Energy Economics 54 (2016) 11–23

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

The impact of oil shocks on exchange rates: A Markov-switching approach

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ARTICLE INFO

Article history:
Received 24 April 2015
Received in revised form 8 October 2015
Accepted 4 December 2015
Available online 13 December 2015

Keywords:
Markov-switching
Exchange rates
Oil shocks

ABSTRACT

This paper uses Markov-switching models to investigate the impact of oil shocks on real exchange rates for a sample of oil exporting and oil importing countries. This is an important topic to study because an oil shock can affect a country's terms of trade which can affect its competitiveness. We detect significant exchange rate appreciation pressures in oil exporting economies after oil demand shocks. We find limited evidence that oil supply shocks affect exchange rates. Global economic demand shocks affect exchange rates in both oil exporting and importing countries, though there is no systematic pattern of appreciating and depreciating real exchange rates. The results lend support to the presence of regime switching for the effects of oil shocks on real exchange rates.

1. Introduction

Numerous studies have explored the empirical relationship between oil prices and exchange rates with mainly three different types of econometric tools: cointegration methods, Granger-causality tests, and vector autoregression (VAR) models. An example for the application of linear cointegration tests to this relationship is Amano and van Norden (1998a). They find evidence, as did others, in favor of cointegration between the real price of oil and the real effective US dollar exchange rate over the period from 1972 to 1993. In addition, real oil prices are shown to Granger-cause real exchange rates and an oil price increase leads to an appreciation of the US dollar in the long run. Bénassy-Quéré et al. (2007) confirm this result with data up to 2004 using similar econometric tools. However, they observe that in the period from 2002 to 2004 the US dollar depreciated while the oil price increased and suggest that a structural break, or regime change, occurred in 2002, though the post-break sample is too small to meaningfully test for breaks. Sadorsky (2000) studies linear vector error-correction models and associated Granger causality for futures prices of crude oil with a trade-weighted index of exchange rates. Cointegration is supported and exchange rates transmit exogenous shocks to energy futures prices in the period 1987 to 1997.

Reboredo (2012) considers instead linear and non-linear correlation, along with copula functions that capture symmetric, asymmetric and time-varying co-movements between the nominal oil price and various US dollar exchange rates for several oil exporting and oil importing, as well as developed and emerging economies, in the period 2000 to 2010. Co-movement is found to be weak, especially among oil-importing countries, but has generally increased after the global financial crisis from mid-2008, a break date associated with the global economic recession. On the other hand, Akram (2009) applies a structural VAR model and finds instead that a weaker (real) US dollar leads to higher real oil prices in the period 1990 to 2007. Fratzscher et al. (2014) also employ a structural VAR that includes the effective US dollar exchange rate along with a measure of options exchange market volatility and a proxy for the financialization of the oil market. Five episodes of different time-varying correlation (heteroscedasticity) regimes are calculated from VAR residuals in order to aid with the identification of structural shocks. They find bi-directional causality between the US dollar and nominal oil prices since the early 2000s. They claim that their model can account for the strong and rising negative correlation between oil prices and the US dollar since the early 2000s.

In a previous paper (Basher et al., 2012), we have used a structural VAR in order to model the oil market with oil supply and demand as advocated in a seminal paper by Kilian (2009), in contrast to the above studies that do not separate out the underlying sources of the oil price movements. Kilian (2009) shows that the impact of oil price changes on the economy depends upon whether the oil price change originates from an oil supply shock, an oil-market specific demand shock, or a global economic demand shock. We find in our paper no significant effects of oil supply shocks on the exchange rate for emerging economies, whereas a positive global demand shock leads to a depreciation of the US dollar, which appears consistent with a declining US dollar over the period 2002–2008. However, we did not explore structural changes.

In this paper, we contribute to the literature by allowing for nonlinearity for the effects of the three oil shocks, constructed according to

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http://dx.doi.org/10.1016/j.eneco.2015.12.004
0140-9883/

Kilian (2009), on real exchange rates for a set of representative oil exporting and oil importing countries at the developed level and the emerging economies level: Canada, Norway and the United Kingdom; Brazil, Mexico, and Russia; and India, Japan and South Korea. The nonlinearity that we consider is in the form of different regimes for the effects of the three oil shocks, with constant parameters within a regime but different parameters across regimes. We apply the Markov-switching model for this purpose.[1] Hamilton (1994, Ch. 22) gives an introduction to Markov-switching models. The Markov approach allows for time-varying causality across regimes instead of linear models with constant parameters and no regime (structural) changes. The Markov-switching model has the advantage that it uses in the estimation information about the varying regime-switching probabilities of being in a particular regime instead of a linear model that would have to be estimated for each regime completely separately. Estimation with linear models is therefore often not feasible due to sub-samples being too small when there are several breaks present in a sample. In other words, more observations are used for estimation in a Markov regime approach. The estimation of parameters in one regime uses partly the dynamics of the system in another regime.[2] Furthermore, to keep the Markov-switching model parsimonious, we limit ourselves to a two-regime Markov-switching model. This is motivated by the work of Engel and Hamilton (1990), Dumas (1992), and Engel (1994). Dumas (1992) shows that, under the assumption of spatially separated countries and shipping costs, the real exchange rate switches between two states and exhibits mean reversion within each regime. Engel and Hamilton (1990) and Engel (1994) show that a simple two-state Markov-switching random walk model with drift allowing both the constant term and variance of innovations to vary during times of appreciation and depreciation is a fitting representation of nominal exchange rate regimes. On the other hand, Mork (1989) argues for asymmetric effects of oil price changes, with increases in the real price of oil having much more predictive power for US real output growth than declines. Hamilton (2003, 2008, 2009) uses a net oil price increase as the relevant variable to model the effect of oil prices on the economy. His oil price measure includes only oil price increases that represent new highs relative to the recent experience, or reversals of recent decreases. Various definitions have been used with varying degrees of looking backwards to determine new highs of the oil price.[3] Instead, the Markov-switching model has the advantage that it determines regimes from the data without imposing a strict formula for switches as Hamilton's net oil price does. The Markov-switching model has recently been applied to the relationship between oil prices and exchange rates by Beckmann and Czudaj (2013). They use a different framework and do not study the sources of price shocks, as we do, when analyzing the Markov-switching dynamics between oil prices and exchange rates. Their short-run nonlinear error-correction follows a Markov-switching regime that is embedded within a long-run linear cointegrating relationship (with no Markov-switching).

We follow Kilian (2009) and apply a two-stage approach to examine the response of real exchange rates of selected individual countries to oil shocks. We first estimate a structural VAR model à la Kilian (2009) based on monthly data and use a Cholesky decomposition to obtain three different structural shocks: global economic demand, oil supply and oil-market specific demand shocks. We then analyze the impact of these shocks on real exchange rates in a Markov-switching framework that captures the dynamic relationship between oil prices and exchange rates across different regimes within our sample. We find significant currency appreciation in oil exporting economies after an oil demand shock but not for an oil supply shock. The adjustment of exchange rates to a global economic demand shock reveals no particular pattern across oil-exporting or oil-importing countries. Our results support the presence of regime switching for the effects of oil shocks on real exchange rates.

The paper is organized as follows. Section 2 offers a brief discussion of theoretical transmission channels between oil prices and exchange rates and an overview of the related literature. Section 3 discusses the empirical strategy, whereas Section 4 describes the data. Section 5 presents the empirical results. Section 6 concludes the paper.

2. Theoretical considerations and literature review

From a theoretical perspective, an oil price shock may be transmitted to a country's exchange rate through two distinct channels: the terms of trade and wealth effect channels. The terms of trade channel impacts both oil-exporting and oil-importing countries, albeit in different ways (e.g., Amano and van Norden, 1998a,b; Backus and Crucini, 2000; Cashin et al., 2004; Chen and Rogoff, 2003; Corden and Neary, 1982). For oil-importing countries, an increase in oil prices generally leads to a deterioration of the trade balance and subsequently to a depreciation of the local currency (Fratzscher et al., 2014). Whereas, for the oil-exporting countries, a positive terms of trade shock may eventually lead to a Dutch Disease phenomenon by driving up the price of the non-tradable goods and an appreciation of the real exchange rate (Buetzer et al., 2012). Empirical evidence for this view is provided by Backus and Crucini (2000), who showed that the variation in oil prices determines most of the variation in the terms of trade.

The distinction between oil-exporting and oil-importing countries appears particularly relevant when we consider transmission through the wealth effect channel. According to this view, an increase in oil prices is associated with wealth transfer from oil-importers to oil-exporters, which leads to a real depreciation (appreciation) of the exchange rates of oil-importing (oil-exporting) economies through current account imbalances and portfolio reallocation, respectively (e.g., Buetzer et al., 2012; Fratzscher et al., 2014; Rasmussen and Roitman, 2011). The basic theoretical framework of this channel is developed by Golub (1983) and Krugman (1983), whereas the related empirical evidence can be found in Bénassy-Quéré et al. (2007), Kilian et al. (2009), and Bodenstein et al. (2011).

The empirical literature on the relationship between oil prices and exchange rate has evolved along multiple directions. Early research on the relationship between oil prices and exchange rates often used cointegration techniques and many studies have found evidence of an appreciation of the US dollar in response to rising oil prices (e.g., Amano and Van Norden, 1998a; Bénassy-Quéré et al., 2007; Chen and Chen, 2007; Coudert et al., 2008). Coudert et al. (2008) find that real oil prices, the real US dollar effective exchange rate and US net foreign assets are cointegrated. Based on their analysis, oil prices affect exchange rates through the impact that oil prices have on US net foreign assets. Cashin et al. (2004) investigate the relationship between the exchange rates of commodity exporting countries and the real prices of commodity exports for a sample of 58 developing countries. For approximately one third of the countries studied, they find a long-run relationship between exchange rates and commodity prices. Cheng (2008) estimates an error correction model between commodity prices, the US dollar, world industrial production, the Federal Funds rate, and commodity inventories. He finds that higher oil prices are associated with a depreciating US dollar and the effect is strongest over a period of several years. Lizardo and Mollick (2010) use cointegration techniques and find that an increase in the real price of oil leads to a depreciation of the US dollar against the currencies of oil exporters like Canada, Mexico, and Russia. For oil importers, an

[1] We rely on stationary variables. The oil shocks in our analysis are generally covariance-stationary variables, as are the real exchange rate returns (expressed as first differences of the logs of real exchange rates) for the various countries. Hence, cointegration modeling is not called for in our framework.

[2] An alternative approach to ours would be a threshold or smooth transition model with an exponential or logistic transition function (Granger and Teräsvirta, 1993). However, this approach requires choosing a variable that triggers the transition between usually two or three regimes with abrupt (threshold) or smooth transition. It is not obvious which variable could fulfill that function in the relationship between the three oil price shocks and exchange rates. The transition variable is not a variable that is observable and it could feasibly be a different transition variable for each of the three oil shocks considered here.

[3] Kilian and Vigfusson (2011a,b) discuss further econometric complications with this measure of oil prices. See also the reply by Hamilton (2011).

increase in oil prices leads to a depreciation of local currency. Exchange rate forecasting models that include oil, tend to outperform those without oil. Akram (2009) estimates a structural VAR on quarterly data of OECD industrial production, real US short-term interest rates, the real trade weighted US dollar exchange rate, and commodity prices (one of which is oil). He finds that a dollar depreciation is associated with higher commodity prices. In reviewing the large and growing literature on the relationship between exchange rates and oil prices, Coudert et al. (2011) find a long-run elasticity between commodity prices and exchange rates of 0.5 for commodity exporting countries and an elasticity value of 0.3 for oil exporting countries.

Given the uncertainty about the direction of causality between oil prices and asset prices (including exchange rates), Fratzscher et al. (2014) use an identification procedure in a structural VAR that exploits the heteroscedasticity in the data that allows them to separate the contemporaneous causality between oil prices and exchange rates from changes due to other observable and unobservable factors. Their results reveal that the causality between exchange rates and oil prices runs in both directions: a 10% increase in the price of oil leads to a 0.28% depreciation of the US dollar effective exchange rate on impact; whereas, a weakening of the US dollar by 1% causes oil price to rise by 0.73%. Interestingly, their variance decomposition shows that a good portion of the observed negative oil price–exchange rate correlation is explained by risk shocks (e.g., the 2008–09 global financial crisis) and the financialization process of oil markets. These results are in line with Grisse (2010) and Beckmann and Czudaj (2013) who also find that the causality runs in both directions.

In contrast to the above studies, Buetzer et al. (2012) use a two-step approach that is similar to ours (in this paper) in the context of assessing the impact of oil price shocks on exchange rates.[4] They first obtain different oil shocks using Kilian's (2009) framework, and then analyze their impact on nominal and real exchange rates, as well as stock returns, for a large database comprising 44 advanced and emerging countries. Contrary to the predictions of the theory, they find no evidence of a systematic relative appreciation of oil exporters' currencies against those of oil importers' following oil shocks that increase the real price of oil. However, they document that an oil demand shock exerts significant appreciation pressures on currencies of oil exporters, which they tend to counter by accumulating foreign exchange reserves. Basher et al. (2012) extend Kilian's (2009) three-variable structural VAR model of the crude oil market with other key macroeconomic variables and use a much less restrictive set-up (i.e., a non-recursive identification scheme) for the analysis of oil shocks in the context of emerging markets. We find in that paper no visible effects of oil supply shocks on the exchange rates, whereas an unanticipated global demand expansion has a downward (i.e., depreciation) impact on the US dollar. In comparison, the impact of a positive oil demand shock is negative (reflecting the so-called *numeraire* effect) and lasts only for five months. This finding supports the conclusion that exchange rate movements are determined primarily by current account movements (Krugman, 1983). Recently, Atems et al. (2015) apply Kilian's (2009) methodology to examine the impact of oil shocks on exchange rates of six developed countries. Their linear model shows that following an oil-specific demand shock, exchange rates depreciate and the response is identical across oil exporting and importing countries. They also consider a nonlinear specification, where nonlinearity (or asymmetry) is defined depending on whether shocks are large/small or positive/negative. In general, they find that large and positive shocks have more significant bearings on exchange rates, than small and negative shocks.

We differ from Buetzer et al. (2012) by incorporating nonlinearities for the effects of the various oil shocks on exchange rates by modeling a Markov-switching process. Beckmann and Czudaj (2013) also apply the Markov-switching model to study the relationship between oil prices and exchange rates. However, they do not model the oil market as in Kilian (2009) and hence do not separate out the sources of oil price shocks. They use a vector-error correction model (VECM) with the monthly oil price, the domestic CPI, the foreign (US) CPI, and the exchange rate against the US dollar from mostly the 1970s to 2011. In addition, comparatively few studies have examined the question of how the impact of oil price shocks differs between oil-exporting and oil-importing countries. For oil-exporting countries, Beckmann and Czudaj (2013) document a causality from exchange rates to oil prices for Brazil, Canada and Russia, whereas for Mexico and Norway an increase in oil prices is related to a depreciation against the dollar. In contrast, their results do not provide a clear pattern of causality for oil-importing countries. They also document evidence of nonlinear adjustment between oil prices and exchange rates stemming from different degrees of volatility and co-movements between these two quantities, as well as oil price shocks triggered by exogenous factors. Similar asymmetric adjustments between oil prices and exchange rates have also been documented by Reboredo (2012), who found that the oil–exchange rate co-movement has intensified in the aftermath of the global financial crisis.[5] This result is somewhat different than that of Fratzscher et al. (2014), who documented a steep decline in the correlation between exchange rates and oil prices during the period of the financial crisis in a linear VAR.

The Markov-switching approach in a VAR (MS-VAR) has been applied in addition to study changes in Granger causality when regimes switch for the relationship between oil prices and stock markets. Balcilar and Ozdemir (2013) use monthly data for crude oil futures prices and a sub-group of the Standard and Poor's (S&P) 500 index in a two-variable MS-VAR with four regimes. For the period from 1995 to 2011, they find that oil futures prices predict the S&P 500 subgroup index but not vice versa. Further, Balcilar et al. (2015) use a Markov-switching model with two regimes, a low and high volatility regime, in a VECM setting. They examine the impact of oil price shocks on the S&P 500 index for monthly data from 1859 to 2013. They find in this two-variable model that high volatility regimes are more prevalent prior to the Great Depression and after 1973. They also detect a tendency towards high volatility in recessionary periods.

3. Empirical approach

We employ a two-stage approach where we first construct the demand and supply shocks in the crude oil market using the identification procedure developed by Kilian (2009). Then, we empirically assess in the second stage the responses of exchange rates of selected oil-exporting and oil-importing countries to the demand and supply shocks in the crude oil market in a Markov-switching framework. In a regression context, this means that the thus constructed oil shocks are orthogonal variables. Such variables are, as long as orthogonality holds, uncorrelated with other included and other omitted regression variables in the second-stage analysis and their regression coefficient estimates are unbiased. In this case, the only effect of omitted variables is to increase the residual variance in the second stage Markov-switching regressions.

The Markov-switching model captures potential nonlinearity or asymmetry in the process that drives the adjustment of the exchange rate to oil shocks. The Markov-switching framework has been proven to be useful in cases where the adjustment seems to be mainly driven by exogenous events. There are numerous examples of such events in our sample period: the Iranian revolution in 1979, the Iraqi invasion of Kuwait in 1990, the Asian financial crisis in 1997/98, production target cuts by OPEC in 1999, the dot-com bubble crisis in 2000, the terrorist attack on the World Trade Center in 2001, the Iraq War in 2003, the Global Financial Crisis in 2007/08, OPEC oil production cuts in 2009, and the

[4] Baxter (1994), Huizinga (1987) and Clarida and Gali (1994) establish the importance of real shocks in affecting exchange rates.

[5] He applied non-linear measures of dependence: Spearman's rho, Kendall's tau and tail dependencies in copulas.

European sovereign debt crisis starting in 2009, among others. We would like to emphasize that these events are treated as exogenous only with respect to triggering a regime switch for the Markov process and not with respect to their effects on the oil market and macroeconomic variables because we use Kilian's (2009) approach to modeling the relationship between oil market events and the macro-economy. In other words, the Markov regime generating process is exogenous. Furthermore, the correlation between oil prices and exchange rates has historically fluctuated between positive and negative values. For example, the recent decline in oil prices has interesting parallels with the collapse in oil prices in 1985–86, when the price of oil declined by 61% (from \$24.68 to \$9.62 per barrel) between January and July 1986 (World Bank, 2015). However, unlike today, the US dollar appreciated sharply during 1980–84 before depreciating even more sharply in 1985–87. This nonlinear or asymmetric interaction between oil prices and exchange rates can be suitably captured by using the two-regime Markov-switching model.[6]

3.1. The identification of global oil shocks

The starting point of the analysis is a structural VAR (SVAR) model specified as

$$A_0 y_t = A(L) y_{t-1} + \varepsilon_t \tag{1}$$

where y_t includes (i) global oil production, (ii) a measure of global economic activity and (iii) the real oil price in US dollars, described further in the Data section; ε_t denotes the vector of serially and mutually uncorrelated structural innovations that have an economic interpretation. The structural innovations are derived by imposing exclusion restrictions on A_0^{-1} in $e_t = A_0^{-1}\varepsilon_t$, where e_t is a vector of errors in a VAR (see Kilian, 2009):

$$y_t = A_0^{-1} A(L) y_{t-1} + A_0^{-1}\varepsilon_t. \tag{2}$$

In particular, the three structural shocks are attributed as follows: ε_{1t} denotes shocks to the global supply of crude oil (hereafter "oil supply shock"); ε_{2t} represents shocks to the global demand for all industrial commodities that are driven by global real economic activity (aggregate demand shock); and ε_{3t} captures an oil-market specific demand shock (oil-specific demand shock). The identification of A_0^{-1} in Eq. (2) is achieved by imposing the following exclusion restrictions:

$$e_t = \begin{pmatrix} e_{1t}^{\Delta prod} \\ e_{2t}^{rea} \\ e_{3t}^{rpo} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{\text{oil supply shock}} \\ \varepsilon_{2t}^{\text{aggregate demand shock}} \\ \varepsilon_{3t}^{\text{oil-specific demand shock}} \end{pmatrix}. \tag{3}$$

The identifying restriction in this structural model assumes that crude oil supply (production) does not respond to innovations to the demand for oil within the same month; i.e., the short-run supply curve of crude oil is vertical. Next, global real economic activity is driven by shocks that are specific to the oil market, but with a delay of at least a month. This restriction is in line with the sluggish adjustment of global real economic activity due to movements in oil prices. Finally, the real price of oil is assumed to respond to innovation to both oil production and global real economic activity within the same month. This restriction is plausible as any exogenous changes in crude oil supply or the real economy are immediately reflected in oil prices. See Kilian (2009, pp. 1059–1060) for a more detailed explanation on these identification schemes. In the estimation of the SVAR we follow Kilian (2009) and use the first difference of the natural logarithm of world oil supply, the detrended index of real global economic activity, and the natural logarithm of real oil prices.

As is quite common in the empirical VAR literature, we follow Kilian (2009) and do not impose unit roots and cointegration on the VAR.[7] Sims et al. (1990) show that consistent parameter estimates can be obtained by applying least squares to levels VARs, even when unit roots and cointegration are ignored. Hamilton (1994, pp. 651–653) provides further discussion on this approach and points out pitfalls of imposing invalid cointegration restrictions.

3.2. Markov-switching

As a starting point and in order to provide some baseline results, a linear regression model is estimated for each exchange rate.

$$\Delta fx_{i,t} = \beta_{0,i} + \beta_{1,i}\varepsilon_{i,t}^s + \beta_{2,i}\varepsilon_{i,t}^d + \beta_{3,i}\varepsilon_{i,t}^p + \beta_{4,i}\Delta fx_{i,t-1} + u_{i,t} \tag{4}$$

where $\Delta fx_{i,t}$ is the first difference of the log real exchange rate for country i. The oil shock variables are from the SVAR model described in the previous section (oil supply shock (ε^s), global economic demand shock (ε^d), oil demand shock (ε^p)). Notice that we make the assumption that the oil shocks are pre-determined. This is consistent with Kilian (2009, pp. 1065–1066). We also do not include lags of the oil shocks as explanatory variables because exchange rate markets are very efficient and new information is quickly absorbed by the exchange rate market when the shock occurs. A one period lag of the dependent variable is included as an explanatory variable because this specification provided better regression fit and residual diagnostics than a model without the lagged dependent variable.

In order to account for the possible non-linear relationship between real exchange rates and oil shocks, a Markov-switching model for Eq. (4) is specified as follows.

$$\Delta fx_{i,t} = \beta_{0,i,s_t} + \beta_{1,i,s_t}\varepsilon_{i,t}^s + \beta_{2,i,s_t}\varepsilon_{i,t}^d + \beta_{3,i,s_t}\varepsilon_{i,t}^p + \beta_{4,i,s_t}\Delta fx_{i,t-1} + u_{i,t}. \tag{5}$$

The Markov-switching model takes into account the possibility that the impact of oil shocks on exchange rates is state (s_t) dependent. The probability of transition from state l at time period t to state m at time period $t+1$ depends upon the state at time period t and not any other state.[8] It is assumed that the stochastic regime generating process follows an ergodic, homogeneous, first-order Markov chain with a finite number of regimes (M) and constant transition probabilities.

$$p_{lm} = \Pr(s_{t+1} = m s_{t+1} = l),\ p_{lm} \geq 0, \sum\nolimits_m^M Plm = 1. \tag{6}$$

The Markov-switching models for exchange rates were estimated using the fMarkovSwitching package in R (Perlin, 2008). The models were estimated with two states, state dependent regression coefficients and state dependent volatility for the error process. Exchange rates are known to exhibit volatility clustering which is why we allow volatility to vary across regimes. Models were estimated using two different assumptions about the error term (normal, Student-t).

Since the Markov chain is unobservable, the estimation output includes the probabilities of being in a specific state. A good fitting Markov-switching model is one that provides a sharp classification of

[6] For an application of the two-regime Markov-switching model to capture US business cycle expansion and contraction phases (regimes) that closely match the dates established ex-post by the National Bureau of Economic Research, see Hamilton (1989). Hamilton (1990) provides the econometric theory for Markov switching. In addition, Engel and Hamilton (1990), Engel (1994), and Bergman and Hansson (2005) conclude that several real exchange rates can be described by a Markov switching autoregressive model.

[7] Standard tests show clear evidence in favor of unit roots and cointegration for the change of the log of global oil production and the log of the real oil price, which are the variables that we used in our VAR. On the other hand, the global economic activity index is stationary in levels.

[8] It should be noted that, within each regime, the Markov switching is conditionally linear; and the switching between regimes is inherently stochastic. The switching between regimes is assumed to be stochastic based on a time-varying transition probability matrix. In our model, the transition probability matrix changes depending on the values of the intercept, the variance, the three oil shocks and the one period lag of the dependent variable.

regimes and has smoothed probabilities that are either close to one or zero. The regime classification measure (RCM) of Ang and Bekaert (2002) is used to determine the accuracy of the Markov-switching models. This statistic is computed using the following formula:

$$RCM(S) = 100S^2 \frac{1}{T} \sum_{t=1}^{T} \prod_{j=1}^{S} \tilde{p}_{j,t}. \quad (7)$$

The RCM is computed as the average of the product of smoothed probabilities $\tilde{p}$, where S is the number of regimes (states, S). The switching variable follows a Bernoulli distribution and as a result, the RCM provides an estimate of the variance. The RCM statistic ranges between 0 (perfect regime classification) and 100 (failure to detect any regime classification) with lower values of the RCM preferable to higher values of the RCM. Thus to ensure significantly different regimes, it is important that a model's RCM is close to zero and its smoothed probability indicator be close to 1.

4. Data

For this study, monthly data are required on world oil supply, global real economic activity, oil prices, and exchange rates. Real oil prices in dollars per barrel are measured using US refiner acquisition cost of crude oil (http://www.eia.gov/petroleum/data.cfm#prices) deflated by the US CPI. World oil supply (in millions of barrels per day) and oil prices are sourced from the US Energy Information Administration (http://www.eia.gov/totalenergy/data/monthly/index.cfm). An index of global real economic activity is taken from Lutz Kilian's website (http://www-personal.umich.edu/~lkilian/paperlinks.html). The data are similar to those used by Kilian (2009) and Kilian and Park (2007).

Nominal exchange rate data for Brazil, Canada, Mexico, Norway, India, Japan, South Korea, and the United Kingdom are sourced from the St. Louis Federal Reserve's FRED database (http://research.stlouisfed.org/fred2/categories/15). Except for the UK, exchange rates are quoted as foreign currency per US dollar. For the UK, the exchange rate is quoted as US dollars per pound.[9] Nominal exchange rates are converted to real exchange rates using the appropriate price (CPI) ratio between the two countries. The CPI data are available from the OECD (http://stats.oecd.org/Index.aspx?querytype=view&queryname=221). The exchange rate between the Russian ruble and the US dollar is sourced from Quandl (https://www.quandl.com/). Brazil, Canada, Mexico, Norway, and Russia and the United Kingdom are classified as oil exporting countries. The United Kingdom became a net oil importer in 2005 but for most of the estimation period, the UK was a net oil exporter. India, Japan, and South Korea are classified as oil importing countries. The estimation sample period varies by country due to data limitations. For Canada, Norway, India, Japan, and the United Kingdom, models are estimated over the period February 1976 to February 2014. For the other countries the estimation period is: Brazil (February 1995 to February 2014), Mexico (December 1993 to February 2014), Russia (February 1998 to February 2014), and South Korea (May 1981 to February 2014). Consistent with previous studies, our choice of countries is determined by data availability of large oil exporting or importing countries with flexible exchange rates. Some large oil exporters (e.g., countries in the Middle East) and large oil importers (China) are excluded from our analysis because they have exchange rates fixed to the US dollar.

Analysis is conducted for a group of oil exporting countries (Brazil, Canada, Mexico, Norway, Russia and the United Kingdom) and oil importing countries (India, Japan, South Korea). The plots of real exchange rates for oil exporting countries (Fig. 1) and oil importing countries (Fig. 2) show that each real exchange rate has experienced considerable variability across time. The real exchange rates of Mexico and Russia show a sharp appreciation followed by a long slow depreciation. The Indian real exchange rate has appreciated slightly over the sample period while the Japanese real exchange rate has depreciated. Notice that for several of the countries (Brazil, Canada, Mexico, Norway, South Korea, and the UK) the starting and ending values for their respective real exchange rates are similar.

The structural oil supply, demand, and oil price shocks are derived from the SVAR in Eq. (2). The SVAR was estimated with 24 lags. All of the characteristic roots are within the unit circle and the residuals are randomly distributed indicating a good fit for the SVAR. The structural shocks are plotted in Fig. 3. Oil supply shocks show more variability in the first half of the data sample. Global economic demand shocks show more variability after the 2008–2009 global economic recession. Oil demand shocks display more variability in the latter portion of the plot.

For each country, monthly real returns on exchange rates are constructed using $r_t = 100 * \ln(p_t / p_{t-1})$ where p_t is the real exchange rate in period t. Summary statistics on the shocks and real exchange rate returns are presented in Table 1. The mean value of each of the three shock variables is zero (to three decimal places) and each shock has a standard deviation close to unity. Each shock displays similar variability (difference between the maximum value and minimum value). Average exchange rate returns are small compared to their respective standard errors. The Russian Ruble has the greatest amount of variability (as measured by the difference between the maximum and minimum values). The currencies of Canada and Norway have the least variability. Compared to the other currencies, the currencies of Russia and South Korea have very high amounts of kurtosis. According to the Shapiro–Wilk test (normtest.w and p-values denoted by normtest.p in Table 1), none of the variables are distributed normally.

In order to further investigate the time series properties of the data, a series of unit root tests were conducted for each data series (Table 2). Two versions of the Elliot, Rothenberg and Stock (1996) Dickey–Fuller unit root test (DF-GLS) are shown: one with a constant (c) term and one with a trend (t). For these tests, 12 lags were chosen. In addition two versions of the Kwiatkowski et al. (1992) KPSS tests are calculated (one with a constant (μ) and one with a trend (τ)). For the KPSS tests, the number of lags, for a sample size of n, was chosen according to $\sqrt[4]{4 \times \left(\frac{n}{100}\right)}$.[10] In summary, there is ample evidence that each variable is stationary. Based on the DF-GLS and KPSS test results, the three oil shocks seems to follow stationary processes, except for the DF-GLS test with a deterministic time trend for the supply shock. Further, the DF-GLS test supports that the real exchange rate returns follow stationary processes at the 5% significance level for almost all cases, whether a trend is included or not, except for India where only the trend specification supports it and Canada where the "constant only" case is supported at the 10% level. The KPSS test results are in agreement with these results, except that for stationarity for Russia requires excluding the trend.

The BDS test (Brock et al., 1987; Brock et al., 1996) is used to investigate the spatial dependence of the real exchange rate returns. The BDS test is one of the most popular tests for nonlinearity. This test is carried out by testing if increments to a data series are independent and identically distributed (iid). This test is asymptotically distributed as standard normal under the null hypothesis of iid increments. The BDS test is based on the concept of a correlation integral. A correlation integral is

[9] We have stayed with the conventional way of quoting currency. Since the US dollar is the dominant traded currency, most exchange rates are quoted in direct form (the amount of foreign currency one US dollar buys). Currencies for commonwealth countries like England and Australia are, for historical reasons, quoted in indirect form (e.g., how much US currency one British pound buys). We have decided to stay with this convention.

[10] Kwiatkowski et al. (1992) study the performance of the KPSS test in Monte Carlo simulations when the lag length is increased in small samples of typical size encountered in applications. They find that there is a trade-off between better size properties and a loss of power. They look at replacing 4 under the radical with 12 and find that power losses are quite large, though size accuracy improves. They point out that, in contrast to other related tests, the distribution of their test under the alternative hypothesis depends on the ratio of lags to sample size, even asymptotically, so that choosing more lags will cost power. Hence, we opt for less lags here in order to achieve reasonable test powers, as recommended by Kwiatkowski et al. (1992). However, we also re-estimated the KPSS tests using 12 lags and found the results to be similar to those reported in Table 2.

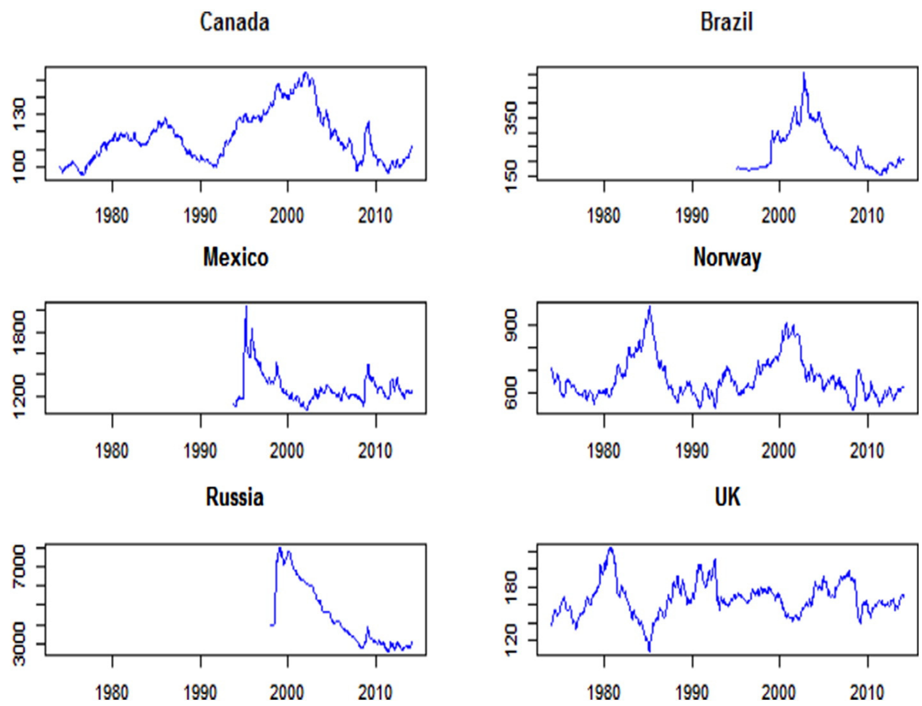

Fig. 1. Real exchange rates — oil exporting countries.

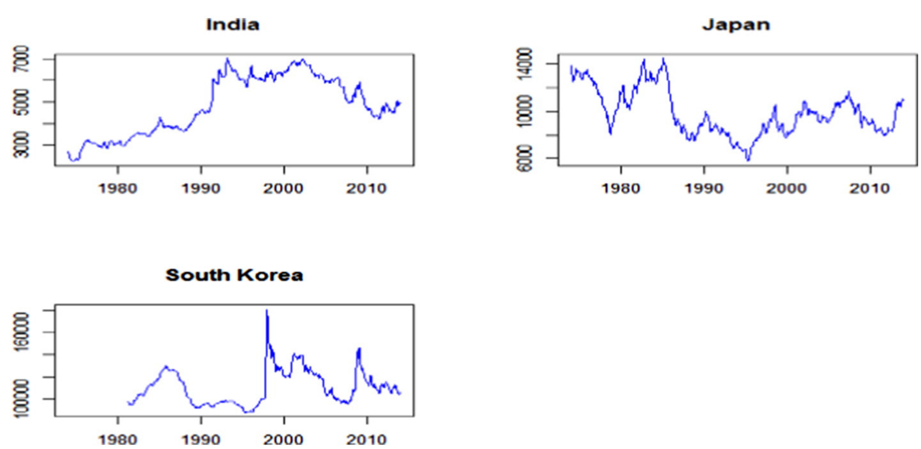

Fig. 2. Real exchange rates — oil importing countries.

a measure of the frequency with which temporal patterns are repeated in the data. For each real return exchange rate series, the null hypothesis that the data are iid is rejected for most combinations of m (embedding dimension) and ε (epsilon value for close points) at conventional levels of significance (Table 3). The plots of the real exchange rates (Figs. 1 and 2) indicate little evidence of a linear structure. This observation combined with the results from the BDS test indicates there is likely to be a nonlinear structure in the real foreign exchange rate data.

5. Results

5.1. The impact of oil shocks on real exchange rates

As a first look at the impact of oil shocks on real exchange rates, a series of linear regression models (Eq. (4)) is estimated where each country's real exchange rate (FX) monthly return is regressed on the oil shocks and a one period lag of the real exchange rate monthly return (Table 4). These results can be viewed as baseline results showing the relationship between real exchange rates and oil shocks in the absence of any switching effects. The R-squared values for these regression range from a low of 0.0450 (Mexico) to a high of 0.1976 (South

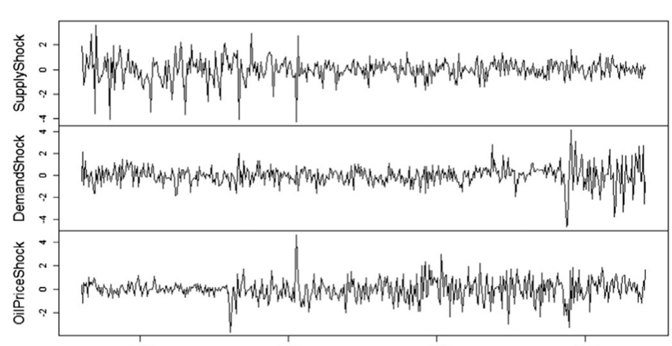

Fig. 3. Oil supply shocks, global economic activity demand shocks, and oil price shocks.

Table 1
Summary statistics on oil shocks and monthly real exchange rate returns.

	Supply	Demand	Oil	BRA	CAN	MEX	NOR	RUS	UK	IND	JAP	KOR
Observations	457	457	457	229	457	243	457	193	457	457	457	394
Min	−4.267	−4.664	−3.607	−11.785	−6.421	−15.775	−5.698	−6.904	−11.180	−6.367	−10.951	−8.571
Max	3.625	4.156	4.618	23.282	11.320	31.704	11.751	58.057	11.185	17.345	8.229	34.256
Median	0.035	0.012	0.046	−0.193	0.000	−0.390	−0.052	−0.601	0.034	0.039	0.139	−0.044
Mean	0.000	0.000	0.000	0.071	0.027	0.040	−0.009	−0.137	0.020	0.105	−0.042	0.021
SE.mean	0.043	0.043	0.043	0.270	0.069	0.231	0.112	0.356	0.117	0.091	0.133	0.137
Std.dev	0.918	0.918	0.917	4.080	1.481	3.608	2.385	4.947	2.502	1.942	2.840	2.726
Skewness	−0.682	−0.382	−0.028	1.783	0.628	3.187	0.265	8.606	−0.024	1.736	−0.501	5.496
Kurtosis	4.023	4.197	2.025	8.863	7.636	26.635	0.917	96.837	1.915	14.115	0.876	65.110
normtest.W	0.938	0.947	0.981	0.857	0.943	0.726	0.989	0.434	0.982	0.898	0.983	0.635
normtest.p	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000

Supply denotes a global oil supply shock, Demand denotes a shock to global economic activity, and Oil denotes a shock to global oil prices.

Korea). For each country the one period lag of exchange rates has a positive and statistically significant coefficient with values ranging from a low of 0.0677 (Russia) to a high of 0.4374 (S. Korea) indicating a low to moderate degree of persistence in the real exchange rates. The results indicate that oil supply shocks have no statistically significant effects on real exchange rates in any country. This is consistent with the findings in Atems et al. (2015). For Canada, demand and oil price shocks each have negative and statistically significant impacts on real exchange rates. Shocks to these variables weaken the real \$C/\$US exchange rate which corresponds to an appreciation of the Canadian dollar relative to the US dollar. For Norway and Russia, the estimated coefficient on the oil price shock variable is negative and statistically significant. For the United Kingdom, the estimated coefficient on the demand shock is positive and statistically significant indicating that a global demand shock raises the real US/UK exchange rate. For Brazil, Mexico, India, Japan, and South Korea oil shocks have no statistically significant impact on real exchange rates. Overall, for five of the nine countries studied, oil shocks have no statistically significant impact on real exchange rates. This may in fact be the case or it is also possible that the relationship between exchange rates and oil shocks is non-linear and not being detected by a linear regression framework.

To investigate the possibility of a non-linear relationship between exchange rates and oil shocks we now turn to the results from the Markov-switching models (Eq. (5)). A number of features stand out. For the oil exporting countries (Brazil, Canada, Mexico, Norway, Russia, and the UK), the estimated coefficient on the lagged exchange rate variable is statistically significant in at least one of the regimes (Table 5). This result is important in showing that the importance of lagged exchange rates varies by regime. This pattern is also observed for the oil importing countries (India, Japan, and South Korea). For the oil exporting countries, the estimated coefficient on the oil price shock variable is negative and statistically significant in at least one regime for Brazil, Canada, Norway and Russia. These results indicate that positive oil price shocks have a negative impact on real exchange rates (measured as domestic currency per US \$1) indicating an appreciation of the local currency relative to the US dollar. For the United Kingdom, a positive oil price shock has a positive impact on US/UK exchange rate, indicating a real appreciation. This is consistent with prior expectations and empirical evidence that rising oil prices cause an appreciation of an oil exporter's currency. In the case of Mexico, however, oil price shocks have no statistically significant (albeit negative) impact on exchange rates. Global economic demand shocks have a significant impact on exchange rates in Canada, Mexico and the United Kingdom. For both Canada[11] and the United Kingdom, a positive global demand shock appreciates the real exchange rates, while it causes a real depreciation for Mexico. A global demand-driven shock would affect the oil exporters' currencies both through a change in the price of oil and through a change in the demand for other goods they exports. Typically, this results in an appreciation of the domestic currency, thus generating a Dutch-disease-type effect. However, depending on the share of commodity exports to a country's total exports, central banks have incentives to actively counter appreciation pressure by accumulating foreign exchange reserves (see Buetzer et al. (2012) for empirical evidence). This effect may lessen a systematic appreciation of exchange rates in oil-exporting countries (as predicted by the theory) in response to a positive global demand shock. Except for Brazil, oil supply shocks do not have a statistically significant impact on exchange rates for oil exporting countries, which may seem surprising because for some countries (Canada, Norway, and the United Kingdom) the sample starts in the middle of the 1970s, which coincide with the large production cuts during the second energy crisis in 1979. However, the energy crises of the 1970s were soon overshadowed by the oil glut in the 1980s. Comparing the RCM values for the oil exporting countries, we see that the Markov-switching model fits the data for the United Kingdom the best (smallest RCM value) while the poorest fit is recorded for Norway (largest RCM value).

Turning now to the oil importing countries, we find that in response to a positive oil price shock the real exchange rates of India and Japan switch between depreciating and appreciating regimes. However, the variance of the appreciating/depreciating state is different between the two countries. Although it is difficult to pinpoint an exact rationale for these results, the swings may originate from economic fundamentals. For example, Kaminsky (1993) argues that if economic growth is relevant for exchange rates, then business cycle differences between countries can lead to persistent swings. Moreover, Evans and Lewis (1995) point out that rational traders' forecast of the future exchange rate might explain the exchange rate switches between appreciating and depreciating regimes. Interestingly, both oil supply and demand shocks have a negative (i.e., appreciating) effects on the real exchange rate of South Korea, while a positive global demand shock causes a real depreciation, with all impacts being statistically significant in

Table 2
Unit root tests on oil shocks and monthly real exchange rate returns.

	DF-GLS (c)	DF-GLS (t)	KPSS (μ)	KPSS (τ)
Supply	−1.653[c]	−1.713	0.092	0.035
Demand	−2.580[b]	−4.227[a]	0.116	0.085
Oil	−3.641[a]	−4.165[a]	0.162	0.100
BRA	−3.557[a]	−4.050[a]	0.207	0.105
CAN	−1.883[c]	−3.478[b]	0.179	0.072
MEX	−2.552[b]	−3.924[a]	0.053	0.048
NOR	−4.434[a]	−5.674[a]	0.045	0.038
RUS	−4.485[a]	−4.328[a]	0.199	0.165[b]
UK	−4.428[a]	−5.366[a]	0.032	0.030
IND	−1.429	−2.995[b]	0.351[c]	0.085
JAP	−3.056[a]	−4.536[a]	0.142	0.040
KOR	−4.793[a]	−5.435[a]	0.052	0.041

Supply denotes a global oil supply shock, Demand denotes a shock to global economic activity, and Oil denotes a shock to global oil prices. [a, b,] and [c] denote significance at the 1%, 5%, and 10% level of significance respectively.

[11] Charnavoki and Dolado (2014) find that a positive global demand shock appreciates the real exchange rate for Canada.

Table 3
BDS tests for monthly real exchange rate returns.

	m	ε (1)	ε (2)	ε (3)	ε (4)
BRA	2	6.6948	5.5320	6.1247	6.0450
	2	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	9.8731	7.5959	7.3864	6.5504
	3	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CAN	2	4.5261	3.8869	3.4533	3.1324
	2	(0.0000)	(0.0001)	(0.0006)	(0.0017)
	3	6.1864	4.9403	4.6208	4.4270
	3	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MEX	2	2.8992	3.5319	4.4941	4.7191
	2	(0.0037)	(0.0004)	(0.0000)	(0.0000)
	3	3.1968	4.2920	5.0696	5.1645
	3	(0.0014)	(0.0000)	(0.0000)	(0.0000)
NOR	2	4.5071	5.8962	5.5082	5.6350
	2	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	6.1613	7.4496	6.4042	6.0449
	3	(0.0000)	(0.0000)	(0.0000)	(0.0000)
RUS	2	3.3897	1.9659	−0.2357	−0.4948
	2	(0.0007)	(0.0493)	(0.8137)	(0.6208)
	3	5.0478	3.1643	−0.1150	−0.5129
	3	(0.0000)	(0.0016)	(0.9085)	(0.6080)
UK	2	4.9102	5.1158	5.2905	5.4070
	2	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	5.6912	6.5310	6.2205	5.8020
	3	(0.0000)	(0.0000)	(0.0000)	(0.0000)
IND	2	6.5695	5.9633	4.6265	2.7523
	2	(0.0000)	(0.0000)	(0.0000)	(0.0059)
	3	9.0179	8.1957	6.2021	3.8031
	3	(0.0000)	(0.0000)	(0.0000)	(0.0001)
JAP	2	2.1881	2.9852	3.6363	4.7036
	2	(0.0287)	(0.0028)	(0.0003)	(0.0000)
	3	1.6504	1.8585	2.5903	3.6454
	3	(0.0989)	(0.0631)	(0.0096)	(0.0003)
KOR	2	9.8749	9.1612	10.0039	11.2724
	2	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	12.1156	10.4099	10.6452	11.3000
	3	(0.0000)	(0.0000)	(0.0000)	(0.0000)

The parameter m is the embedding dimension and ε is the epsilon values for close points (numerical values not reported). p values are reported in parentheses.

state 1 only. This counterintuitive finding that a positive oil price shock causes the oil importer's real exchange rate to appreciate implies that a deterioration in the oil component of South Korea's trade balance is not offset by an improvement in the non-oil trade balance, especially in the high volatility regime. Although in state 2 (low volatility regime) an oil shock leads to a real depreciation, the effect is not statistically significant. By comparison, global demand shocks have a positive and significant impact on exchange rates for South Korea. Note that, by definition, global demand shocks are symmetric shocks, hitting both producers and consumers, in the same direction at the same time. Overall, the responses of the real exchange rates to various oil shocks vary substantially across oil-exporting and oil-importing countries, reflecting that exchange rates are affected by various country-specific differences in monetary and fiscal policies, exchange rate regimes, and product and labor market rigidities (Cashin et al., 2014).

Among the oil importing countries, the RCM indicates the Markov-switching model has the highest classification for India and the lowest classification for Japan. This is confirmed by the very low values of the expected duration of being in a particular state (the Du1 or Du2 values reported in Table 5). Furthermore, based on the smoothed probability for all countries, each regime is highly persistent, as evidenced by the large constant regime probabilities p_{11} and p_{22}, respectively.

Notice also that the estimated coefficient on sigma is positive in each country and statistically significant in both states for each country except state 2 for Russia.[12] Sigma refers to the standard deviation of each regime. It provides the magnitude of volatility (measured by the standard deviation) of each regime. The state with the largest estimated coefficient on sigma is the "high" volatility regime, while the state with the smallest estimated coefficient on sigma is the "low" volatility regime. The estimated coefficients of sigma support this switching between high- and low-volatility regimes. Table 5, for example, shows that for exchange rates of three emerging countries (Brazil, Mexico, and Russia), there is a strong distinction between a high- and low-volatility regime, where the unconditional variance in the former is three to four times as large. The relative strength of the high volatility and low volatility regime is smaller in other countries. Except for India, the estimated sigma value in state 1 is larger than the estimated sigma value in state 2 indicating that state 1 has more volatility for eight of the nine countries studied. In the case of India, state 2 is the high volatility state. The RCM values are in agreement with the plots of the smoothed probabilities of being in the high volatility state (Figs. 4 and 5). Smaller RCM values correspond to a clearer pattern in switching between states.[13] According to the RCM values, the Markov-switching model with normal errors fits the best for India (smallest RCM) and the poorest for Norway (largest RCM).

These results are different from the estimates in Atems et al. (2015), who find that the responses of exchange rates to oil price shocks are identical (i.e., depreciation) for exporting and importing countries. The most likely explanation seems to be that we use a non-linear framework, while Atems et al. (2015) employ a linear framework. Although they conduct some non-linear (or asymmetric) analyses in terms of how the effect of oil shocks vary between large and small countries and whether positive or negative shocks matter for exchange rates, their regression framework is essentially linear. Our analysis, therefore, emphasizes the need to use a non-linear framework to obtain theoretically consistent results.

Table 4
The impact of oil shocks on real exchange rates — linear models.

	Constant	Supply	Demand	Oil	ΔFX(−1)	R squared
Brazil	0.0692	−0.0419	−0.2155	−0.3192	0.3754[a]	0.1630
	(0.3086)	(−0.0908)	(−0.8396)	(−1.0019)	(5.7493)	
Canada	0.0269	0.0799	−0.2844[b]	−0.2456[b]	0.1686[a]	0.0957
	(0.3961)	(1.0458)	(−2.3053)	(−2.5386)	(3.2076)	
Mexico	0.0723	−0.4620	0.0745	−0.3232	0.1811[a]	0.0450
	(0.4544)	(−0.9044)	(0.4337)	(−1.1508)	(7.3463)	
Norway	−0.0046	−0.0069	−0.1718	−0.3716[b]	0.3194[a]	0.1348
	(−0.0467)	(−0.0730)	(−0.9723)	(−2.4246)	(8.4156)	
Russia	−0.0539	−1.6292	0.0494	−0.7140[a]	0.0677[c]	0.0663
	(−0.1420)	(−1.3711)	(0.1913)	(−2.6693)	(1.8233)	
UK	0.0123	−0.1082	0.2750[c]	0.1828	0.2967[a]	0.1100
	(0.1140)	(−0.8430)	(1.8864)	(1.2204)	(6.6569)	
India	0.0754	−0.0844	0.0127	−0.1184	0.2169[a]	0.0524
	(0.8731)	(−1.1685)	(0.1119)	(−1.3546)	(4.7188)	
Japan	−0.0264	−0.0164	0.1500	0.0661	0.3213[a]	0.1051
	(−0.2115)	(−0.1249)	(0.9564)	(0.3996)	(9.6528)	
S. Korea	0.0118	−0.1241	−0.0322	−0.1482	0.4374[a]	0.1976
	(0.1234)	(−0.8744)	(−0.2460)	(−1.0207)	(9.0386)	

The dependent variable is the monthly return on real exchange rates. Supply denotes a global oil supply shock, Demand denotes a shock to global economic activity, and Oil denotes a shock to global oil prices. HAC t-statistics are shown in parentheses. [a], [b], and [c] denote significance at the 1%, 5%, and 10% level of significance respectively.

[12] As with any numerically intensive optimization calculation there can be instances where standard errors fail to compute even after convergence of the estimation process. When this occurs, the table entries read NA. This can arise when the distribution assumption is not able to fully capture the properties of the data. In Table 6, the Markov-switching model for Russia fits better and all of the coefficient standard errors are computed.

[13] The transition probabilities vary across countries. It is not surprising that the responses of the real exchange rates to various oil shocks vary substantially across oil-exporting and oil-importing countries given the fact that, in practice, exchange rates are affected by a myriad of factors including the degree of pro- and counter-cyclicality of monetary and fiscal policies across countries, their exchange rate regimes, the degree of trade and financial openness, and the types of nonlinearities (e.g., real wage rigidities) that are present in the product and labor markets.

Table 5
The impact of oil shocks on real exchange rates — Markov-switching models (normal distribution for the errors).

A. Estimated coefficients

Country	State	Intercept	Supply	Demand	Oil	ΔFX(−1)	Sigma	LL
Brazil	S1	0.4229	−0.1840	−0.4250	0.3196	0.5781[a]	4.9422[a]	−568.50
		(0.8447)	(−0.2372)	(−0.9116)	(0.6318)	(4.5322)	(12.4503)	
	S2	−0.3995[a]	0.1311	−0.2129	−0.7003[a]	0.0528	1.2725[a]	
		(−2.7387)	(0.5305)	(−1.5418)	(−4.9149)	(1.2776)	(7.6921)	
Canada	S1	−0.1987	0.3290	−1.4628[a]	−0.4109	0.0737	1.8698[a]	−763.85
		(−0.7181)	(0.7951)	(−5.2712)	(−1.5542)	(0.5942)	(9.5107)	
	S2	0.1022	0.0901	0.0278	−0.1546[b]	0.1279[a]	1.1548[a]	
		(1.6193)	(1.2564)	(0.3669)	(−2.1983)	(2.6855)	(24.9532)	
Mexico	S1	1.2493	−4.9106	−0.4853	−3.1247	0.2955	9.5998[a]	−553.35
		(0.4521)	(−1.1060)	(−0.2514)	(−0.8813)	(1.0283)	(5.1387)	
	S2	−0.1916	−0.0281	0.3075[b]	−0.0639	0.1577[b]	1.9285[a]	
		(−1.2936)	(−0.1159)	(2.2597)	(−0.4893)	(2.4116)	(14.1916)	
Norway	S1	0.2365	−0.1804	−0.2895	−1.1172[b]	0.1889[c]	2.2991[a]	−1001.93
		(0.7805)	(−0.7083)	(−1.2868)	(−2.2812)	(1.6865)	(15.2517)	
	S2	−0.2592	0.1713	−0.0079	0.3595	0.4542[a]	1.7573[a]	
		(−0.9411)	(0.7891)	(−0.0290)	(0.9377)	(3.3580)	(4.5335)	
Russia	S1	0.2478	−2.0472	−0.0180	−0.9643	−0.2472[c]	7.5180[a]	−500.73
		(0.2437)	(−1.3016)	(−0.0309)	(−1.0774)	(−1.7185)	(7.6728)	
	S2	−0.4111	−0.6874	0.0781	−0.5014[a]	0.8183	1.6783	
		NA	NA	NA	(−4.5489)	NA	NA	
UK	S1	−0.0362	−0.0460	0.5770[b]	0.6234[c]	0.3317[a]	2.9050[a]	−1011.32
		(−0.1664)	(−0.2176)	(2.4650)	(1.9542)	(4.9140)	(15.5006)	
	S2	0.1346	−0.1325	0.0705	−0.1302	0.1774[b]	1.7370[a]	
		(1.1066)	(−0.8756)	(0.5146)	(−1.0635)	(2.5626)	(20.8041)	
India	S1	−0.0054	−0.0367	−0.0783	0.1787[a]	0.3516[a]	0.9704[a]	−862.38
		(−0.0828)	(−0.4496)	(−0.8128)	(2.6180)	(5.2593)	(17.2354)	
	S2	0.1904	−0.1690	0.0327	−0.5667[b]	0.1851[a]	2.5837[a]	
		(1.0017)	(−0.7480)	(0.1988)	(−2.4626)	(2.6136)	(17.7752)	
Japan	S1	−0.7622[b]	−0.0423	−0.0337	0.5762[b]	0.4451[a]	2.9770[a]	−1079.97
		(−2.3352)	(−0.1703)	(−0.1394)	(2.2555)	(4.8273)	(17.7723)	
	S2	0.8765[a]	0.0699	0.2540	−0.6761[a]	0.1851[b]	1.5924[a]	
		(3.8458)	(0.3594)	(1.1622)	(−2.9010)	(2.4245)	(7.4531)	
Korea	S1	−3.6918[b]	−4.5626[b]	2.0698[a]	−5.1592[a]	2.5984[a]	3.3742[a]	−763.85
		(−2.1556)	(−2.4248)	(3.5555)	(−4.2330)	(10.0830)	(4.7410)	
	S2	−0.0988	−0.0178	−0.0067	0.0403	0.2611[a]	1.4936[a]	
		(−1.2563)	(−0.1922)	(−0.0696)	(0.4758)	(8.5521)	(24.8543)	

B. Transition probabilities and expected durations

	P11	P12	P21	P22	DU1	DU2	RCM
Brazil	0.8377	0.1448	0.1623	0.8551	6.16	6.90	35.89
Canada	0.9146	0.0143	0.0854	0.9857	11.71	70.09	58.31
Mexico	0.6709	0.0275	0.3291	0.9725	3.04	36.36	53.18
Norway	0.5559	0.5314	0.4441	0.4686	2.25	1.88	86.66
Russia	0.4601	0.4081	0.5399	0.5919	1.85	2.45	62.93
UK	0.9805	0.0149	0.0195	0.9851	51.28	67.19	22.46
India	0.9617	0.0504	0.0383	0.9496	26.11	19.83	21.62
Japan	0.5339	0.5853	0.4661	0.4147	2.15	1.71	74.20
Korea	0.4091	0.0239	0.5909	0.9761	1.69	41.85	39.74

The dependent variable is the monthly return on real exchange rates. Supply denotes a global oil supply shock, Demand denotes a shock to global economic activity, and Oil denotes a shock to global oil prices. Sigma refers to the standard deviation of each state. Student *t* statistics are shown in parentheses. [a], [b], and [c] denote significance at the 1%, 5%, and 10% level of significance respectively. The maximized log likelihood value is denoted as LL. RCM is the regime classification measure. The transition probabilities are reported as p_{ij}. The expected duration of being in state *i* are reported as Dui, i.e., Du1 for state 1 and Du2 for state 2.

5.2. A robustness check on the error distribution

In this section, we investigate how robust the results of the Markov-switching model are to the choice of the probability distribution for the errors. In particular, we re-estimate the Markov-switching model using a *t* distribution for the errors (Table 6). The use of a *t*-distribution is particularly useful in regime-switching models as it enhances the stability of regimes. This is because, with a normal distribution, "a large innovation in the low-volatility period will lead to a switch to the high-volatility regime earlier, even if it is a single outlier in an otherwise tranquil period" (Klaassen, 2002; p. 368). See Hamilton and Susmel (1994) for an early Markov-switching approach with *t*-distributed innovations. A comparison of the RCM values for each country shows that the Markov-switching model with a *t* distribution fits better (lower RCM value) for Mexico, Norway, Russia, India, Japan, and South Korea. For Brazil, Canada, and the United Kingdom, the Markov-switching model with a normal distribution fits better.

Lagged exchange rates have a positive and significant impact on exchange rates in each country (Table 6). Also of interest is the fact that the estimated coefficient on the oil price variable is negative and statistically significant in at least one state for each of the oil exporting countries (Brazil, Canada, Mexico, Norway, and Russia) and positive and significant in the case of the United Kingdom. This is consistent with the view that for oil exporting countries, higher oil prices lead to an appreciation of the local currency. Global economic demand shocks have a negative and statistically significant impact on exchange rates for Canada, Norway and Russia, and a positive and significant impact on exchange rates for Mexico. For the United Kingdom, the estimated coefficient on the global economic shock is positive and significant in state 1 and negative and significant in state 2. This is interpreted as an appreciation of the local

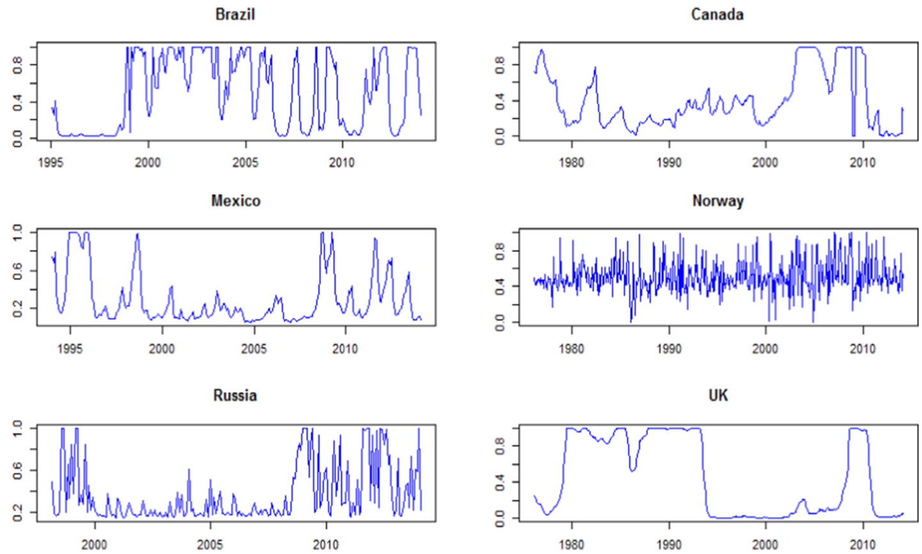

Fig. 4. Smoothed probability of high volatility state (state 1 for all countries) — oil exporting countries (normal distribution for the errors).

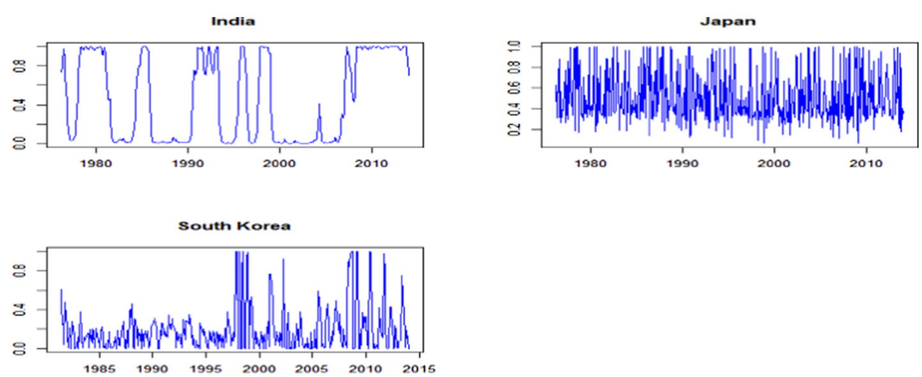

Fig. 5. Smoothed probability of high volatility state (state 1 for Japan and South Korea, state 2 for India) — oil importing countries (normal distribution for the errors).

exchange rate in state 1 and a depreciation of the local currency in state 2. An oil supply shock has a negative impact on Brazil's exchange rate in state one and a positive and significant impact on exchange rates in state two. In the case of Mexico, an oil supply shock has a negative significant impact on exchange rates in state two. For the United Kingdom, a supply shock decreases the real exchange rate ($US/$UK).

For the oil importing countries, there is evidence that oil price shocks impact exchange rates in India, Japan, and South Korea. There is evidence of global economic demand shocks affecting exchange rates in Japan and South Korea. Overall, there is more evidence to show that oil shocks affect the exchange rates of oil exporting countries.

Except for Brazil and Canada, the estimated coefficient on sigma is larger in state 1 than state 2 indicating higher volatility in state 1 for these countries. Plots of being in the high volatility state are shown in Figs. 6 and 7. The Markov-switching model with a *t*-distribution produces very clear state switching for Russia, India and South Korea which are consistent with the low RCM values recorded for these countries. In the case of Russia, for example, real exchange rates are in the high volatility state during the late 1990s and from 2008 onwards. The smoothed probability of the high volatility state for South Korea is even more pronounced with exchange rates in the high probability state from 1996 to the end of the sample period. A general pattern emerges from the analysis that indicates that the Markov-switching model delivers clear regime inferences for most countries, as the RCMs are far from 100 (except for Canada) and the smoothed probability plots show clear evidence of switching between states.

A reviewer asked a question about which set of results (those in Table 5 or those in Table 6) we prefer. If we have to choose between the two results, we should select the one with the *t*-distribution.[14] This is because, when residuals are normally distributed, a large innovation in the low-volatility period will lead to a switch to the high-volatility regime earlier, even if it is a single outlier in an otherwise tranquil period. Allowing for a *t*-distribution will thus enhance the stability of the regimes. Indeed, our results show that the staying probabilities p_{11} and p_{22} in a particular regime are relatively higher when the residual has a *t*-distribution (see Tables 5 and 6). Likewise, the expected duration of regimes (expressed in months) is slightly higher with a *t*-distribution. As such, the *t*-distribution includes the normal distribution as the limiting case where the degrees of freedom go to infinity. Also notice that the RCM values for the Markov-switching model estimated with a *t*-distribution are lower than the comparative values for the Markov-switching model estimated with a normal distribution for 6 of the 9 countries.

6. Conclusions and implications

There is a considerable literature looking at the impact of oil prices and oil price shocks on exchange rates. This is an important topic to study because an oil shock can affect a country's terms of trade which

[14] Marcucci (2005) illustrates the importance of fat tailed innovations, particularly for the purpose of regime identification.

Table 6
The impact of oil shocks on real exchange rates — Markov-switching models (Student-*t* distribution for the errors).

A. Estimated coefficients

Country	State	Intercept	Supply	Demand	Oil	ΔFX(−1)	Sigma	LL
Brazil	S1	−0.1507	−0.5374[c]	0.0375	−0.4085[b]	0.2813[a]	1.8637[a]	−564.43
		(−0.9293)	(−1.8783)	(0.2163)	(−2.4827)	(3.8750)	(8.1877)	
	S2	1.5582	4.5684[c]	−2.1362	1.1501	0.3741[c]	7.0149[a]	
		(0.9402)	(1.8290)	(−0.9980)	(0.6419)	(1.9261)	(3.8468)	
Canada	S1	−0.3769	0.0450	−1.8914[a]	−0.6513[b]	0.4808[b]	1.1586[a]	−765.61
		(−1.1997)	(0.1328)	(−7.9187)	(−2.2061)	(2.2298)	(5.9439)	
	S2	0.0839	0.0532	0.0357	−0.1813[b]	0.1273[a]	1.2037[a]	
		(1.2136)	(0.7353)	(0.4473)	(−2.4708)	(2.8410)	(25.2607)	
Mexico	S1	−0.7222[a]	0.0781	0.1140	−0.0693	−0.0131	1.4861[a]	−548.09
		(−5.1567)	(0.3740)	(0.8714)	(−0.5821)	(−0.3434)	(10.1699)	
	S2	2.6186[a]	−1.3303[a]	0.4519[b]	−0.8523[a]	0.4693[a]	1.1586[b]	
		(7.4140)	(−3.7067)	(2.4539)	(−3.1730)	(4.6565)	(2.1735)	
Norway	S1	−0.0261	0.0126	−0.4233[a]	−0.2658[b]	0.3229[a]	2.1280[a]	−996.17
		(−0.2387)	(0.1107)	(−3.3475)	(−2.2081)	(7.0025)	(23.1249)	
	S2	0.4941[b]	−0.0527	0.4128[a]	−1.3278[a]	0.3311[a]	1.5693	
		(2.3184)	(−0.2238)	(2.6290)	(−5.5179)	(2.9624)	NA	
Russia	S1	0.0177	−0.2202	0.1969	−1.2523[a]	0.0228	2.1179[a]	−391.00
		(0.0570)	(−0.4071)	(0.8404)	(−4.7220)	(0.7719)	(7.3972)	
	S2	−0.5439[a]	−0.0742	−0.4548[a]	−0.1144	0.3399[a]	0.9791[a]	
		(−3.9201)	(−0.4343)	(−2.8600)	(−1.2028)	(3.6997)	(9.3628)	
UK	S1	0.0947	−0.0245	0.5469[a]	0.0486	0.2985[a]	2.1653[a]	−1016.75
		(0.7506)	(−0.1692)	(4.1312)	(0.3548)	(5.8214)	(17.2416)	
	S2	−0.5806[a]	−0.5159[a]	−1.2064[a]	0.8213[a]	0.1153	0.7149[a]	
		(−3.2185)	(−3.1758)	(−7.3882)	(5.1184)	(1.1385)	(5.2539)	
India	S1	0.1100	−0.1537	0.0036	−0.5013[b]	0.1990[a]	1.9201[a]	−847.06
		(0.6874)	(−0.8010)	(0.0251)	(−2.4021)	(3.0670)	(11.8510)	
	S2	−0.0084	−0.0214	−0.0489	0.1924[a]	0.3658[a]	0.9022[a]	
		(−0.1262)	(−0.2620)	(−0.4914)	(2.8915)	(5.2255)	(12.4472)	
Japan	S1	1.08959[a]	0.0986	0.2482[c]	−0.2801[c]	0.3161[a]	1.7994[a]	−1078.87
		(4.3241)	(0.7346)	(1.7378)	(−1.8352)	(6.0243)	(10.6192)	
	S2	−2.4663[a]	−0.1561	0.1553	0.5270[b]	0.6036[a]	1.6912[a]	
		(−6.2522)	(−0.5279)	(0.6727)	(2.5195)	(6.6396)	(6.1245)	
Korea	S1	−0.1727	−0.0344	0.2359	−0.1684	0.3102[a]	2.1662[a]	−690.50
		(−0.9968)	(−0.1201)	(1.3897)	(−0.9838)	(6.5112)	(34.5928)	
	S2	0.0141	−0.0038	−0.2313[a]	0.1197[b]	0.4848[a]	0.6523	
		(0.2735)	(−0.0786)	(−3.1304)	(2.0444)	(8.8405)	NA	

B	P11	P12	P21	P22	DU1	DU2	RCM
Brazil	0.9774	0.1550	0.0226	0.8450	44.19	6.45	44.77
Canada	0.2215	0.1078	0.7785	0.8922	1.28	9.28	74.07
Mexico	0.8440	0.5746	0.1560	0.4254	6.41	1.74	51.70
Norway	1.0000	0.0204	0.0000	0.9796	1.00E + 06	49.03	45.62
Russia	0.9827	0.0119	0.0173	0.9881	57.70	84.01	7.84
UK	0.9118	0.4925	0.0882	0.5075	11.34	2.03	39.30
India	0.9619	0.0328	0.0381	0.9672	26.26	30.46	20.89
Japan	0.6157	0.8132	0.3843	0.1868	2.60	1.23	50.16
Korea	0.9946	0.0053	0.0054	0.9947	183.90	190.29	3.26

The dependent variable is the monthly return on real exchange rates. Supply denotes a global oil supply shock, Demand denotes a shock to global economic activity, and Oil denotes a shock to global oil prices. Sigma refers to the standard deviation of each state. Student *t* statistics are shown in parentheses. [a, b,] and [c] denote significance at the 1%, 5%, and 10% level of significance respectively. The maximized log likelihood value is denoted as LL. RCM is the regime classification measure. The transition probabilities are reported as p_{ij}. The expected duration of being in state *i* are reported as Dui.

can affect its competitiveness. The impact of oil shocks on exchange rates will differ depending upon whether a country is a net oil exporter of net oil importer. Most of the literature uses linear models to estimate the impact of oil prices on exchange rates.

Our approach in this paper is to estimate the impact of oil shocks on real exchange rates using Markov-switching models. This approach has the advantage of capturing possible non-linear impacts of oil shocks on exchange rates that linear models would be unable to detect. Moreover, in addition to including an oil price shock we also include variables to account for oil demand and oil supply shocks. This provides a more complete understanding of how the oil market affects real exchange rates.

There are several important findings that stem from the present analysis. First, the application of Markov-switching regime models with two regimes lends support to the underlying nonlinearities between the real exchange rate and oil shocks (demand and supply) for both oil exporting and importing economies. In the linear regression model, oil shocks had a statistically insignificant impact on exchange rates for five of the nine countries studied, indicating that with a linear model evidence of oil shocks affecting real exchange rates is limited. In the Markov-switching model, oil shocks had a statistically significant impact on exchange rates in at least one state for each country providing more substantial evidence of oil shocks affecting real exchange rates. Additionally, the regime classification measure of Ang and Bekaert (2002) confirms that the estimated Markov-switching models distinguished very well between the two regimes.

Second, we detect significant appreciation pressures in oil exporting economies after oil demand shocks. These results are robust across two different assumptions regarding the error distribution of residuals (normal and *t* distribution). In the case of oil importing countries the impact of oil demand shocks on exchange rates is more complex. We find only limited evidence that oil supply shocks affect exchange rates for either oil exporting or oil importing countries.

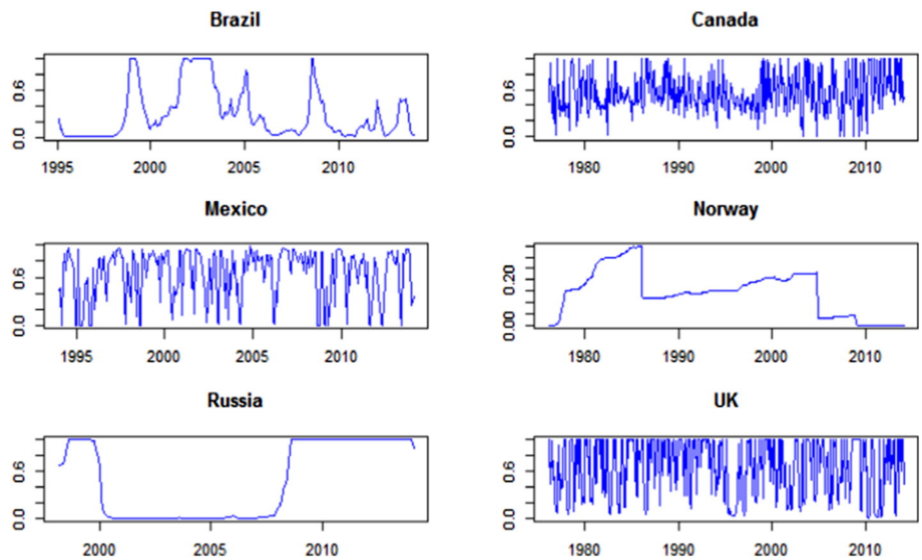

Fig. 6. Smoothed probability of high volatility state (state 2 for Brazil and Canada, state 1 for others) — oil exporting countries (*t* distribution for the errors).

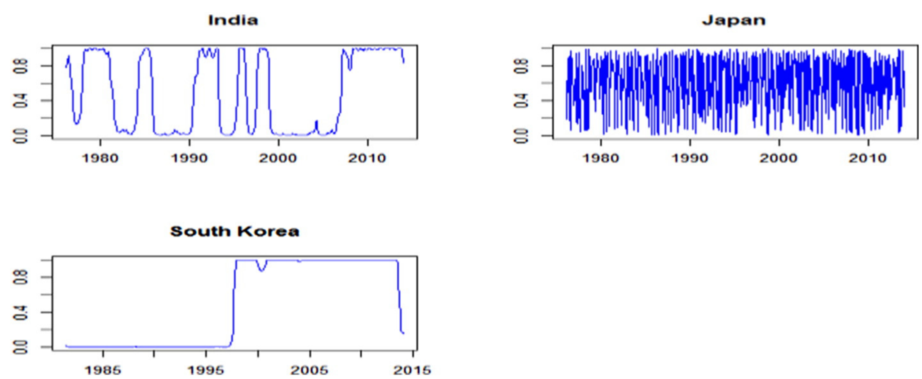

Fig. 7. Smoothed probability of high volatility state (state 1 for all countries) — oil importing countries (*t* distribution for the errors).

Third, global economic demand shocks affect both oil exporting and oil importing countries, but the adjustments of exchange rates may differ according to their relative competitiveness in international markets. Therefore, a main implication of our findings is that oil (demand) shocks are an important factor in exchange rate configurations in oil exporting countries.

Acknowledgments

The authors thank three anonymous reviewers and Latika Lagalo, as well as other participants, at the 2015 WEAI Conference in Honolulu for very helpful and constructive comments.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2015.12.004.

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