# A Markov regime-switching model of crude oil market integration

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**Abstract**

This paper revisits the globalization-regionalization hypothesis for the world crude oil market. We examine long-run equilibrium relationships between major crude oil prices – WTI, Brent, Bonny Light, Dubai and Tapis – and focus on the adjustment behaviour following disequilibrium states. We account for a changing adjustment behaviour over time by using a Markov-switching vector error correction model. Our overall findings suggest that the crude oil market is globalized. Dubai turned out to be the only weakly exogenous price in all regimes, indicating its important role as a benchmark price. Furthermore, an interesting finding of our study is that the degree of market integration seems to be connected to global economic uncertainty.

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## 1. Introduction

The discussion on whether world crude oil markets are globalized or regionalized has received a great deal of attention in recent years. Adelman (1984) described the world

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crude oil market as ‘one great pool’. Changes in market conditions in one region are then expected to affect other geographical regions immediately. An existing price differential in local oil markets that exceeds the transportation costs of third party exporters gives rise to arbitrage opportunities. The subsequent supply pressure is expected to close the difference in prices. The idea of ‘one great pool’ was challenged by Weiner (1991) who finds empirical support for a high degree of regionalization. His findings imply that the world crude oil market is fragmented and the effects of price shocks to regional crude oil prices are restricted to this specific regional market.

This initial discussion has triggered numerous empirical studies, among them Gue-len (1999), Fattouh (2010), Reboredo (2011) and Ji and Fan (2015), that tackle the ‘globalization-regionalization’ hypothesis from different angles. The majority of recent studies finds evidence for a globalized crude oil market. However, the structure of the market does not seem to be stable over time.

Our paper contributes to the literature by proposing a regime-switching model for the long-run relationships among benchmark crude oil prices. This allows us to relax the assumption of constant dynamics over the sample period which has to hold for linear cointegration models. More specifically, we apply a Markov-switching vector error correction model (MSVECM) to capture changing roles of crudes in the world crude oil market and a changing degree of market integration. This enables us to identify regime-shifts from the data without the need to pre-specify structural breaks. We aim to account for increasingly volatile crude oil prices and changing economic and geopolitical conditions over a sample reaching from 1987 to 2015. Our data-set consists of five major crude oil benchmark prices – WTI, Brent, Bonny Light, Dubai and Tapis – representative of five crude oil producing regions.

The question whether the crude oil market is globalized or regionalized has important policy implications. Developed countries hold strategic petroleum reserves to provide emergency crude oil in times of disruptive supply shocks. Members of the International Energy Agency are required to stockpile crude oil equal to 90 days of prior year's net oil imports[1]. If effects of supply shocks were restricted to one region, higher reserves would have to be stockpiled than in a globalized market where arbitrage opportunities lead to supply of cheaper oil from other production sites.

Furthermore, a precise assessment of the market behaviour is needed to anticipate the scope of new energy policies. Energy markets are currently experiencing fundamental changes since production of giant oil fields declines (Höök, Hirsch, and Aleklett (2009)) whereas new technologies, like hydraulic fracturing, are used to revitalize existing oil fields. Also, the interest in renewable energy has recently increased as might be reflected by the renewable energy directive of the European Union (European Commission (2016)). The decision to invest in the energy sector requires an accurate prediction of future crude oil prices. Focussing on the classical benchmarks (WTI and Brent) or only on local benchmark prices might prevent assessing the correct market behaviour if they do not reflect global supply and demand.

Moreover, a precise assessment of crude oil prices is needed for hedging purposes and the pricing of other derivatives related to crude oil prices. It is therefore of interest which benchmark price reflects crude oil market developments first and leads the pricing process. This may become even more important since activity in commodity exchange contracts has risen in recent years which is discussed under the term 'financialization' of commodity markets in the literature (see, for example, Buyuksahin and Harris (2011) and Tang and Xiong (2012)). Although activity in crude oil exchange trading has increased accordingly, trading physical oil is still carried out in large quantities and is

[1]The International Energy Agency (IEA) was founded in the wake of the first oil crisis. Historically, the majority of member states were net oil importers. Net exporters are exempt from this requirement. Although the role of the US as a net importer has to be reconsidered, following the resurgence of shale oil fields, the largest crude oil stockpiles are concentrated in the US.

non-transparent to the public. In practice, price reporting agencies, like Platts, provide assessments of benchmark crude oil prices. The prices in the physical oil market are collected by a window or market-on-close process in which bids, offers and the trade volume are assessed and prices are published as an end-of-day value. This leads to price-discovery which rests on voluntary and selective disclosure by market participants as well as subjective judgement of the price reporting agency. Although WTI, Brent and Dubai are considered to be the most important crude oil benchmarks, there is no universally recognized *global* crude oil spot price. Market agents exposed to crude oil price risks, therefore, are particularly interested in how different crude oil benchmarks interact and which of them responds fastest to changing conditions on the crude oil market.

The remainder of the paper is organized as follows. Section 2 describes the structure of the world crude oil market and the role of benchmark prices. In Section 3, we review the literature on crude oil market integration, Section 4 outlines the econometric framework used in the empirical part of the paper, Section 5 reports the results of the empirical application, Section 6 relates our findings to previous studies and Section 7 concludes.

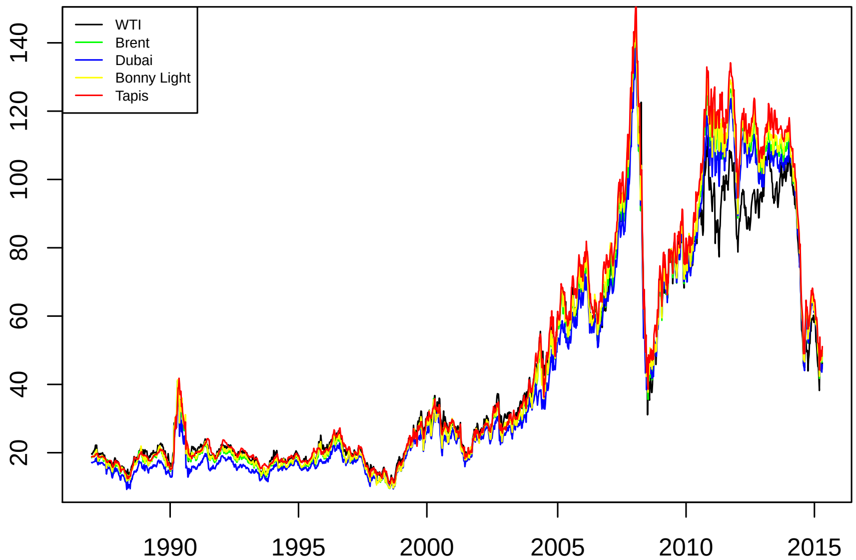
## 2. Market structure and the role of benchmark prices

Internationally traded crude oil comes in different qualities and characteristics. Lighter crude oils yield a higher percentage of gasoline and diesel fuel than heavier crudes (usually measured in American Petroleum Institute (API) gravity). Since sulphur is an undesirable component, 'sour' crudes with a higher sulphur level are less sought after than 'sweet' crudes. Generally, light and sweet crudes are priced at a premium relative to heavy and sour crudes. Buyers and sellers of crude oil rely on the use of benchmark crude oils (price markers) to price the different types of crude oil. These benchmarks typically exhibit the following properties: First, the volume of production must be sufficiently large to ensure physical liquidity. Second, the oilfield has to be located in a geopolitically and financially stable region to encourage market interactions. Third, delivery points have to be provided at locations suitable for trade with other market hubs to enable arbitrage. Finally, a diverse ownership of production should be present to prevent market interference and price manipulation. In practice, however, major crude oil benchmarks do not fulfil all the requirements equally. Non-benchmark crudes are priced relative to the benchmark crude at a premium or discount depending on their quality. This is known as formula pricing.

Brent is the reference for about 65% of crude oil traded around the globe according to the Intercontinental Exchange, whereas WTI is the dominant benchmark in the US (Intercontinental Exchange (2016)). Dubai is the main reference for Persian Gulf oil delivered to the Asian market. Bonny Light is a benchmark for West African oil fields and Tapis serves as a benchmark crude for the Asian Pacific region. Figure 1 shows the trajectories of the five benchmark prices from 1987 to 2015. The amount of oil production over time is depicted in Figure 2.

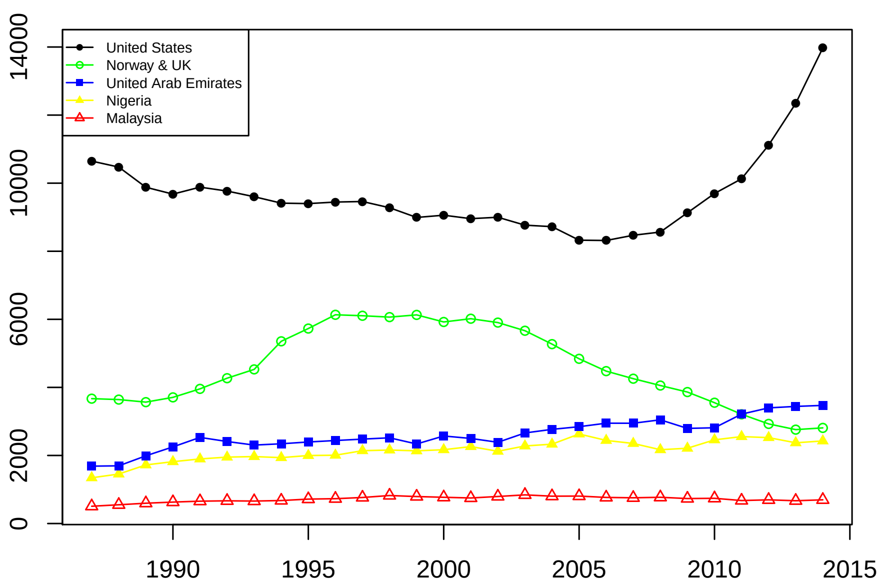
Originally, crude oil extracted from the Brent oilfield, which was discovered in 1971, formed the Brent benchmark (API gravity of 38.3° and 0.37% sulphur). Production from the Brent oilfield started to decline in the mid-1980s which led to volatile prices. Commingling Brent with oil produced in the Ninian oil field, also located in the North Sea, alleviated this problem temporarily. A further decline in production led to the inclusion of oil from the Forties, Oseberg and Ekofisk fields (Fattouh (2006)). Today, the production is still declining (see Figure 2) and a substantial share of Europe's crude oil supply comes from Russia, which raises the question whether Brent has retained its role as a benchmark price.

Figure 1: Time series plots for regional crude oil price series (WTI, Brent, Dubai, Bonny Light, Tapis)




Source: DATASTREAM (see Section 5.1).

Figure 2: Temporal evolution of crude oil production in five production sites denoted in thousand barrels per day




Source: [dataset] US Energy Information Agency (no date).

The North American crude oil West Texas Intermediate (WTI), which has an API of 39.6° and contains 0.24% sulphur, making it a light and sweet crude, is transported from the extraction sites via pipelines to Cushing, Oklahoma. In 1983, NYMEX chose Cushing as the official delivery point for its light sweet crude futures contract which in turn connects the oil fields to refineries and ports. Following the explosive growth in production from shale oil fields, the Cushing pipeline nexus has turned out to be a bottleneck. Oil is transported to Cushing in large quantities but the ill-equipped infrastructure delayed the distribution of oil. Consequently, the build-up in inventory caused WTI to trade at a discount compared to other benchmark crude oils and to decouple from the world crude oil market. This phenomenon is known in the literature as the 'broken benchmark' (Fattouh (2007), Fattouh (2010) and Ji and Fan (2015)). If WTI was considered the global price setter, a decoupling effect would severely impair effective hedging against risks related to energy prices and would lead to incorrect pricing of other derivatives based on crude oil.

WTI and Brent held a constant price differential until around 2010. Historically, WTI traded at a premium compared to Brent, attributed to the fact that WTI is the lighter and sweeter crude oil. Beginning in 2010, the spread has been reversed. The hydraulic fracturing boom in the US helped to increase the US crude oil production by 75% from 2008 to 2014 according to the US Energy Information Agency (US Energy Information Agency (2016)) and subsequently ensured full inventories. Hydraulic fracturing is not utilized with the same intensity in the oil fields of the North Sea. A significant widening of the price differential can be observed after the shale oil boom in the US picked up speed. Moreover, the US ban on crude oil exports during our observational period may have prohibited the reduction of overcapacities through international trade[2].

Dubai is of slightly lower grade than WTI or Brent. An API gravity of 31° and 2% sulphur makes Dubai a medium heavy and sour crude. It comprises of crudes from

[2] The US have lifted the crude oil export ban in January 2016.

different oil fields in Dubai, Oman and Abu Dhabi. Despite the existence of other regional crudes with a larger physical base, Dubai serves as a benchmark price for oil extracted in the Gulf region.

Bonny Light is a sweet but medium heavy crude oil (API 33.4°, 0.16% sulphur). The Bonny Light production is concentrated in the onshore and offshore areas of the Niger Delta of Nigeria. West African crude oil is mostly refined outside the region, in Asia, Europe and the US. Violent conflicts in the Niger region led to temporary disruption of the oil production in September 2004.

Tapis is produced offshore in the South China Sea (the Seligi, Guntong, Tapis, Semangkok, Irong Barat, Tebu, and Palas fields). It is of the highest quality with an API gravity of 45.2° and low sulphur content (0.03%).

Historically, none of the five benchmark prices in our study has emerged as a universally recognized global price setter. A price setter is defined as a price that influences other prices in the same category directly or indirectly without being influenced itself. In terms of our empirical application which focuses on a cointegrated system, a price setter can be identified as a variable which does not adjust to deviations from the long-run equilibrium which is instead maintained by the remaining variables. The price setter takes the role of a *lead* variable whereas the remaining variables act as *lag* variables.

We believe that focussing on benchmark prices reduces the problem encountered by studies involving both benchmark and non-benchmark prices (Wlazlowski, Hagströmer, and Giulietti (2011) and Candelon, Joëts, and Tokpavi (2013)): Non-benchmark prices are priced in relation to the regional benchmark with price adjustments made depending on quality and transportation costs (formula pricing). While we expect the benchmark/non-benchmark relation to be strong, we are primarily interested in the relationship between geographically separated markets. Only if we find long-run comovement and short-run adjustments among prices without a formula pricing relationship, we can argue in favour of a globalized crude oil market.

### 3. Literature

After Adelman (1984) and Weiner (1991) initiated the discussion on the integration of international crude oil markets, a substantial body of literature on the subject has emerged. Empirical studies mostly employ cointegration models to assess the relations among crude oil prices. For instance, Rodriguez and Williams (1993) aim to test the 'one great pool' hypothesis using a cointegration analysis for monthly data from 1982 to 1992. They claim to find evidence for integrated crude oil markets by rejecting the hypothesis of no cointegration which implies the presence of a long-run stable relationship among regional crude oil prices. However, Weiner (1993) emphasizes that, although prices follow a common trend, the short-run dynamics are important to characterize the relationship among regional prices. More precisely, Weiner (1993) argues that only price reactions to changes in other crude oil prices in the short-run should lead to a rejection of the 'regionalization' hypothesis. He criticizes the use of linear cointegration models which are not able to capture the true dynamics of a changing world crude oil market.

Guelen (1999) tries to account for structural change by applying cointegration models to subsamples of falling and rising crude oil prices. He finds evidence for stronger co-movement in periods of increasing prices, implying that linear cointegration models indeed are not well-suited for the analysis of price dynamics in global crude oil markets. Further, he finds that WTI and Brent take the role of global benchmark prices. Bentzen (2007) specifies a vector error correction model for daily crude oil prices from the Middle East, North America and the North Sea. Using data from January 1988 to December 2004, evidence is found for a globalized market with an increasing role of OPEC prices, thereby reducing the strength of WTI and Brent as global benchmarks.

Hammoudeh, Ewing, and Thompson (2008) and Fattouh (2010) use threshold cointegration models to capture a potentially non-linear relationship among crude oil prices. More specifically, Hammoudeh et al. (2008) examine the relationship among four benchmark prices (WTI, Brent, Dubai, Maya) based on daily data from 1990 to 2006. They use momentum threshold autoregressive (MTAR) models which allow for different adjustment depending on whether the spread between crudes is widening or narrowing. While all price pairs are cointegrated, Brent and WTI are found to be leading the pricing process in the long-run. Instead, Fattouh (2010) analyzes crude oil price differentials at a weekly frequency from 1997 to 2008 using threshold autoregressive (TAR) models. Prices of crude oils with a similar quality show a strong comovement over the sample whereas divergence of prices for crudes of different qualities can be observed.

Liu, Chen, and Wan (2013) investigate the role of China in the world crude oil market. Since China is one of the major oil importers with increasing demand in recent years, China's energy policy has an important influence on regional crude oil prices. If price changes of the regional benchmark, Daqing, were transmitted to world crude oil prices, indications of market integration would be found. However, the results of a threshold VECM reveal only a one-directional effect from world crude oil markets to the regional Daqing benchmark. Wilmot (2013) focusses on the Canadian-US market integration. He argues that the 'globalization' hypothesis also requires that a long-run relationship among secondary 'non-benchmark' crudes exists. Evidence from a cointegration analysis of Edmonton Par, a light crude, and Western Canadian Select, a heavy crude, and its US (Mexican) analogues, confirm a long-run relationship. However, the analysis reveals a structural break in the cointegrating vector and the breakpoint is determined to coincide with the Financial Crisis.

More recently, Ji and Fan (2015) investigate the long-run equilibrium relationships among the five major regional crude oil benchmarks (WTI, Brent, Dubai, Bonny Light, Tapis) by using a VECM combined with a directed acyclic graph technique. Based on tests for the presence of structural breaks, they split their sample at the break point in October 2010. They find that WTI was a price setter before 2010 while Brent is in a leading role since 2011. Tapis has always been a price taker whereas Dubai and Bonny Light have taken both roles at times. Mann and Sephton (2016) use band-TAR threshold cointegration models to examine the long-run relationships between WTI and Brent and WTI and Oman. They find these crude oil price pairs to be tied together in the long-run. Since each price adjusts to the long-run equilibrium at some point, they conclude that a unique global benchmark prices does not exist.

Additionally, there are further studies that focus on the changing conditions on the crude oil market. Reboredo (2011) models the dependence structure between crude oil benchmark prices using a copula approach. Upper and lower tail dependence is found, suggesting that benchmark crude oils boom and crash simultaneously. This is considered evidence for a globalized world crude oil market. Candelon et al. (2013) examine causal linkages at regional oil markets when prices are on average extremely high or low. The study reveals benchmark prices besides WTI and Brent. Moreover, market integration is found to be weaker during extreme times. Instead of Candelon et al. (2013)'s set of 32 different crudes, Lu, Hong, Wang, Lai, and Liu (2014) restrict their analysis to four benchmark prices (WTI, Brent, Dubai, Tapis) and find a stronger market integration after disruptive events take place. Zhang and Zhang (2015) employ a Markov-switching autoregressive model to investigate the short-run dynamics between Brent and WTI. They find three price regimes which are characterized by different dynamics.

In all, evidence is mounting that crude oil markets are 'globalized'. Crude oil prices seem to hold long-run equilibrium relationships. However, the degree of market integration does not seem to be stable over time.

## 4. Econometric methodology

The long-run and short-run dynamics of the crude oil prices, collected in a vector $y_t$, are modelled using a vector error correction model (VECM). The model assumes that the prices are linked by stable long-run relationships. However, the variables deviate from these equilibrium relationships in the short-run due to random shocks. Maintaining the long-run relationships requires that deviations are corrected by the variables in the short-run. Put differently, the variables are said to adjust to equilibrium errors. Following Johansen (1988)'s notation, the linear VECM is given as

$$\Delta y_t = \mu + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma^i \Delta y_{t-i} + u_t, \tag{1}$$

where $y_t$ is a $N \times 1$ vector of $I(1)$ variables, $\mu$ is a vector of drift parameters and $u_t$ is a vector of white noise error terms. The $k \times k$ parameter matrix $\Pi = \alpha\beta'$ captures both the long-run equilibrium relations and the adjustment behaviour. The matrix $\beta$ contains $r$ cointegrating vectors and $\alpha$ carries the loadings in each of the $r$ vectors.

A particular feature of the linear VECM is that it assumes constancy of all parameters in its data generating process. Certainly, this assumption appears to be restrictive in the context of a volatile crude oil market. Previous studies described relevant disruptive events concerning the energy market (see Lu et al. (2014) for a list of events from 2002 to 2011), and specific issues on the crude oil market, for example WTI, as a 'broken benchmark'. These events are likely to induce structural changes in the relations among crude oil prices. Although we expect the crude oil prices to maintain constant long-run equilibria since crude oils are close substitutes[3], the roles of crude oils in the market, for example, switching from price takers to prices setters and vice versa, might change over time. Particularly, a decoupling of WTI from the world crude oil market might have led to exogeneity of WTI for this period. We therefore study the evolution of the adjustment coefficients while the long-run equilibrium relationships are assumed to stay constant over time.

To account for potential time-varying adjustment, we apply a Markov-switching VECM (MSVECM) to the data. Markov-switching models in a time series econometrics framework were introduced by Hamilton (1989) and the MSVECM used in this paper was proposed by Krolzig (1997). We consider a $q$-regime VECM which allows the parameters to be state-dependent. The MS($q$)-VECM takes the form of

$$\Delta y_t = \mu_{s_t} + \Pi_{s_t} y_{t-1} + \sum_{i=1}^{p-1} \Gamma^i_{s_t} \Delta y_{t-i} + u_t, \qquad u_t | s_t \sim N(0, \Sigma_{s_t}), \tag{2}$$

where $\mu_{s_t}$ are state-dependent drift terms, $\Pi_{s_t}$ is the state-dependent long-run impact matrix, $\Gamma^i_{s_t}$ are state-dependent short-run dynamics and the error terms have a normal distribution conditional on the state $s_t$. A Cholesky decomposition of the error term variance-covariance matrix gives $\Sigma = LS^2L'$ where $L$ is a normalized lower triangular matrix and $S$ is diagonal. The error term variance can either be restricted to stay fixed over all states, $\Sigma_{s_t} = \Sigma$ for all $s_t = 1, 2, \ldots, q$, or change over states. We distinguish between a switching scale, $\Sigma_{s_t} = LS^2_{s_t}L'$, and a fully switching variance, where each element of $\Sigma_{s_t}$ is switching according to $s_t$, $\Sigma_{s_t} = L_{s_t}S^2_{s_t}L'_{s_t}$. A fully switching variance-covariance matrix comes at the cost of an increasing number of parameters that have to be estimated.

[3]Differences in quality (density and sulphur content) are reflected in discount or premium prices.

The state of the data-generating process is governed by a latent integer state variable $s_t$. The probability that $s_t$ attains some particular value $j \in \{1, 2, \dots, q\}$ depends only on the most recent value $s_{t-1}$:

$$P(s_t = j | s_{t-1} = i, s_{t-2} = k, \dots) = P(s_t = j | s_{t-1} = i) = p_{ij} \quad \forall\, i, j = 1, 2, \dots, q. \tag{3}$$

Such a process is described as an $q$-state Markov chain with constant transition probabilities $p_{ij} > 0, \sum_{j=1}^{q} p_{ij} = 1$ (Hamilton (1994)). We assume the Markov chain to be irreducible and ergodic, which means that each regime can be reached from any previous regime (absence of absorbing states) and no regime has a periodic occurrence.

The state-dependent long-run impact matrix $\Pi_{s_t}$ is decomposed in the constant cointegrating vectors and the state-dependent weighting matrix $\alpha_{s_t}$,

$$\Pi_{s_t} = \alpha_{s_t} \beta', \tag{4}$$

where $\alpha_{s_t}$ contains the state-dependent adjustment coefficients which measure the reaction to deviations from the long-run equilibria for each regime. In our application, we are particularly concerned with the evolution of the adjustment coefficients over time and regimes. The adjustment coefficients can be interpreted in the context of a lead-lag relationship among the crude oil prices. If one of our crudes was a global price setter, it would not adjust to deviations from the long-run equilibrium induced by random shocks. The price setting crude thus takes the role of a *lead* variable. Analyzing the long-run relationships among crude oil prices via a MSVECM provides further insights in the structure of the world crude oil market since it enables us to identify exogenous benchmark prices under particular regimes of the process.

The dynamic properties are further investigated by observing the behaviour of the system after shocks to variables of the system using regime-specific orthogonalized impulse response functions. For this matter, we need to transform the VECM representation given in (2) to a vector moving average (VMA) representation,

$$y_t = u_t + \Psi^1_{s_t} u_{t-1} + \Psi^2_{s_t} u_{t-2} + \Psi^3_{s_t} u_{t-3} + \dots \tag{5}$$

Since the error terms $u_t$ are correlated with each other, we use the Cholesky decomposition of the regime-specific error term variance-covariance matrix again and construct orthogonalized impulse response functions,

$$IRF^1_{s_t}(\hat{\theta}) = \widehat{L}_{s_t}, \quad IRF^2_{s_t}(\hat{\theta}) = \widehat{\Psi}^1_{s_t}\widehat{L}_{s_t}, \quad \dots, \quad IRF^h_{s_t}(\hat{\theta}) = \widehat{\Psi}^{h-1}_{s_t}\widehat{L}_{s_t}, \tag{6}$$

where $\hat{\theta}$ denotes the entirety of all estimated parameters.

Naturally, the number of parameters to estimate increases with the number of states which are specified in the MSVECM, so that a parsimonious model specification leads to a maximum of two or three states. However, the exact number of states is usually not known a priori and has to be jointly selected with additional variables, that is, further lags to capture short-run dynamics. Psaradakis and Spagnolo (2006) found that information criteria can accurately identify the appropriate number of states for a Markov-switching model. Awirothananon and Cheung (2009) argued for the use of the BIC to select the number of states based on results of Monte Carlo experiments. In the following application, we follow Awirothananon and Cheung (2009) and use the BIC for model selection with respect to the number of states, the lag length and switching behaviour of the drift terms as well as elements of the variance-covariance matrix.

## 5. Empirical analysis

### 5.1. Data

For this study, we observe crude oil price data at weekly frequency from May 1987 until October 2015. All crude oil prices are free on board (FOB) spot prices[4], observed at each Monday and denominated in US dollars per barrel. The time series are obtained from DATASTREAM[5] and the original observations were transformed by taking natural logarithms.

First, the time series are tested for their order of integration. The results of ADF and KPSS unit root tests are reported in Table 1. Furthermore, we apply the Lee-Strazicich (LS) unit root test which accounts for two structural breaks in the null and alternative (Lee and Strazicich (2003)). The null hypothesis of the ADF and LS tests cannot be rejected at the 1% significance level for all prices while the null hypothesis of the KPSS test is rejected at all conventional significance levels. We obtain opposite results for the returns. The tests support the hypothesis that all prices follow a unit root process and are integrated of order one.

Table 1: Unit root tests of the logarithmized crude oil prices.

| Variables | ADF | LS | KPSS | Variables | ADF | LS | KPSS |
|---|---|---|---|---|---|---|---|
| WTI | $-2.635$ | $-2.846^{*}$ | $0.668^{***}$ | $\Delta$ WTI | $-22.153^{***}$ | $-37.433^{***}$ | 0.064 |
| Brent | $-2.901$ | $-3.087^{**}$ | $0.738^{***}$ | $\Delta$ Brent | $-20.234^{***}$ | $-34.436^{***}$ | 0.068 |
| Dubai | $-2.794$ | $-3.459^{**}$ | $0.742^{***}$ | $\Delta$ Dubai | $-19.773^{***}$ | $-41.847^{***}$ | 0.071 |
| Bonny Light | $-2.520$ | $-3.014^{*}$ | $0.742^{***}$ | $\Delta$ Bonny Light | $-20.167^{***}$ | $-31.848^{***}$ | 0.069 |
| Tapis | $-2.575$ | $-3.485^{**}$ | $0.725^{***}$ | $\Delta$ Tapis | $-18.630^{***}$ | $-42.166^{***}$ | 0.072 |

Note: The ADF, LS and KPSS test equations are estimated including an intercept and trend for the variables in levels. The test equations for the first differences include an intercept. Lag selection is based on the Bayesian Information Criterion (BIC).
$^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$

[4] Pertains to a transaction whereby the seller makes the product available within an agreed on period at a given port at a given price; it is the responsibility of the buyer to arrange for the transportation and insurance. (US Energy Information Administration)

[5] The data can be found using Mnemonic (Code): OILTPMY (S214WT), OILDUBI (T15609), OILBRNP (S04107), CRUDWTC (S369VW), OILAFRB (S00112).

*5.2. Linear cointegration analysis*

To test for cointegration, we rely on the Johansen rank test which is based on the VECM specified in Equation (1). The cointegrating rank $r$ is determined by the number of estimated eigenvalues of the estimated adjustment coefficient matrix $\Pi$ that are significantly greater than zero. Johansen (1988, 1991) proposed likelihood ratio type tests of which we use the trace test variant[6]. The trace test examines the null hypothesis, $\text{rank}(\Pi) = r_0$, against the alternative hypothesis, $r_0 < \text{rank}(\Pi) \leq k - 1$.

The results of the cointegration test are presented in panel (a) of Table 2. Since the null hypothesis $r_0 = 3$ can soundly be rejected, we assume the maximum number of cointegrating vectors of four. The normalized cointegrating vectors are displayed in Panel (b) of Table 2. We find that the price differentials between WTI and the four remaining crudes are relevant long-run equilibria. The trade-off between a parsimonious specification and sufficiently capturing the short-run dynamics of the system leads to two additional lagged differences ($K = 2$).

We now briefly turn to the results of the linear VECM to obtain a useful summary of the 'average' adjustment dynamics provided by a linear specification. The adjustment coefficients of the linear VECM are reported in panel (c) of Table 2. A surprising feature of the results is the adjustment of the cointegrated system to the WTI-Brent price differential. Neither WTI, nor Brent adjust strongly to the deviations from their long-run equilibrium. By contrast, Bonny Light and Dubai react to deviations from the WTI-Brent price differential in the previous period. Tests for weak exogeneity of particular crude oil prices are presented in panel (d). The tests suggest weak exogeneity of Dubai, although it adjusts significantly to the WTI-Brent and WTI-Bonny Light price differentials. This discrepancy can be attributed to a generally lower power of Wald-

[6] The maximum eigenvalue test reaches the same conclusion: The null hypothesis of at most three cointegration vectors is rejected.

Table 2: Cointegration tests and linear VECM

| | $N-r$ | $r$ | Eig.value | Trace | 5% Crit. val. | $p$-Value |
|---|---|---|---|---|---|---|
| *Panel (a): I(1)-analysis* | | | | | | |
| | 5 | 0 | .1084 | 361.75 | 76.07 | 0.000 |
| | 4 | 1 | .0651 | 192.16 | 53.12 | 0.000 |
| | 3 | 2 | .0374 | 92.61 | 34.91 | 0.000 |
| | 2 | 3 | .0292 | 36.22 | 19.96 | 0.000 |
| | 1 | 4 | .0013 | 1.95 | 9.24 | 0.783 |

| | WTI | Brent | Bonny | Dubai | Tapis | $\mu$ |
|---|---|---|---|---|---|---|
| *Panel (b): Cointegration vectors* | | | | | | |
| $\beta_1$ | -1.087 | | | | 1 | .276 |
| $\beta_2$ | -1.136 | | | 1 | | .584 |
| $\beta_3$ | -1.097 | | 1 | | | .355 |
| $\beta_4$ | -1.094 | 1 | | | | .363 |
| *Panel (c): Adjustment coefficients* | | | | | | |
| $\alpha_1$ | $.066^{*}$ | $.104^{***}$ | $.110^{***}$ | .049 | $-.162^{***}$ | |
| | (1.879) | (2.974) | (3.159) | (1.514) | $(-6.198)$ | |
| $\alpha_2$ | .028 | $.064^{**}$ | $.063^{**}$ | $-.016$ | $.061^{***}$ | |
| | (1.005) | (2.270) | (2.238) | $(-.606)$ | (2.877) | |
| $\alpha_3$ | $-.214^{*}$ | $-.229^{**}$ | $.432^{***}$ | $-.272^{***}$ | $-.001$ | |
| | $(-1.933)$ | $(-2.062)$ | $(-3.915)$ | $(-2.638)$ | $(-.018)$ | |
| $\alpha_4$ | $.198^{*}$ | .053 | $.257^{**}$ | $.242^{**}$ | .090 | |
| | (1.701) | (.451) | (2.216) | (2.237) | (1.028) | |
| *Panel (d): Weak exogeneity* | | | | | | |
| LR(4) | $16.47^{***}$ | $22.87^{***}$ | $33.38^{***}$ | 7.54 | $43.07^{***}$ | |

| Lag | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| *Panel (e): Test for residual autocorrelation* | | | | | |
| | 3.398 | 9.366 | $66.174^{***}$ | $148.79^{***}$ | $196.38^{***}$ |
| *Panel (f): Test for ARCH effects* | | | | | |
| | $2081.5^{***}$ | $2937.7^{***}$ | $3790.5^{***}$ | $4971.8^{***}$ | $5529.4^{***}$ |

Note: Panel (a) reports Johansen (1988) cointegration tests. The critical values are taken from Osterwald-Lenum (1992). $p$-values are computed using a simulation study with 10,000 replications. Panel (b) displays the estimates of the cointegrating vectors. Insignificant variables have been excluded from the cointegrating vector. Panel (c) reports the estimates of the adjustment coefficients with $t$-statistics in parentheses. Estimates of the short-run dynamics, drift terms and variance-covariance matrix are not shown to conserve space. Panel (d) reports weak exogeneity tests. The likelihood ratio (LR) statistics are $\chi^2$ distributed with degrees of freedom in parentheses. Panel (e) shows the results of vector portmanteau tests of the residuals. Panel (f) shows the results of tests for ARCH effects.
$^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$

type statistics. WTI is found to adjust to all price differentials except WTI-Dubai. Hence, WTI does not seem to be an exogenous price setter although it is the most closely watched benchmark crude oil price in the US.

### 5.3. Markov-switching error correction models

Given the evolution of the market conditions, described in Section 2, we suspect that the adjustment coefficients among crude oil prices do not remain constant over time and therefore consider a MSVECM which allows the model parameters to change between different regimes. As noted previously, the model specification of the MSVECM in terms of number of states is typically not clear a priori. Therefore, we consider both a two-state and a three-state specification and choose the final model specification based on the BIC[7]. Further, in line with the principle of parsimony, we reduce the number of parameters to estimate by testing whether allowing a switching behavior in a parameter matrix improves the model with regard to the BIC. More specifically, in the two-state MSVECM with two lags, henceforth MS(2)VECM(2), the vector of drift terms is restricted to be constant over both states and the variance-covariance matrix $\Sigma$ is allowed to switch over states. In the three-state MSVECM with two additional lags, henceforth MS(3)VECM(2), we impose constancy of the drift terms and allow for a switching scale of the variance-covariance matrix. A comparison between the MS(2)VECM(2)[8] and MS(3)VECM(2) based on the BIC suggest that the increased goodness-of-fit of a three-state MSVECM indeed outweighs the increasing number of parameters. The regime-specific adjustment parameters for the MS(3)VECM(2) are reported in Table 3. We have excluded the short-run dynamics to conserve space and focus on the adjustment to the long-run equilibria. We find evidence for distinct regime-switching, reflected by non-zero transition probabilities and a state variable that assumes state 1 in 17%, state 2 in 15% and state 3 in 68% of the sample period. We refer to those points in time in which the model is confident of being in state 1 as regime 1 (R1), in state 2 as regime 2 (R2) and in state 3 as regime 3 (R3). Smoothed probabilities reflect the estimated probabilities of occurrence of each state at each point in time. This allows us to gain insights into the evolution of the adjustment dynamics over time. The smoothed probabilites are depicted in Figure 3.

[7]Higher order MSVECM ($q > 3$) are not in line with a parsimonious model specification

[8]The results for the MS(2)VECM(2) specification are reported in Table 4 in the appendix.

Table 3: Markov-switching error correction model for major crude oil prices (three-state model).

| | WTI | | | Brent | | | Bonny Light | | | Dubai | | | Tapis | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | R1 | R2 | R3 | R1 | R2 | R3 | R1 | R2 | R3 | R1 | R2 | R3 | R1 | R2 | R3 |
| *Panel (a): Switching adjustment coefficients* | | | | | | | | | | | | | | | |
| $\alpha_1(s_t)$ | −.030 | .083 | .073$^{*}$ | −.059 | .136 | .115$^{***}$ | .016 | .090 | .127$^{***}$ | −.067 | .065 | .057 | −.099$^{***}$ | −.312$^{***}$ | −.108$^{***}$ |
| | (−.620) | (.673) | (1.740) | (−1.080) | (−1.080) | (2.630) | (.314) | (.725) | (2.920) | (−1.300) | (.562) | (1.520) | (−4.660) | (−3.430) | (−3.240) |
| $\alpha_2(s_t)$ | .019 | .031 | .039 | .004 | .052 | .095$^{**}$ | −.037 | .073 | .096$^{**}$ | −.076 | −.007 | .002 | −.009 | .137$^{**}$ | .039 |
| | (.368) | (.383) | (1.020) | (.077) | (.641) | (2.390) | (−.727) | (.930) | (2.390) | (−1.460) | (−.087) | (.072) | (−.369) | (2.330) | (1.300) |
| $\alpha_3(s_t)$ | .094 | −.944$^{***}$ | .052 | .114 | −.740$^{**}$ | .006 | −.301$^{*}$ | −.953$^{***}$ | −.060 | −.053 | −.735$^{**}$ | −.012 | .119$^{*}$ | −.402 | .197$^{*}$ |
| | (.615) | (2.780) | (.347) | (.686) | (−2.19) | (.039) | (−1.950) | (−2.880) | (−.393) | (−.335) | (−2.320) | (−.091) | (1.780) | (−1.630) | (1.660) |
| $\alpha_4(s_t)$ | .045 | 1.236$^{***}$ | −.150 | −.060 | .714$^{*}$ | −.254 | .321$^{**}$ | .969$^{**}$ | −.200 | .255 | .821$^{**}$ | −.073 | −0.000 | .661 | −.162 |
| | (.287) | (3.180) | (.951) | (−.350) | (1.830) | (−1.560) | (2.000) | (2.510) | (−1.230) | (1.570) | (2.260) | (−.515) | (−.003) | (2.370) | (−1.290) |
| *Panel (b): Weak exogeneity* | | | | | | | | | | | | | | | |
| LR(4) | 5.770 | 17.128$^{***}$ | 5.858 | 1.251 | 6.980 | 19.261$^{***}$ | 4.428 | 10.661$^{**}$ | 20.992$^{***}$ | 7.088 | 5.970 | 5.029 | 23.571$^{***}$ | 21.208$^{***}$ | 12.919$^{**}$ |
| LR(12) | | 29.252$^{***}$ | | | 30.275$^{***}$ | | | 38.908$^{***}$ | | | 17.759 | | | 58.702$^{***}$ | |

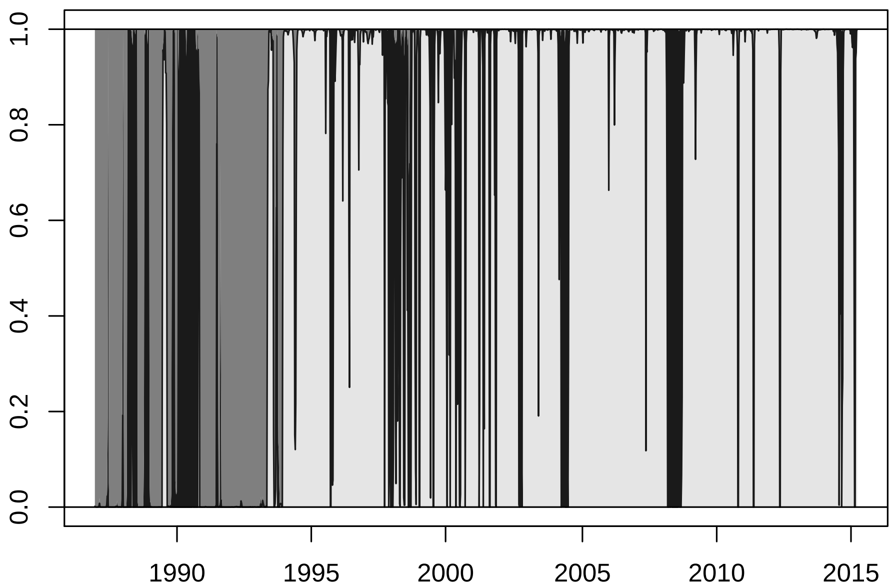
| Lag | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel (c): Test for residual autocorrelation* | | | | | | | | | | |
| | 4.615 | 13.313 | 51.284 | 89.917 | 121.29 | 142.67 | 177.06 | 212.82 | 250.97 | 275.12 |
| | (0.999) | (0.999) | (0.984) | (0.755) | (0.577) | (0.652) | (0.442) | (0.254) | (0.113) | (0.132) |
| *Panel (d): Test for ARCH effects* | | | | | | | | | | |
| | 1.631 | 1.352 | 1.314 | 1.316 | 1.303 | | | | | |
| | (0.025) | (0.050) | (0.037) | (0.020) | (0.014) | | | | | |

| | R1 | R2 | R3 |
|---|---|---|---|
| *Panel (e): Transition probabilities* | | | |
| R1 | 0.952 | 0.200 | 0.021 |
| R2 | 0.042 | 0.761 | 0.039 |
| R3 | 0.005 | 0.043 | 0.940 |

Note: R1 refers to the 'early regime', R2 to the 'crisis regime' and R3 to the 'tranquil regime', respectively. Panel (a) reports the estimates of the adjustment coefficients for three regimes with $t$-statistics in parentheses. The estimated cointegrating vectors are identical to panel (a) in Table 2. Estimates of the short-run dynamics, drift terms and variance-covariance matrix are not shown to conserve space. Panel (b) reports weak exogeneity tests for each regime (first row) and over all three regimes (second row). The likelihood ratio (LR) statistics are $\chi^2$ distributed with degrees of freedom in parentheses. Panel (c) shows the results of vector portmanteau tests of the residuals with $p$-values in parentheses. Panel (d) shows the results of tests for ARCH effects with $p$-values in parentheses. Panel (e) displays the estimated transition probabilities.

$^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$

Figure 3: Smoothed probabilities MS(3)VECM(2).




This figure shows the probabilities for the cointegrated system being in the 'early regime' (grey), probabilities of being in the 'crisis regime' (black) and probabilities of being in the 'tranquil regime' (light-grey). The probabilities sum up to one in each period.

The cointegrated system seems to be predominantly in state 1 at the beginning of the observational period. The first regime, thus, comprises almost exclusively of the first part of the sample, reaching from 1987 to 1994 and we refer to this as the 'early regime'[9]. High probabilities of state 2 can be linked to exogenous global events and volatile economic environments. Probabilities close to one coincide with, among others, the period around the events of September 11, 2001, the period after the invasion of Iraq in 2003, and the Financial Crisis beginning in 2008. The second regime can therefore be associated with volatile economic and geopolitical times, hence we call it the 'crisis regime'. The remaining regime associated with state 3 is referred to as the 'tranquil regime' and reflects behavior of the system in periods of relative calm.

[9]Please note that the labelling of the regimes primarily serves the purpose of illustration. The transition probabilities are estimated to be nonzero. Hence, it is, for example, possible that the state variable takes value one at a later point in time and the system switches to the 'early regime' again.

We investigate the role of each crude oil price in all three regimes. The regime-specific dynamics help us to obtain new insights regarding the changing roles of regional crudes in the world crude oil market.

We report the results of regime-specific and overall weak exogeneity test in panel (c) of Table 3. We find no evidence against the null hypothesis of weak exogeneity of WTI in the 'early regime' and in the 'tranquil regime' during the later parts of the sample period. However, WTI adjusts significantly to the WTI/Bonny Light and WTI/Brent price differential in the 'crisis regime'. The hypothesis of overall weak exogeneity is rejected which can be attributed to the significant adjustment in the 'crisis regime'. In other words, WTI seems to react to other crude oil prices primarily in times of uncertainty about future supply and demand. Brent is a weakly exogenous variable in the 'early regime' and the 'crisis regime'. However, Brent adjusts to the WTI/Tapis and WTI/Dubai price differentials in the 'tranquil regime'. Bonny Light is weakly exogenous in the 'early regime', adjusts to WTI/Bonny Light and WTI/Brent price differentials in the 'crisis regime' and to the WTI/Tapis and WTI/Dubai price differentials in the 'tranquil regime'. These findings suggest that WTI and Brent are important signals of world crude oil market news for Bonny Light in crisis periods whereas the price differentials with the Arabian Dubai and the Asian Pacific Tapis are constant factors in the price determination of Bonny Light. This can in parts be explained by the fact that Dubai is a close regionally competitor to the Nigerian Bonny Light. A reaction to its WTI price differential is attributed to the fact that the US is the largest importer of Nigerian crude oil so that US crude oil demand shocks are transmitted to the price of Bonny Light.

Dubai is the only weakly exogenous variable in all regimes. The results of the overall weak exogeneity test for Dubai in the three-state model is in line with the findings for the two-state MSVECM and the linear model (see panel (d) in Table 2 and panel (c) in Table 4). Also, an alternative normalization in which Dubai is allowed to be an exogenous variable in each equation left the results virtually unchanged. The results of this model are reported in Table 6 in the appendix. Economically, the result implies that Dubai acts as a price setter in this set of benchmark crude oil prices. Finally, Tapis is a price taker in all three states.

The orthogonalized impulse response functions[10] are displayed in Figure 4. We find that shocks to one variable in the 'early regime' do not evoke strong responses from the other variables. In contrast, shocks in the 'crisis regime' lead to visible reactions of the system. Adjustment to shocks is relatively fast whereas it takes the system more time to adjust to shocks in the 'tranquil regime'. These findings are in line with Ji and Fan (2015) who document stronger market integration if global exogenous shocks occur.

## 6. Discussion

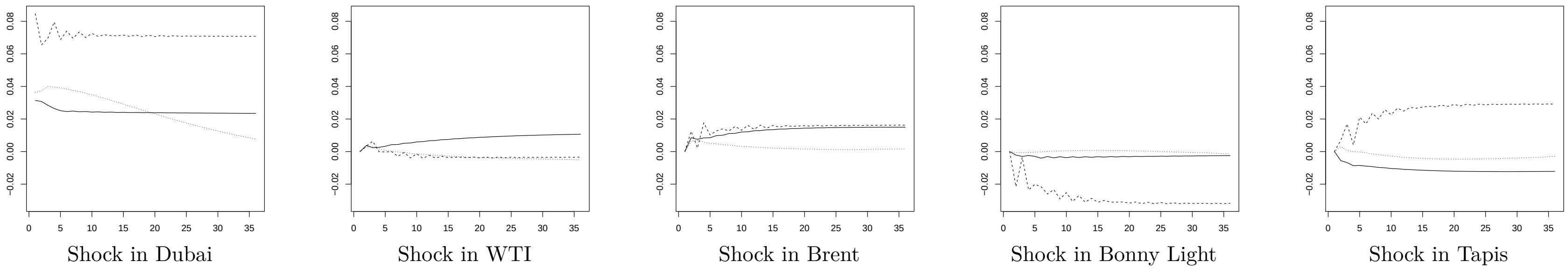
Overall, the results are in line with the findings of Lu et al. (2014) and Ji and Fan (2015), indicating a stronger market integration in turbulent times. While a globally stable oil market promotes the use of nearby oil fields with lower transportation costs, extreme economic conditions create incentives to re-evaluate the attractiveness of different crude oil sources. Therefore, crude oil prices have to incorporate global information beyond the regional supply and demand changes.

Furthermore, the allocation of regime 1 to the earlier part of our sample, helps to emphasize the evolution of the world crude oil market. With the exception of Tapis, we do not reject weak exogeneity for any crude oil in the 'early regime'. The later part of the sample is partitioned into the 'tranquil regime' and the 'crisis regime', so that either Brent and Bonny Light adjust to long-term equilibria in tranquil times or WTI

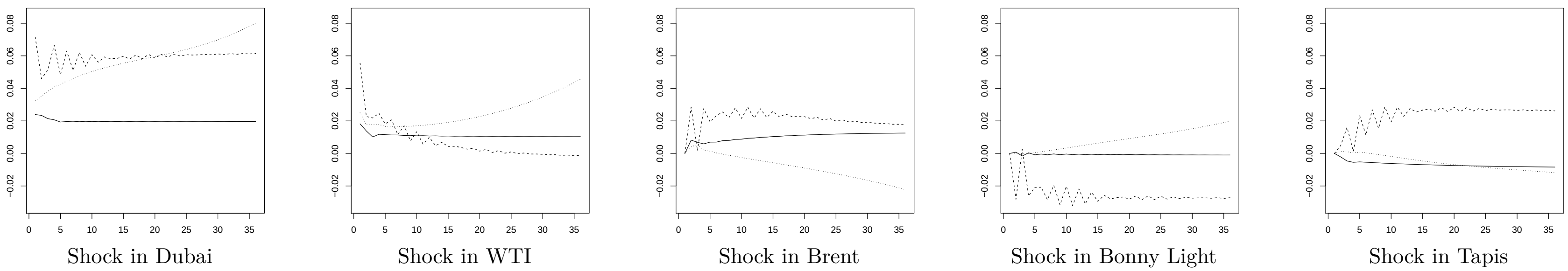
[10] The ordering of the variables which is used for the Cholesky decomposition is given as follows: Dubai $\rightarrow$ WTI $\rightarrow$ Brent $\rightarrow$ Bonny Light $\rightarrow$ Tapis.

Figure 4: Regime-specific orthogonalized impulse response functions for one standard deviation shock in Dubai, WTI, Brent, Bonny Light and Tapis. The dotted, dashed and solid lines represent the OIRF in the 'early regime', the 'crisis regime' and the 'tranquil regime', respectively.

*Panel (a): Response by Dubai*




*Panel (b): Response by WTI*




*Panel (c): Response by Brent*

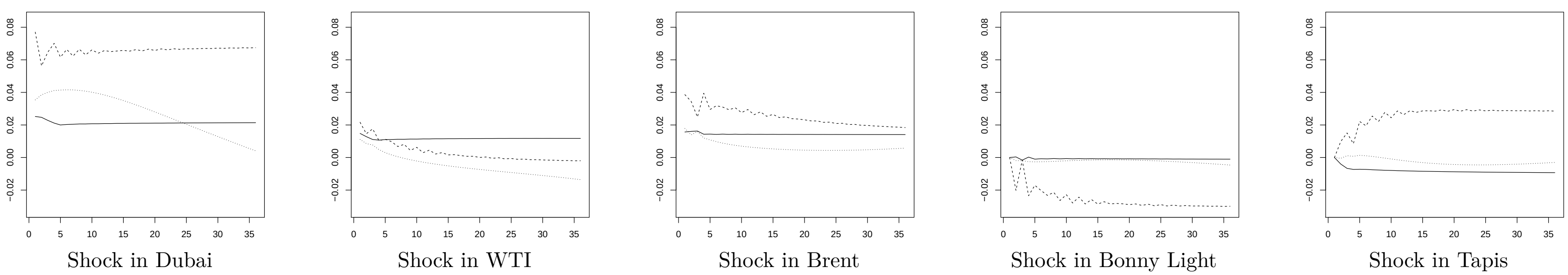
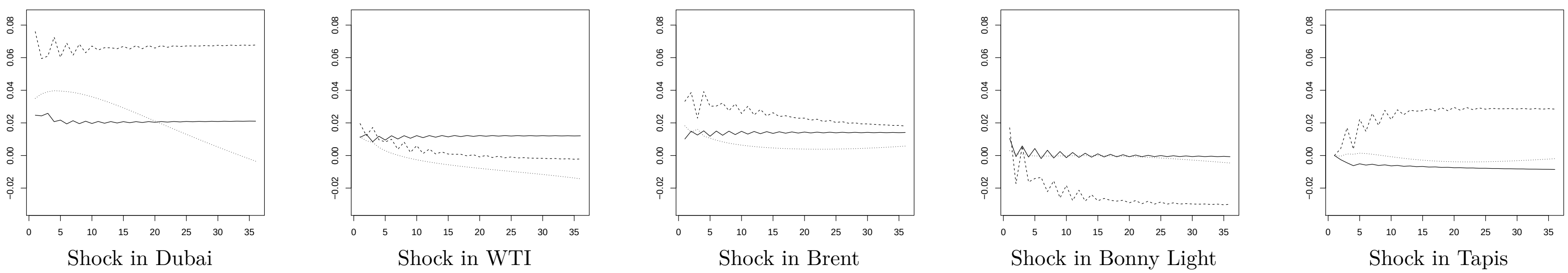
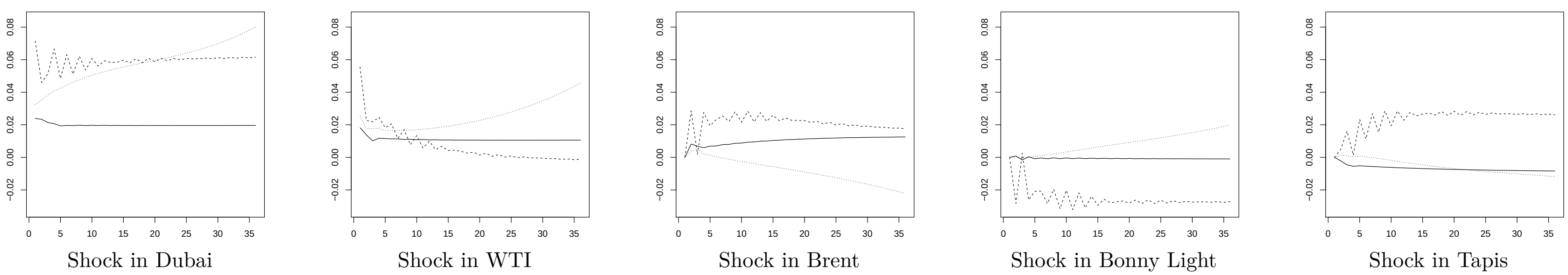


Figure 4 *(continued)*: Regime-specific orthogonalized impulse response functions for one standard deviation shock in Dubai, WTI, Brent, Bonny Light and Tapis. The dotted, dashed and solid lines represent the OIRF in the ‘early regime’, the ‘crisis regime’ and the ‘tranquil regime’, respectively.

*Panel (d): Response by Bonny Light*




*Panel (e): Response by Tapis*

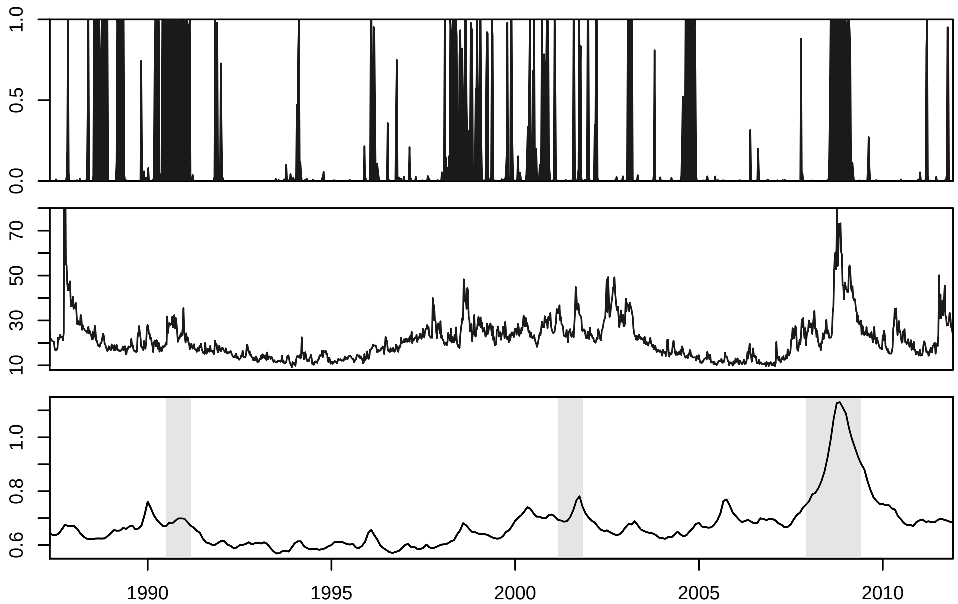


adjusts to its WTI/Brent and WTI/Bonny Light price differentials to maintain a long-run equilibrium relationship under extreme economic conditions. Dubai's price setting role supports the hypothesis in Bentzen (2007) which states that OPEC prices are gaining influence in the world crude oil market.

Similar to our results, Guelen (1999) finds that crude oil market integration is not stable and is especially strengthened during tight market conditions. His results, however, rely on a pre-specified structural break (the full sample is divided into two subperiods 1991-1993 and 1994-1996). Our study, following a more flexible approach, reveals that focusing only on the magnitude of prices does not seem to provide a more comprehensive picture of the crude oil market dynamics. Specifically, the application of a Markov-switching model to a longer and more varied sample period shows that crude oil market integration is strengthened in periods following geopolitical and economic events. The prices of benchmark crude oil reflect changing market conditions and, for example, tend to increase if supply is uncertain, but we document faster adjustment primarily in high volatility periods.

Moreover, the extent of market integration seems to coincide with the level of macroeconomic and financial uncertainty. To illustrate our notion, we compare the occurrence of the 'crisis regime' with two measures for financial and economic uncertainty. First, we contrast the evolution of the state indicator variable with the CBOE Volatility Index (VXO) which is based on 30-day S&P 100 index at-the-money options. It is a widely used measure for uncertainty in the financial market and has the advantage over other uncertainty measures that it spans the full sample period and is available at weekly frequency. The VXO, however, primarily measures uncertainty in the financial markets while *economic* uncertainty may also be influenced by fluctuations in real activity. Second, we therefore also compare the occurrence of 'crisis' episodes in the crude oil market with a measure for macroeconomic uncertainty, recently developed by Jurado, Ludvigson, and Ng (2015). This new measure for macroeconomic uncertainty essentially is an index based on various indicators including real output and income, unemployment, consumer spending and foreign exchange measures. The smoothed probabilities for the 'crisis regime' and our uncertainty measures are depicted graphically in Figure 5. It is obvious that the occurrence of the 'crisis regime' matches

Figure 5: Smoothed probabilities of the 'crisis regime' and uncertainty measures.




Source: [dataset] Jurado et al. (2015), [dataset] NBER (no date)

This figure compares the smoothed probabilities of the cointegrated system being in the 'crisis regime' (row one) with the CBOE Volatility Index (row two) and the measure for macroeconomic uncertainty (grey shaded area: NBER recession dates) by Jurado et al. (2015) (row three).

various peaks in the VXO, particularly, after the stock market crash in 1987, during the Persian Gulf crisis 1990-1991, the September 11, 2001 attack in the US, the 2003 Iraq war and the Financial Crisis starting late 2007. Likewise, peaks in macroeconomic uncertainty match 'crisis' episodes in the crude oil market. Compared to the VXO, Jurado et al. (2015)'s measure for macroeconomic uncertainty, however, is much smoother and its relation with the 'crisis regime' appears to be generally less pronounced. Finally, we consider the linear relation between the VXO and the ‘crisis regime’ indicator.[11] The contemporary correlation of the two time series is 0.277.

In essence, these findings provide descriptive evidence for a link between global economic uncertainty and world crude oil market integration. While they support our notion they do not enable an inferential analysis which we leave for future research.

## 7. Conclusion

This study provides a dynamic perspective on crude oil market integration. We employ a Markov regime-switching model based on the vector error correction model to study regime-switching adjustment behavior to constant long-run equilibria. Thereby, we identify three regimes to describe the adjustment behavior in different market conditions. The results highlight the changing landscape of the world crude oil markets. While the crude oil prices did not seem to maintain a long-run equilibrium from 1987 to 1994, the degree of crude oil market integration has strengthened in the later part of the sample. However, the roles of price setter and price taker can change drastically depending on the state of the global economy. Moreover, the results reveal the important role of Dubai as a price setter. Understanding crude oil market dynamics should therefore not be confined to a precise monitoring of WTI and Brent prices but should include Dubai as a third important benchmark price. Although the relationship between crude oil benchmark prices is changing over time, we do not find evidence for a decoupling of the WTI benchmark after the introduction of hydraulic fracturing to the shale oil fields of the US. It seems, that instead global events trigger adjustment to other regional benchmarks, thereby increasing world crude oil market integration.

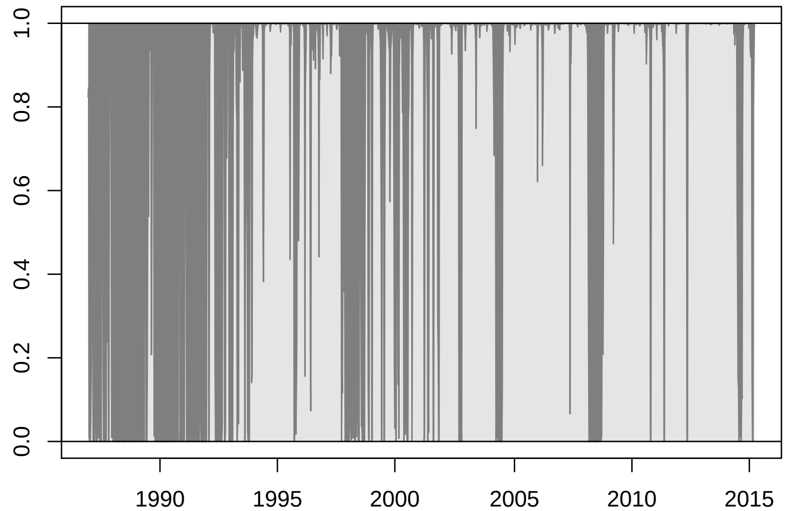
[11] Computing correlations between our state indicator variables and the measure for macroeconomic uncertainty is not possible due to different data frequencies.

## 8. Acknowledgements

We thank Robert Jung, Alexander Schmidt and the editor, Marcel Prokopczuk, as well as two anonymous referees for valuable comments and suggestions. Further, we thank the organizers and participants of DAGStat 2016 in Göttingen as well as the participants of the doctoral seminars at the University of Hohenheim. Access to Thomson Reuters Datastream, provided by the Hohenheim Datalab (DALAHO), is gratefully acknowledged. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

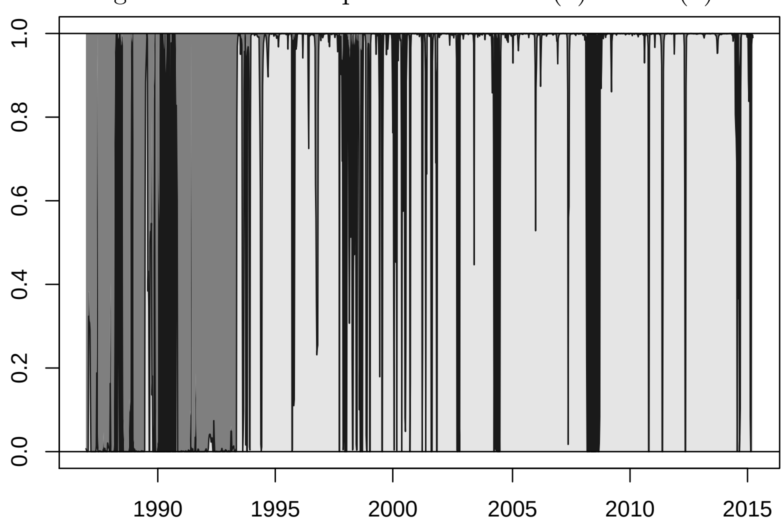
## 9. Appendix

Figure 6: Smoothed probabilities MS(2)VECM(2).




This figures depicts the probabilities for the cointegrated system being in regime 1 (grey) and probabilities of being in regime 2 (light-grey). The probabilities sum up to one in each period.

Figure 7: Smoothed probabilities MS(3)VECM(2).




Probabilities for the cointegrated system being in the 'early regime' (medium-grey), probabilities of being in the 'crisis regime' (dark-grey) and probabilities of being in the 'tranquil regime' (light-grey). The probabilities sum up to one in each period.

Table 4: Markov-switching error correction model for major crude oil prices (two-state model).

| | WTI | | Brent | | Bonny Light | | Dubai | | Tapis | |
|---|---|---|---|---|---|---|---|---|---|---|
| | R1 | R2 | R1 | R2 | R1 | R2 | R1 | R2 | R1 | R2 |
| *Panel (a): Switching adjustment coefficients* | | | | | | | | | | |
| $\alpha_1(s_t)$ | .039 | .092** | .064 | .142*** | .052 | .155*** | .031 | .063* | −.227*** | −.097*** |
| | (.553) | (2.340) | (.884) | (3.550) | (.731) | (3.870) | (.454) | (1.780) | (−4.560) | (−3.110) |
| $\alpha_2(s_t)$ | 0.022 | .055 | .032 | .122*** | .036 | .124*** | −.024 | .007 | 0.093** | .038 |
| | (.422) | (1.550) | (.600) | (3.350) | (.683) | (3.400) | (−.468) | (.224) | (2.500) | (1.330) |
| $\alpha_3(s_t)$ | −.538*** | .044 | −.431** | −.015 | −.709*** | −.082 | −.497** | −.040 | −.154 | .174 |
| | (−2.630) | (.319) | (−2.070) | (−.108) | (−3.470) | (−.598) | (−2.480) | (−.326) | (−1.070) | (1.580) |
| $\alpha_4(s_t)$ | .772*** | −.178 | .436* | −.289** | .735*** | −.235 | .589*** | −.053 | .321** | −.146 |
| | (3.410) | (−1.230) | (1.890) | (−1.970) | (3.240) | (−1.610) | (2.670) | (−.414) | (2.010) | (−1.260) |
| *Panel (b): Weak exogeneity* | | | | | | | | | | |
| LR(4) | 22.131*** | 10.941** | 6.328 | 34.432*** | 14.024*** | 37.712*** | 7.319 | 5.571 | 28.873*** | 11.757** |
| LR(8) | 35.555*** | | 42.029*** | | 52.948*** | | 12.586 | | 41.605*** | |

| Lag | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel (c): Test for residual autocorrelation* | | | | | | | | | | |
| | 3.090 | 7.793 | 44.582 | 94.171 | 118.78 | 148.50 | 189.55 | 228.23 | 275.35** | 297.66** |
| *Panel (d): Test for ARCH effects* | | | | | | | | | | |
| | 4.028*** | 3.241*** | 2.704*** | 3.616*** | 3.413*** | | | | | |

| | R1 | R2 |
|---|---|---|
| *Panel (e): Transition probabilities* | | |
| R1 | 0.938 | 0.140 |
| R2 | 0.062 | 0.860 |

Note: Panel (a) reports the estimates of the adjustment coefficients for two regimes (R1 and R2) with $t$-statistics in parentheses. The estimated cointegrating vectors are identical to panel (a) in Table 2. Estimates of the short-run dynamics, drift terms and variance-covariance matrix are not shown to conserve space. Panel (b) reports weak exogeneity tests for each regime (first row) and over both regimes (second row). The likelihood ratio (LR) statistics are $\chi^2$ distributed with degrees of freedom in parentheses. Panel (c) shows the results of vector portmanteau tests of the residuals. Panel (d) shows the results of tests for ARCH effects. Panel (e) displays the estimated transition probabilities.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Cointegration tests and linear VECM (Dubai normalization).

| | $N-r$ | $r$ | Eig.value | Trace | 5% Crit. val. | $p$-Value |
|---|---|---|---|---|---|---|
| *Panel (a): I(1)-analysis* | | | | | | |
| | 5 | 0 | .1084 | 361.75 | 76.07 | 0.000 |
| | 4 | 1 | .0651 | 192.16 | 53.12 | 0.000 |
| | 3 | 2 | .0374 | 92.61 | 34.91 | 0.000 |
| | 2 | 3 | .0292 | 36.22 | 19.96 | 0.000 |
| | 1 | 4 | .0013 | 1.95 | 9.24 | 0.783 |
| | **WTI** | **Brent** | **Bonny** | **Dubai** | **Tapis** | **$\mu$** |
| *Panel (b): Cointegration vectors* | | | | | | |
| $\beta_1$ | | | | $-.958$ | 1 | $-.284$ |
| $\beta_2$ | | | 1 | $-.966$ | | $-.209$ |
| $\beta_3$ | | 1 | | $-.963$ | | $-.200$ |
| $\beta_4$ | 1 | | | $-.881$ | | $-.515$ |
| *Panel (c): Adjustment coefficients* | | | | | | |
| $\alpha_1$ | $.066^{*}$ | $.104^{***}$ | $.110^{***}$ | .049 | $-.162^{***}$ | |
| | (1.879) | (2.974) | (3.159) | (1.514) | $(-6.198)$ | |
| $\alpha_2$ | $-.214^{*}$ | $-.229^{**}$ | $.432^{***}$ | $-.272^{***}$ | $-.001$ | |
| | $(-1.933)$ | $(-2.062)$ | $(-3.915)$ | $(-2.638)$ | $(-.018)$ | |
| $\alpha_3$ | $.198^{*}$ | .053 | $.257^{**}$ | $.242^{**}$ | .090 | |
| | (1.701) | (.451) | (2.216) | (2.237) | (1.028) | |
| $\alpha_4$ | $-.086^{***}$ | .007 | .001 | $-.003$ | .011 | |
| | $(-3.254)$ | (0.277) | (0.050) | $(-.110)$ | (0.570) | |
| *Panel (d): Weak exogeneity* | | | | | | |
| LR(4) | $16.47^{***}$ | $22.87^{***}$ | $33.38^{***}$ | 7.54 | $43.07^{***}$ | |
| **Lag** | **1** | **2** | **3** | **4** | **5** | |
| *Panel (e): Test for residual autocorrelation* | | | | | | |
| | 3.398 | 9.366 | $66.174^{***}$ | $148.79^{***}$ | $196.38^{***}$ | |
| *Panel (f): Test for ARCH effects* | | | | | | |
| | $2081.5^{***}$ | $2937.7^{***}$ | $3790.5^{***}$ | $4971.8^{***}$ | $5529.4^{***}$ | |

Note: Panel (a) reports Johansen (1988) cointegration tests. The critical values are taken from Osterwald-Lenum (1992). $p$-values are computed using a simulation study with 10,000 replications. Panel (b) displays the estimates of the cointegrating vectors. Insignificant variables have been excluded from the cointegrating vector. Panel (c) reports the estimates of the adjustment coefficients with $t$-statistics in parentheses. Estimates of the short-run dynamics, drift terms and variance-covariance matrix are not shown to conserve space. Panel (d) reports weak exogeneity tests. The likelihood ratio (LR) statistics are $\chi^2$ distributed with degrees of freedom in parentheses. Panel (e) shows the results of vector portmanteau tests of the residuals. Panel (f) shows the results of tests for ARCH effects.
$^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$

Table 6: Markov-switching error correction model for major crude oil prices (three-state model, Dubai normalization).

| | WTI | | | Brent | | | Bonny Light | | | Dubai | | | Tapis | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel (a): Switching adjustment coefficients* | | | | | | | | | | | | | | | |
| | R1 | R2 | R3 | R1 | R2 | R3 | R1 | R2 | R3 | R1 | R2 | R3 | R1 | R2 | R3 |
| $\alpha_1(s_t)$ | $-.018$ | $.080$ | $.068$ | $-.036$ | $.102$ | $.122^{***}$ | $.016$ | $.063$ | $.134^{***}$ | $-.030$ | $.025$ | $.055$ | $-.144^{***}$ | $-.312^{***}$ | $-.105^{***}$ |
| | $(-.393)$ | $(.535)$ | $(1.590)$ | $(-.719)$ | $(-.666)$ | $(2.650)$ | $(.305)$ | $(.405)$ | $(2.910)$ | $(-.658)$ | $(.175)$ | $(1.440)$ | $(-3.660)$ | $(-2.700)$ | $(-3.280)$ |
| $\alpha_2(s_t)$ | $-.073$ | $-.826^{**}$ | $.072$ | $-.053$ | $-.645^{*}$ | $.009$ | $-.479^{***}$ | $-.835^{**}$ | $-.055$ | $-.217$ | $-.615^{*}$ | $-.015$ | $.035$ | $-.360$ | $.202^{*}$ |
| | $(-.453)$ | $(-2.220)$ | $(.495)$ | $(-.313)$ | $(-1.740)$ | $(.062)$ | $(-2.660)$ | $(-2.220)$ | $(-.369)$ | $(-1.390)$ | $(-1.750)$ | $(-.115)$ | $(.256)$ | $(-1.270)$ | $(1.860)$ |
| $\alpha_3(s_t)$ | $.166$ | $1.124^{***}$ | $-.176$ | $.094$ | $.627$ | $-.284^{*}$ | $.513^{***}$ | $.853^{**}$ | $-.232$ | $.350^{**}$ | $.720^{*}$ | $-.079$ | $.074$ | $.611^{*}$ | $-.172$ |
| | $(.968)$ | $(2.670)$ | $(-1.140)$ | $(.524)$ | $(1.470)$ | $(-1.750)$ | $(2.680)$ | $(1.970)$ | $(-1.430)$ | $(2.160)$ | $(1.800)$ | $(-.552)$ | $(.511)$ | $(1.890)$ | $(-1.480)$ |
| $\alpha_4(s_t)$ | $-.098$ | $-.426^{***}$ | $-.018$ | $.018$ | $-.142$ | $.036$ | $.023$ | $-.160$ | $.035$ | $-.022$ | $-.127$ | $.027$ | $.027$ | $-.084$ | $.033^{*}$ |
| | $(-1.450)$ | $(-3.320)$ | $(-.738)$ | $(.256)$ | $(-1.120)$ | $(1.450)$ | $(.315)$ | $(-1.240)$ | $(1.420)$ | $(-.338)$ | $(-1.050)$ | $(1.210)$ | $(.488)$ | $(-.852)$ | $(1.740)$ |
| *Panel (b): Weak exogeneity* | | | | | | | | | | | | | | | |
| LR(4) | 3.277 | $13.250^{**}$ | 5.962 | 0.962 | 4.173 | $18.255^{***}$ | 7.744 | 6.271 | $19.733^{***}$ | 6.013 | 3.491 | 4.816 | $14.596^{***}$ | $12.992^{**}$ | $13.814^{***}$ |
| LR(12) | | $23.029^{**}$ | | | $26.316^{***}$ | | | $36.293^{***}$ | | | 13.450 | | | $42.970^{***}$ | |

| Lag | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel (c): Test for residual autocorrelation* | | | | | | | | | | |
| | 5.615 | 12.342 | 43.175 | 82.409 | 103.99 | 126.05 | 138.06 | 196.39 | 229.13 | 250.39 |
| | (0.999) | (0.999) | (0.999) | (0.999) | (0.914) | (0.923) | (0.816) | (0.559) | (0.411) | (0.481) |
| *Panel (d): Test for ARCH effects* | | | | | | | | | | |
| | 2.583 | 2.382 | 2.317 | 2.048 | 1.964 | | | | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | | | | | |

| | R1 | R2 | R3 |
|---|---|---|---|
| *Panel (e): Transition probabilities* | | | |
| R1 | 0.952 | 0.182 | 0.047 |
| R2 | 0.037 | 0.770 | 0.033 |
| R3 | 0.012 | 0.048 | 0.919 |

Note: R1 refers to the 'early regime', R2 to the 'crisis regime' and R3 to the 'tranquil regime', respectively. Panel (a) reports the estimates of the adjustment coefficients for three regimes with $t$-statistics in parentheses. The estimated cointegrating vectors are identical to panel (a) in Table 5. Estimates of the short-run dynamics, drift terms and variance-covariance matrix are not shown to conserve space. Panel (b) reports weak exogeneity tests for each regime (first row) and over all three regimes (second row). The likelihood ratio (LR) statistics are $\chi^2$ distributed with degrees of freedom in parentheses. Panel (c) shows the results of vector portmanteau tests of the residuals with $p$-values are given in brackets. Panel (d) shows the results of tests for ARCH effects with $p$-values are given in brackets. Panel (e) displays the estimated transition probabilities.
$^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$

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