0.8845	0.0658	0.6998	0.8185	0.7502	0.8115	0.4488	0.6433	0.3715	0.2029
$\Delta\log(oilp_{t-1})$	0.0021	0.0092	0.0027	0.0009	0.0005	0.0008	0.0005	0.0013	0.0029	0.0046
p-value	0.1320	**0.0076**	0.1287	0.2553	0.5099	0.3864	0.6391	0.2983	**0.0223**	0.1949
Sample period	08/2008	~ 12/2018								
Estimated order of p	4									
Estimated order of q	2									

Table 5: ESTIMATION OF THE BENCHMARK MODEL USING LOG OF LEVEL OBSERVATIONS. This table shows the two-step estimation results using the benchmark model and error correction model. Each column in panel (a) shows the long-run parameter estimators in the error correction model and the quantile model for each quantile level in T. The long-run parameters in the error correction model were estimated by Stock and Watson's (1993) DOLS estimation, and those in the quantile model were estimated by the QARDL estimation in Cho, Kim and Shin (2015). The columns in panel (b) show the short-run parameter estimators. The short-run parameters in the error correction model were estimated by the OLS estimation, and those in the quantile model were estimated by the quantile regression. The p-values less than 0.05 are marked by the boldface font.

τ	ECM	0.020	0.125	0.250	0.375	0.500	0.625	0.750	0.875	0.980
panel (a): long-run parameters										
$\log(cds_t)$	-0.1094	-0.0751	-0.0977	-0.0713	-0.0582	-0.0664	-0.0442	-0.0452	-0.0378	11.9619
p-value	**0.0000**	0.1207	0.9086	0.9774	0.9907	0.9901	0.9934	0.9811	0.9604	0.0637
$\log(oilp_t)$	-0.2343	-0.1033	-0.0342	-0.1476	-0.1299	-0.1035	-0.1467	-0.1641	-0.1374	4.5478
p-value	**0.0000**	0.4592	0.9889	0.9838	0.9928	0.9947	0.9925	0.9762	0.9500	0.8069
panel (b): short-run parameters										
cnst	0.0340	0.0378	0.0204	0.0219	0.0145	0.0147	0.0163	0.0274	0.0236	-0.0051
p-value	**0.0000**	**0.0005**	**0.0000**	**0.0114**	**0.0303**	0.0808	0.1827	**0.0000**	**0.0000**	**0.0288**
$coint.\ error_{t-1}$	-0.0133	-0.0206	-0.0127	-0.0106	-0.0073	-0.0076	-0.0079	-0.0126	-0.0113	-0.0002
p-value	**0.0000**	**0.0003**	**0.0000**	**0.0107**	**0.0295**	0.0808	0.1836	**0.0000**	**0.0000**	**0.0021**
$\Delta\log(pres_{t-1})$	1.4693	1.3351	1.4217	1.5597	1.6164	1.5786	1.5044	1.3471	1.3441	0.9098
p-value	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0100**
$\Delta\log(pres_{t-2})$	-0.5116	-0.4437	-0.4583	-0.6019	-0.6475	-0.6086	-0.5305	-0.3916	-0.4072	-0.0754
p-value	**0.0000**	**0.0066**	**0.0000**	**0.0000**	**0.0001**	**0.0064**	0.1364	**0.0000**	**0.0000**	0.8202
$\Delta\log(rsrv_t)$	0.0080	0.0090	-0.0086	-0.0058	-0.0069	-0.0141	-0.0090	-0.0157	-0.0358	-0.0291
p-value	0.4711	0.6256	0.2998	0.3631	0.3308	0.1678	0.3336	0.0625	**0.0000**	0.3535
$\Delta\log(rsrv_{t-1})$	-0.0234	-0.0784	-0.0467	-0.0098	-0.0132	-0.0170	-0.0133	-0.0278	-0.0235	-0.0392
p-value	**0.0363**	**0.0113**	**0.0055**	0.2496	0.1008	0.1376	0.2464	**0.0099**	**0.0294**	0.1130
$\Delta\log(cds_{t-1})$	0.0005	0.0003	0.0001	0.0002	0.0002	0.0003	0.0002	0.0001	-0.0001	-0.0018
p-value	0.2977	0.5287	0.7217	0.5330	0.1978	0.2511	0.4376	0.8322	0.7057	0.1502
$\Delta\log(oilp_{t-1})$	0.0025	0.0074	0.0048	0.0017	0.0014	0.0015	0.0013	0.0006	-0.0002	0.0003
p-value	0.0784	**0.0315**	0.1678	0.2816	0.1760	0.2457	0.3367	0.6553	0.8770	0.9500
Sample period	08/2008 $\sim$ 12/2018									
Estimated order of p	3									
Estimated order of q	2									

Table 6: ESTIMATION OF THE EXTENSIVE-FORM MODEL USING LOG OF LEVEL OBSERVATIONS. This table shows the two-step estimation results using the benchmark model and error correction model. Each column in panel (a) shows the long-run parameter estimators in the error correction model and the quantile model for each quantile level in T. The long-run parameters in the error correction model were estimated by Stock and Watson's (1993) DOLS estimation, and those in the quantile model were estimated by the QARDL estimation in Cho, Kim and Shin (2015). The columns in panel (b) show the short-run parameter estimators. The short-run parameters in the error correction model were estimated by the OLS estimation, and those in the quantile model were estimated by the quantile regression. The p-values less than 0.05 are marked by the boldface font.