Oil Prices in the Determination of Sovereign CDS Spreads: The Case of Russia.

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Our paper explores the relevance of the relations between the Credit Default Swap (CDS) spreads for Russia and its domestic and global risk explanatory factors. The Markov-switching models help to identify two regimes in the dynamics of these CDS spreads over a period spanning from July 2003 to June 2017. Local factors (government balance, Russian stock prices) and global factors (US investment grade spread versus US Treasuries, US stock prices, exchange rates) drive the dynamic of Regime 1 whereas Regime 2 is only impacted by financial factors (foreign and local stock prices, etc.). In addition, oil prices steer the transition probabilities from one regime to another. These empirical results are confirmed by robustness checks and they could be useful for other large oil exporting countries such as Saudi Arabia and other Gulf Cooperation Council countries.

JEL classification: C13; G12; G15

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Credit default swaps (CDS) are financial products which allow investors to trade and hedge assets which bear credit risks with a certain ease. They are insurance contracts offering protection against the default of a corporate or sovereign debt issuer. Basically, the buyer of a CDS pays the seller an annuity premium, defined as a percentage on the notional hedged *i.e.* the CDS spreads. In order to have a first glimpse on the development of CDS markets, we briefly investigate the figures regarding this financial instrument. Over the last decades, the CDS displayed large variations with a global maximum at the end of 2007 when its notional amounts outstanding reached a peak of about USD 62 trillion. The global financial turmoil of 2008-2010 (subprime crisis, sovereign debt crisis in Europe, etc.) had a negative impact on this market that led to a severe decrease in the notional amounts outstanding (USD 9.9 trillion by end-2016 BIS, 2017). The trading volume of CDS represents about a third of the total trading volume of the credit (Avino and Nneji, 2014).

Even though CDS contracts represent a relatively small proportion of the contracts on the credit derivatives market (less than 3% of the notional outstanding of the total of derivative products at the end of 2016), they are one of the most interesting and promising derivatives products. Indeed, they provide us with a good overview of the dynamics of the credit around the world; the CDS spreads are considered as an alternative and direct measure of default risk and a good indicator of hedging (Amato, 2005, Longstaff *et al.*, 2011). These characteristics of CDS help to justify the reasons why CDS have been topics of increasing interest since their introduction (mid-nineties by JP Morgan) in the financial assets *(Broad Index Secured Trust Offering*).

Due to the significance of emerging countries such as Russia in the recent development of the global real and financial economy, it is essential to have a good perception on the evolution of the potential default risk regarding these countries. It is also crucial to identify the links between this asset and its explanatory factors and especially oil as Russia is heavily reliant on commodities trade. The additional motivation of the analysis of the links between Russia's CDS spreads and its determinants such as global risk factors stems from the importance of trade between Russia and the developed countries. Our motivation to focus the analysis on oil prices in the determination of sovereign risks stems from the fact that Russia is a large non-OPEC oil exporting country. As such, oil is a key factor for such a country not only in terms of revenues but also because investors' perception of sovereign risk (i.e. the risk premium requested by markets) is likely to shift with oil price swings.

Therefore, it is increasingly interesting to keep checks on the robustness of the links between Russia's CDS spreads and its determinants. These investigations could also prove useful for Gulf Cooperation Council (GCC) countries. Indeed, they recently started emitting increased volumes of sovereign debt securities (see for example Saudi Arabia). Unfortunately, due to the lack of reliable data, we are still not able to perform any robust econometric analysis for these countries.

To our knowledge, the relationships between oil and sovereign risks have not been systematically explored in the literature over the recent period. From this view point, it is crucial for both researchers and regulators to identify the channels through which the diverse factors and especially oil can affect the CDS spreads of large emerging countries and to evaluate the magnitudes of the effects of these factors of risk.

The objectives of this paper are fourfold: i) To explore the relations between the CDS spreads of Russia and its domestic and global risk factors; ii) To disentangle the effects of the risk factors linked to oil; iii) To test the relevance of the nonlinearity of these relationships; iv) To check the strength and the robustness of these relationships.

The main questions addressed in this paper are: i) What are the main triggers or drivers for the CDS spreads dynamics of Russia? ii) Are the effects of oil meaningful and to what extent do they explain the CDS spreads? iii) Is a nonlinear framework more appropriate to the investigation of the dynamics of the CDS spreads?

This paper is related to the strand of literature on the pricing and fundamental determinants of CDS. It complements and extends the body of work based on the seminal paper by Merton (1974) and on more recent papers by Longstaff *et al.* (2011), Fender *et al.* (2012) or Chan and Marsden (2014).

In particular, we implement a nonlinear model, a Markov-switching model (Avino and Nneji, 2014) including economic and financial explanatory factors. We will see below that the hypothesis of the existence of some states in the CDS spreads can be accepted with confidence at a reasonable level. Due to the introduction of financial and macroeconomic factors in the framework, we use monthly data over the period spanning from January 2002 to December 2015.

Our approach is similar to that implemented by Avino and Nneji (2014), Chan and Marsden (2014) or Alexander and Kaeck (2008) who investigated the influence of economic and financial factors on North American or European CDS spreads. It differs from the previous one, as it concerns emerging sovereign CDS spreads and especially scrutinizes the effects of oil to explain these spreads. Only a few recent papers examine the link between oil prices on sovereign credit risk but they do not integrate a nonlinear approach.

Bouri *et al.* (2016) examined the volatility spillovers from commodities to sovereign CDS spreads for seventeen emerging and six frontier countries using daily data. They found stronger effects of energy and precious metals volatility on sovereign CDS spreads for these countries. Using a GARCH-quantile approach, Bouri *et al.* (2017) also find that the volatility of commodity/energy markets shapes CDS dynamics in the middle and upper volatility quantiles of commodities/energy exporters (i.e. Russia). Sharma and Thuraisamy (2013) analyze the impact of oil price uncertainty on sovereign CDS spreads for eight Asian countries using some predictability tests. They found that oil price uncertainty increase out of-sample forecasts of CDS spread for six countries (i.e. Malaysia, Indonesia, Japan, the Philippines, Vietnam and South Korea). Naifar *et al.* (2017) run causality-in-quantiles regressions between sovereign CDS and some risk factors. According to them, the sovereign CDSs of non-GCC oil-exporting countries and especially Russia are the most affected by oil prices. Overall, this stream of literature suggests significant spillovers from commodity markets to sovereign CDS spreads of emerging countries.

We also take into account the recent period including the financial turmoil period, the poor economic performances phases of Russia, the collapse of oil prices and its recent political episodes (i.e. the annexing of Crimea by Russia, sanctions etc.).

Our paper contributes to the empirical literature which relates the CDS spreads changes to the country-specific and global risk factors in both linear and nonlinear frameworks. It disentangles the effects of oil on the CDS spreads. Furthermore, the nonlinear framework implemented allows us to distinguish the effects of the determinants of the CDS spreads in each regime as well as for the country-specific model and the global risk factors-based models. One of the practical implications of this study is that investors can have a better understanding of the dynamics of sovereign CDS spreads of Russia in order to improve the management of their positions. From a policy-maker perspective, our results can enhance government monitoring of the factors that impact the risks perceived by financial markets.

The remainder of the paper is organized as follows: Section I discusses the methodological basis of our approach, provides a brief theoretical background of the model, and presents the model; Section II describes the data and some descriptive statistics; Section III examines the empirical results and their economic bedrock and relevance; Section IV outlines a sensitivity analysis of the estimation results; and Section V sheds light on the main conclusions and policy recommendations of the paper.

1. Model Specification

1.1. Outline on the relevance of the multi-regime approach in the analysis of CDS spreads

Blommestein and Eijffinger (2012), B and M hereafter, showed how a state-dependency relationship between the sovereign CDS spreads and its explanatory factors could be derived (Jeanne and Masson, 2000, J and M hereafter). In other words, the dynamics of the CDS spreads could be described by a Markov-switching process. Indeed, under some assumptions, the probability of default (d_t) can be defined by:

$$d_t = \sum_{s=1}^{n} q(s_t, s) F(f_t, f_s^*) \quad (1)$$

Where:

- f_t is an index of economic fundamentals at time t;

- f_s^* is a the critical value of the index under the state s;

- $F(f_t, f_s^*) = Prob[f_{t+1} < f_s^* / f_t]$;

- $q(s_t, s)$ is the transition probability from current state, s_t at time t, to state s, $1 \leq s \leq n$, at date *t+1*.

In order to derive a formal relationship between the sovereign CDS spreads and its fundamental determinants, some additional assumptions are needed:

a) The fundamental index is assumed to be a linear function of some macroeconomic variables, designated mv_t (a matrix of macroeconomic fundamentals) (J and M ; , B and M):
b) $f_t = \alpha^T mv_t$,
   α^T is a transpose vector of scalars. Under this assumption, J and M showed that the probability of default can be re-written as follows:

$$d_t = \partial_{s_t} + \varphi^T mv_t \quad (2)$$

∂_{s_t}, the intercept, is only state-dependent.

c) The second hypothesis is that CDS spreads vary under the rational expectations assumption which enables us to show that the sovereign CDS spreads are determined by both the probability of default and some macroeconomic variables (designated omv_t) which are not included in mv_t .

In this respect, the linear equation of the sovereign CDS spreads is:

$$CDS_t = \gamma + \theta d_t + \mu^T omv_t \quad (3)$$

where γ is the intercept of the equation 3, θ is an unknown parameter and μ^T is a transpose vector of scalars.

d) Replacing the probability of default in (3) by its expression defined by (2) leads to:

$$CDS_t = \beta_{s_t} + \tau mv_t + \mu^T omv_t \quad (4)$$

where $\beta_{s_t} = \gamma + \theta \partial_{s_t}$, the intercept, is state-dependent while the slope $\tau = \theta \varphi^T$ is time-invariant). Thus, the sovereign CDS spreads dynamics can be described by a Markov-switching model.

e) B and M also showed that, under an alternative hypothesis, the fundamental index could be defined by a state-dependent relationship. Under this assertion, it is easy to show that the slope of the sovereign CDS spreads is also state-dependent. Therefore, the CDS spreads are driven by a complete (intercept and slope) Markov-switching model in which the effects of exogenous variables are also time-varying.

This brief presentation confirms the relevance of the Markov-switching model which takes into account state-dependency in the CDS spreads dynamics. Furthermore, many empirical studies highlighted some evidence on nonlinearity in credit spreads (Chan and Marsden, 2014; Avino and Nneji, 2014; Alexander and Kaeck, 2008; Davies, 2004).

1.2. The selection of the potential explanatory factors

In this session, we propose a brief guideline of the selection of the potential explanatory factors (mv_t and omv_t, see above) of the model based on the studies published in this strand of the literature (see Appendix A for a synthetic presentation of the effects of some selected factors). Some theoretical papers (including Merton's seminal one) are the baseline of our analysis. As shown by Blanco *et al.* (2005) (see also Duffie, 1999 and Hull *et al.*, 2004), CDS prices and credit spreads are theoretically equivalent. Therefore, the theory related to credit spreads can also help explain CDS prices or spreads.

Two main approaches are often mentioned to describe credit spreads and CDS or credit derivative prices:

i) The intensity-based approach that establishes a relation between credit risk and hazard rates; however, the determinants of the credit risk are not theoretically founded;

ii) The structural approach by Merton which shows that the prices of defaultable securities are related to the losses or the economic determinants of financial distress regarding the firm. Basically, Merton's structural approach involves the processes that drive firm value and the default threshold associated with the firm.

Nevertheless, the available empirical results related to the structural model are unclear in the context of the micro determinants of credit spreads. On one hand, Ericsson *et al.* (2009), Zhang *et al.* (2009), among others, confirm the main conclusions of Merton concerning the determinants of credit spreads. For example, Ericsson *et al.* (2009) found that the swap spreads are related to the firm leverage factor and volatility whereas Zhang *et al.* (2009) highlighted the robustness of the relationship between CDS spreads, equity long run historical volatility and risk on individual firms. On the other hand, the firm-level factors do not play a significant role in the dynamics of credit spreads in the work of Collin-Dufresne *et al.* (2001) who mentioned that the spread changes in corporate bonds are driven by supply and demand shocks.

In this paper, we focus on the structural approach and its extensions. The factors that drive changes in the firm value and/or the default threshold are supposed to be the determinants of changes in the credit spreads. In order to ease the comparison between the countries under review and due to the availability of the data, we focus on the effects of macroeconomic and financial factors on the CDS spreads. Indeed, some proxies of general economic conditions which govern the situation of firms are the fundamental determinants of credit spreads in structural models (Wu and Zhang, 2008; Tang and Yan, 2010; Annaert *et al*., 2013). The sectorial and aggregate risk factors (sector-wide risk at industry-level, economy-wide risk indicator, or GDP growth volatility, etc.) often intervene as explanatory variables in structural models of CDS spreads (Ericsson and Renault, 2006; Bhansali *et al.*, 2008; Tang and Yan, 2010).

Firm leverage and liquidity factors also appear as fundamental determinants in this approach (Coro, Dufour, and Varotto, 2013, Bongaerts *et al.*, 2011, Tang and Yan, 2008). Factors related to firms' activity or describing their health are sometimes considered as strong determinants of CDS spreads (high yields markets, etc.). The characteristics of equity markets are often considered as relevant explanatory factors in the structural models (Alexander and Kaeck, 2008). The return on equity markets is a proxy of business conditions. It is a measure of uncertainty (related to the real activity) which can negatively impact the firm's health. Implied volatility is also a good candidate for describing the dynamics of the equity market in structural models. It should be positively correlated to credit spread.

Lastly, there are relatively few papers specifically designed to the identification of the determinants of sovereign credit spreads (Edwards, 1986, Duffie *et al.*, 2003, and Zhang, 2008, for example). Besides, some papers showed that sovereign credit spreads are strongly influenced by global factors, particularly the US factors (Pan and Singleton, 2008, Longstaff *et al.*, 2011, and Ang and Longstaff, 2013). For instance, Pan and Singleton showed that credit spreads regarding some emerging countries are strongly related to the implied volatility of US stock markets. Longstaff *et al.* (2011) decomposed spreads into expected loss and risk premium and showed that sovereign risk premium is explained by the US stock market and high yield markets. Remolona *et al.* (2008) demonstrated that the expected loss is linked to country-specific factors and market liquidity, whereas the risk premium is driven by global investors' risk aversion. Finally, for Fender *et al.* (2012) changes in emerging countries' sovereign CDS spreads were related to global and regional factors. These diverse results are not contrary but they highlight the need to clarify the role of each global risk factor and especially what the role of oil prices. Can we disentangle between the effects of oil and other global/regional risk factors?

1.3. An empirical Markov-Switching model

The state-dependency of certain variables led to an increasing interest for non-linear models capable of dealing with switching regimes. As mentioned above, the switching model suits the CDS dynamics. It allows us to disentangle between the effects of diverse risk factors by regimes. Thus, according to Coro, Dufour and Varotto (2013), while the firm-specific credit risk factor impacts the changes in corporate CDS prices in tranquil periods, the effect of this factor surprisingly vanishes during the period prior to the recent "Great recession". The MS models can deal with these dynamics. We then perform a more in-depth investigation of the Markov-switching (*MS*) models in order to match this framework to stylized facts drawn from the descriptive analysis.

The MS models take into account breaks which are governed by a latent variable. The latter is assumed to follow a Markov process: S_t, the latent variable is associated with *k* states, then, $S_t = 1, \dots, k$. The endogenous variables are related to the latent variable.

The two-state Markov-switching model ($S_t = 1, 2$) is often used in the empirical studies in order to take into account the nonlinearity introduced by the switching from one state to another. The detecting and dating business cycle turning points are a good example of the application for the two-state Markov-switching model.

The Markov-switching (*MS (k)*) models are considered as extensions of the models that allow for the linear regression model's coefficients to be state-dependent. The *MS (k)* model is laid out as follows:

$$y_t = c_{S_t} + \sum_{l=0}^{m} \vartheta_{lS_t} x_{t-l} + \varepsilon_{S_t} \tag{5}$$

Where y_t is the endogenous variable, x_t is a matrix of exogenous factors;ε_{S_t} the error terms which are state-dependent; the intercept c_{S_t} is state-dependent and the exogenous variables $(\vartheta_{lS_t}, l = 1, \dots, m)$ are also state-dependent.

The hypothesis of state dependency of variance-covariance matrix of ε_{S_t} ($\sum_{S_t}$) is accepted:[1]

$$\varepsilon_{S_t} \sim N(0, \textstyle\sum_{S_t}) \tag{6}$$

The state variable S_t is assumed to follow a first-order Markov-process. The transition probability is:

$$\Pr(S_t = v | S_{t-1} = u) = p_{uv}(t) \tag{7}$$

[1] McConnell and Perez-Quiros (2000) introduced two main changes in the standard Markov-switching model by assuming that the dynamics of the mean and the variance are driven by two separate states; furthermore, the state process for the mean depends on the state of variance. Due to data limitations, we will not implement these previous proposals.

$p_{uv}\ (t)$ is the probability at time t that state u at time $t-1$ will be followed by state v at time t.

Assuming that $p_{uv}\ (t)$ is a function of exogenous observables

$$\Pr(S_t = v \middle| S_{t-1} = u) = p_{uv}(\varphi_{t-1}, \delta_v) = \frac{\exp(\varphi_{t-1}{}'\delta_{uv})}{\sum_{j=1}^{k} \exp(\varphi_{t-1}{}'\delta_{vj})} \tag{8}$$

With the identifying normalization condition: $\varphi_{vk} = 0$. The case of constant probabilities is handled by choosing $\varphi_{t-1} = 1$.

The transition probability matrix $P_t(k \times k)$ at t is defined as follows:

$$P_t(k \times k) = P(t) = \begin{pmatrix} p_{11}(t) & \cdots & p_{k1}(t) \\ \vdots & \ddots & \vdots \\ p_{1k}(t) & \dots & p_{kk}(t) \end{pmatrix} \tag{9}$$

With $\sum_{v=1}^{k} p_{uv}(t) = 1$ where *u, v=1,…, k* and $0 \le p_{uv} \le 1$

CDS spreads react faster than bonds to information on the changes in the credit quality (Hull *et al.*, 2004, Blanco *et al.*, 2005, and Annaert *et al.*, 2013). In addition, our current model is not devoted to the forecasts but to the understanding of the variations of CDS in order to improve our interpretation of those changes. Therefore, we impose that the CDS spreads and its main explanatory variables to be contemporaneous ($m = 0$).

The choice of the independent factors (x_t) is based on the findings of structural model and its extensions. The exogenous factors include: i) general economic condition factors (GDP growth, business cycle indicator, commodity prices, government balance, and trade balance, etc.) ; ii) risk factors (return on local or global equity markets, implied volatility, aggregate liquidity proxy, for example, the bid-ask spread, the most widely used liquidity proxy) ; iii) firms' activity indicators (firm specific liquidity proxy, corporate yield, etc.).

Some empirical studies work only on an *MS (k)-ARMA (p, q)* model which do not include exogenous factors. Even though Avino and Nneji (2014) examined a structural linear model in addition to an AR (p) approach, they essentially estimated a *MS (k)-AR(p)* model in their paper. In our study, we propose a MS model which combines some statistical properties of the variables with more structural considerations regarding the financial and economic behavior of the CDS spreads[2]. In addition, we aim to focus on the entire historic data in order to describe the changes of the CDS spreads during tranquil and turbulent periods.

The set of the unknown parameters of the model, Θ, is defined by:

Θ= $(c_{S_t}, \vartheta_{lS_t}, \sigma_{uv}, p_{uv})$ with S_t = *(1, …, k); i = 1, …, p; j = 1,…,q;* $l = 0, ; \dots, m;$ $\sigma_{uv} = cov(\varepsilon_{S_t}, \epsilon_{S_{t'}})\ with\ \varepsilon_{S_t} = u, \epsilon_{S_{t'}} = v;\ u = 1, \dots, k;\ and\ v = 1, \dots, k$

[2] To compare the in-and out-of-sample performances of the linear and nonlinear models, Avino and Nneji (2014) investigated the predictability of the European CDS spreads. For the perspectives of forecasting exercises, they have simplified the MS approach by dropping out the exogenous variables of the MS model. Thus, they mitigated the estimation risk due to the short span of the sample time-series.

We estimated the MS model by the maximum likelihood method based on the Expectation-Maximization (EM) algorithm (Diebold *et al.*, 1994).

The log-likelihood function $Ln\, L(\Theta/Y_t)$ is given by the sum of the log-densities *f (.)* of the observations y_t conditional on the history of the endogenous and exogenous variables ($Y_t = \{y_\tau, \tau = 1, \dots, t\}$, $X_t = \{x_\tau, \tau = 1, \dots, t\}$, t = 1, …, T).

$$Ln\, L(\Theta/\, X_t\, ; Y_t) = \sum_{t=1}^{T} ln\, f(y_t|\, X_{t-1}\, ; Y_{t-1}; \Theta) \quad (10)$$

With

$$f(y_t|\, X_{t-1}\, ; Y_{t-1}; \Theta) = \sum_{u=1}^{k} f(y_t, S_t = u|\, X_{t-1}\, ; Y_{t-1}; \Theta) =$$
$$\sum_{u=1}^{k} f(y_t|S_t = u; X_{t-1}, Y_{t-1}; \Theta) * \Pr(S_t = u)$$

2. Descriptive Analysis

2.1. Data sources and preliminary calculations

We have privileged the monthly data to introduce economic indicators in the framework. We have focused on the dollar-denominated 5-year maturity for senior unsecured debt since these contracts are regarded as the most liquid and active segment of the CDS markets. The CDS spreads data are extracted from *Bloomberg* over the period July 2003 to June 2017. The *MICEX* data (the domestic stock exchange index) and the Rubble – US Dollar exchange rates are drawn from *Bloomberg* database.

The global financial markets factors are:

a) For the stock market risks: the Standard & Poor's 500 index, its implied volatility, the VIX index;
b) For global rate indicators: the ICE Bank of America Merrill Lynch US Investment grade spreads versus US treasuries and the exchange rates versus the US dollar;
c) For energy specific factors: the 1-month FoB Brent barrel price quoted in US dollar, and the London natural gas index price.

The country-specific factors (trade-balance, foreign-currency-reserves, etc.) are extracted from *Datastream*. The fiscal balances are provided by the Ministry of Finance of the Russian Federation. All variables are taken in (monthly) difference or log difference.

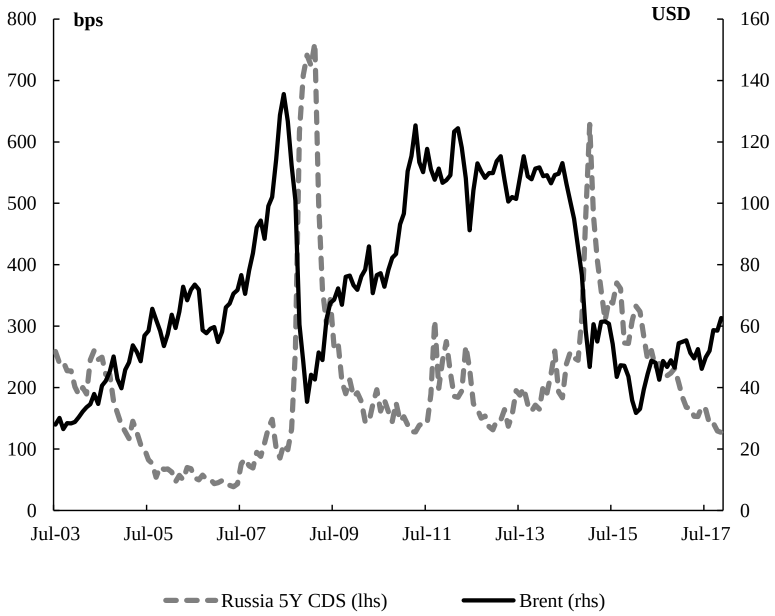


Figure: Russia CDS spreads and crude oil prices

2.2. Stationarity in presence of the different regimes

Evans (1991), among others, shows that the conventional unit root test is not able to detect the explosive behavior of a variable in presence of some breaks or multi-regime processes. The Markov-switching Augmented Dickey–Fuller (*MS-ADF*) tests (Hall *et al.*, 1999; Shi, 2013, see equation 10) are more suitable and powerful than the conventional ADF tests when data are generated by a multi-regime process. It can provide us with information regarding the presence of explosive bubbles in the dynamics of the CDS spreads.

In line with the works of Hall *et al* (1999), we assume that the MS-ADF test is done under the assumption that the error variances are identical in the two regimes (constant variance assumption, CV, the MS-ADF-CV is associated with this additional hypothesis). The alternative MS-ADF test (Shi, 2013) can be performed under the hypothesis that the error variances are regime-dependent (regime-varying variance assumption, RV). In order to detect the explosive bubble behavior of the factors under review by using the MS-ADF model, we privilege the regime-varying assumption which seems more general (MS-ADF-RV). Indeed, the MS-ADF-CV model is a special case of the MS-ADF-RV (with $\sigma_2 = \sigma_1$).

According to Shi (2013), the specification of the MS-ADF-RV model is:

$$\Delta y_t = \mu_{S_t} + \phi_{S_t} y_{t-1} + \sum_{i=1}^{p} \psi_{S_{t,i}} \Delta y_{t-i} + \sigma_{S_t} \epsilon_t \quad (10)$$

With:

$\phi_{S_t} = \phi_1 + (S_t - 1)(\phi_2 - \phi_1)$; $\mu_{S_t} = \mu_1 + S_t(\mu_2 - \mu_1)$; $\psi_{S_{t,i}} = \psi_{1,i} + S_t(\psi_{2,i} - \psi_{1,i})$; p is the lag order. S_t is a two-state variable ($S_t \in \{1,2\}$) following the common first-order Markov process. $\epsilon_t \sim N(0,1)$.

The *MS-ADF* test is defined as follows.[3]

- The null hypothesis of the MS-ADF bubble test is $\kappa_2 \equiv \max(\phi_1, \phi_2) = 0$ versus the alternative $\kappa_2 > 0$. The regime with a larger ADF coefficient is referred to as regime 2 and other is regime 1. If the null hypothesis is rejected then the variable y_t is explosive (non-stationary) in regime 2.
- To investigate the properties of the variable y_t in regime 1, we test the following null hypothesis: $\kappa_1 \equiv min(\phi_1, \phi_2) = 0$; the alternative hypothesis is $\kappa_1 < 0$. The decision rule is similar to that of the previous test.

Finally, in order to assess the critical values of the MS-ADF test, we implement the bootstrapping procedures suggested by van Norden and Vigfusson (1998) (see Table 1). The tests are performed using 1,000 simulated data

In Regime 2, we reject the unit root null hypothesis of κ_2 for Russia's CDS at 5% confidence level. Furthermore, we accept the unit root null hypothesis in Regime 1 for the CDS spreads at a credible significance level. Therefore a mixture of a unit root process and an explosive process prevails. The mixture of these processes confirms the appropriateness of the Markov-switching approach for describing the CDS spreads dynamics for Russia.

TABLE 1: MS-ADF tests for the CDS spreads

		Estimates		Critical Values		
		Coefficients	MS-ADF	10%	5%	1%
Russia	κ_1	-0.42	-0.08	-15.70	-16.11	-17.25
	κ_2	0.24	***1.13***	0.89	***1.05***	1.19

Similar MS-ADF tests are applied to the explanatory factors. The results are comparable with those of the CDS spreads. We do no present them here but they are available from the authors.

We conclude that the log differences of the CDS spreads and the first-order differences or log differences of its explanatory factors are each integrated of order 0 (the raw series are integrated of order 1).

3. Empirical Results

3.1. Baseline models

We choose to model Russia's CDS spreads with different explanatory factors and especially with oil prices in the equation driving the regime transition probabilities. We tested taking into account local/global macroeconomic and financial variables.

As conventional criteria could be biased under the state-dependency hypothesis, before identifying and estimating the Markov–switching model, we implemented the Markov Switching Criterion (MSC) (Smith *et al.*, 2006) in the diagnosis procedure.[4] Indeed, the MSC

[3] For example, See Shi (2013) for an application of these procedures. The simulations are run using the codes provided by Perlin Marcelo on his site: (http://sites.google.com/site/marceloperlin/matlab-code/).

[4] $MSC = -2 * LL + \sum_{i=1}^{k} \frac{T_i(T_i+\lambda_i K)}{\delta_i T_i - \lambda_i K - 2}$; LL is the log-likelihood function associated with the estimation; k is the number of states, T_i is the sum of smoothing probabilities of each state *i*, λ_i = k and δ_i = 1 as suggested by Smith *et al.* (2006).

can facilitate the selection of both the number of regimes and the lags order in the baseline equation. Regarding the MSC, the decision rule is: The best specification corresponds to the lowest MSC in absolute terms.

TABLE 2[(1)]: Markov Switching Criterion (MSC)

	MSC
M(1)	-1.55
M(2)-FTP (without oil)	-115.09
M(2)-TVTP	-149.01*

** Indicates the best specification; M (k) means model with k regimes augmented with exogenous variables; FTP stands for Fixed Transition Probabilities and TVTP for Time Varying Transition Probabilities. In the case of 1 regime, the MSC is equivalent to the AIC.*
(1)The models with 3 regimes fail to converge numerically for both FTP and TVTP. Source: authors' calculations

Table 2 shows that 2-regime model with Time Varying Transition Probabilities prevails.

In order to clarify the representation of the regimes, one can define them as follow:

- Regime 1 is associated with decreasing CDS spreads and corresponds to a significantly lower and negative average of the endogenous variable (about -3.5%);
- Symmetrically, Regime 2 is associated with a positive average of the explained variable (+1%);
- In both regimes, variance is moderate and close to 0.03;
- Out of 168 observations, 55 are associated with Regime 1 while 113 are associated with Regime 2.

The coefficients of Regime 1 are consistent with theory and intuition and show a mixture of local/global macro/financial variables as determinants of CDS spreads (see Table 3). In this regime, better government finance (although the coefficient is close to 0 but significant), higher local stock market, stronger currency, lower global rate spreads and lower global market volatility leads to lower CDS spreads. In the opposite, Regime 2 is driven purely by global financial variables: the exchange rate (here the coefficient is higher than in Regime 1) and by the US stock market (once again, the coefficient is significantly higher than in Regime 1). Finally, our most interesting finding is that oil prices drive transition probabilities. In particular, lower oil prices in Regime 2 allow us to stay in this regime during the next period and vice-versa (see Appendix B). The average expected duration of Regime 2 is 8 months while it is slightly over 1 month for Regime 1.

TABLE 3: Estimates of *M(2)-TVTP*

	Regime 1	**Regime 2**
Government Balance	2.04E-03***	-
Russian Stock Market	-0.65***	-0.72***
USD/RUB	0.87***	1.36***
US Investment Grade spread vs Treasuries	0.31***	-
US Stock Market	-0.38***	-1.35*
VIX	0.06***	-
Intercept	-	-
σ^2	3E-04 ***	0.01***
Transition Matrix Parameters		
Intercept - $p_{1,2}$	3.08***	
Oil - $p_{1,2}$	-	
Intercept - $p_{2,2}$	1.06***	
Oil - $p_{2,2}$	-10.1***	
Log-likelihood	156.5	

****, **, and * denote respectively 1%, 5% and 10% significance.* WITH $\sum_{v=1}^{2} p_{uv}(t) = 1 \; u = 1,2$

3.2. Does the non- linear framework matter?

A large body of literature has been devoted to the tabulation of theoretical distributions under the null hypothesis of linear model (Davies, 1987; Cho and White, 2007; Carter and Steigerwald, 2012). However, the current results on the asymptotical distributions under the null hypothesis are appropriate under specific conditions. One way to reach an acceptable result is to use Davies' linearity tests (Davies, 1987) with approximations to the critical values. Here, we complete this approach by alternative tests such as the regime classification measure (RCM) by Ang and Bekaert (2002). The nonlinearity hypothesis is accepted when the RCM statistic is less than 50. The similarity of the results of Davies and RCM tests could help make a decision (see Table 4).

The Davies tests show that the *MS(2)* models (including macroeconomic and financial factors) with time varying transition probabilities dominate the others. The RCM statistics are weaker or close to 50 for all models. These results validate the relevance of the two-regime hypothesis. In addition, the estimation of the *MS* models with time varying transition probabilities and alternative variables confirms the existence of two regimes for the CDS spread dynamics of Russia. In any case, our baseline model seems preferable to those alternates.

Table 4: Non-linearity Tests

RCM	*MS(2)-FTP without oil*	45.89
	MS(2)-TVTP	**42.05**
	MS(2)-TVTP with alternative variables	43.54
	MS(2)-TVTP on oil trend	32.73
	MS(2)-TVTP on natural gas	11.91
	MS(2)-TVTP until Dec. 2015	44.16
Davies' tests	*MS(2)-FTP without oil*	1.11
	MS(2)-TVTP	**1.14**
	MS(2)-TVTP with alternative variables	1.12
	MS(2)-TVTP on oil trend	1.12
	MS(2)-TVTP on natural gas	1.14
	MS(2)-TVTP until Dec. 2015	1.14

MS(2) means model with 2 regimes augmented with exogenous variables; FTP stands for Fixed Transition Probabilities and TVTP for Time Varying Transition Probabilities. Davies' tests for the null of a linear equation model with exogenous variables.

Source: authors' calculations

3.4 Sensitivity analysis

To examine the robustness of our models, first, we estimate a less flexible *MS(2)* in which the transition probabilities are fixed (FTP) without oil in the regressors; second, we run a *MS(2)* model with TVTP including alternative variables : MSCI Russia instead of *MICEX*, exchange rate versus the euro instead of US dollar, US High Yield spreads instead of Investment Grade, MSCI World index instead of S&P 500 index and the VStoxx (implied volatility on Euro Stoxx) instead of Vix; finally we estimate our baseline model until December 2015. The models are compared with the baseline model presented in the previous session. Finally, we substituted oil prices by oil price trend and natural gas prices in the equations of transition probabilities. Although these estimations exhibit superior RCMs, both variables are not significant in these equations. In addition, in both cases, one regime seems over-identified with all exogenous coefficients significant at the 5% level. As a consequence, we stick with our baseline model. All results and statistics from the estimated models are not presented here but are available on request.

All in all, standard tests indicate that our baseline model is rather robust; our choice of exogenous variables, the time varying transition probabilities (see Appendix B) framework and the inclusion of oil in the model seem relevant. It is also worth mentioning that the results hold when taking a shorter data sample (until December 2015), with quite stable coefficients (see Appendix C).

5. Conclusion

A Markov-switching approach seems appropriate to examine CDS spreads dynamics for Russia. Indeed, we isolate two states driven by macroeconomic and financial factors. In the case of Russia, there are macroeconomic and financial factors which impact the CDS spreads. In particular, we notice that one regime is driven by both macroeconomic and financial factors while another is driven only by financial factors. Notably, the effects of financial factors (domestic and global: corporate yield, stock markets returns and implied volatility) comply qualitatively with the findings of Chan and Marsden (2014).

Furthermore, our economic intuition is confirmed since the inclusion of oil in the modelling is relevant. Furthermore, we find that oil plays a key role in the determination of Russia's CDS spreads as it is driving the transition probabilities from one state to another. These findings are confirmed by some robustness checks.

One of the main implication from our analysis is that large oil exporters such as Russia need to pay close attention to oil prices since lower prices on top of lower revenues from exports also implies higher risks premiums hence higher debt service. With this in mind, Russia's participation in the recent OPEC production limits appears as a reasonable strategy. GCC countries and especially Saudi Arabia, which have been increasingly emitting debt after the oil price collapse of 2014, can also integrate these findings in their analytical framework.

References

Ang, A. and Bekaert, G., 2002. "Regime Switches in Interest Rates". *Journal of Business and Economic Statistics 20(2),* 163-182.

Ang, A. and Longstaff, F.A., 2013. "Systemic Sovereign Credit Risk: Lessons from the US and Europe". *Journal of Monetary Economics 60(5),* 493-510.

Alexander, C. and Kaeck, A., 2008. "Regime Dependent Determinants of CDS spreads". *Journal of Banking and Finance* 32, 1008-1021.

Annaert, J. De Ceuster, M. Van Roy, P. and Vespro, C., 2013. "What Determines Euro Area CDS Spreads?" *Journal of International Money and Finance* 32, 444-461.

Baker, S., Bloom, N. and Davis, S. 2016, "Measuring Economic Policy Uncertainty", *The Quarterly Journal of Economics* 131(4), 1 November 2016, 1593–1636.

Bhansali, V., Gingrich, R. and Longstaff, F., 2008. "Systemic Credit Risk: What is the Market Telling Us?", *Financial Analysts Journal 64,* 16-24.

BIS, 2017 "BIS Statistical Bulletin", December 2017 Issue.

Blanco R., Brennan S. and Marsh I.W., 2005. "An Empirical Analysis of the Dynamic Relationship between Investment-Grade Bonds & Credit Default Swaps", *Journal of Finance 60 (5),* 2255-2281.

Blommestein, H.J. and Eijffinger, S.C.W., 2012. "Animal Spirits in the Euro Area Sovereign CDS Market". CEPR Discussion Paper 9092, Center for Economic Policy Research.

Bongaerts, D., de Jong, F. and Driessen, J., 2011. "Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market". *The Journal of Finance 66(1),* 203-240.

Bouri, E., de Boyrie, M. and Pavlova, I., 2016. "Volatility Transmission from Commodity Markets to Sovereign CDS Spreads in Emerging and Frontier Countries". *International Review of Financial Analysis.*

Bouri, E., Jalkh, N. and Roubaud, D., 2017. "Commodity Volatility Shocks and BRIC Sovereign Risk: A GARCH-Quantile". *Resources Policy.*

Carter, A.V. and Steigerwald, D.G., 2012. "Supplement to Testing for Regime-Switching: A Comment". *Econometrica 80(4),* 1809-1812.

Chan, K.F. and Marsden, A., 2014. "Macro Risk Factors of Credit Default Swap Indices in a Regime-Switching Framework". *Journal of International Financial Markets, Institutions and Money 29*, 285-304.

Cho, J. S. and White, H., 2007. "Testing for Regime-Switching". *Econometrica 75(6),* 1671-1720.

Collin-Dufresne, P., Goldstein, R.S. and Spencer, J.M., 2001. "The Determinants of Credit Spread Changes". *Journal of Finance 56,* 2177-208.

Davies, A., 2004. "Credit Spread Modelling with Regime-Switching Techniques". *Journal of Fixed Income 14,* 36-48.

Davies, R.B., 1987. "Hypothesis Testing when a Nuisance Parameter is Present only under The Alternative". *Biometrika 74(1),* 33-43.

Diebold F.X., Lee, J.-H. and Weinbach, G.C., 1994. “Regime Switching with Time-Varying Transition Probabilities”. In: C. Hargreaves (ed.), *Non Stationarity Time Series Analysis and Cointegration.* (Advanced Texts in Econometrics, C.W.J. Granger and G. Mizon, eds.), Oxford: Oxford University Press, 283-302.

Duffie, D., Pedersen, L.H. and Singleton, K.J., 2003. “Modeling Sovereign Yield Spreads: A Case Study of Russian Debt”. *Journal of Finance 58(1),* 119-159.

Duffie, D., 1999. “Credit Swap Valuation”. *Financial Analysts Journal 55,* 73-85.

Edwards, S., 1986. “The Pricing of Bonds and Bank Loans in International Markets: An Empirical Analysis of Developing Countries’ Foreign Borrowing”. *European Economic Review 30(3),* 565-589.

Ericsson, J., Jacobs, K. and Oviedo-Helfenberger, R., 2009. “The Determinants of Credit Default Swap Premia”. *Journal of Financial & Quantitative Analysis 44(01),* 109-132.

Ericsson, J. and Renault, O., 2006. “Liquidity and Credit Risk”. *Journal of Finance 61,* 2219-2250.

Fender, I., Hayo, B. and Neuenkirch, M., 2012. “Daily Pricing of Emerging Market Sovereign CDS Before & During the Global Financial Crisis”. *Journal of Banking and Finance 36(10),* 2786-2794.

Hall, S.G., Psaradakis, Z. and Sola M., 1999. “Detecting Periodically Collapsing Bubbles: A Markov-Switching Unit-Root Test”. *Journal of Applied Econometrics 14,* 143-154.

Hull J., Predescu, M. and White A., 2004. “The Relationship Between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements”. *Journal of Banking and Finance 28,* 2789-2811.

Jeanne, O. and Masson, P., 2000. “Currency Crises, Sunspots and Markov-Switching Regimes”. *Journal of International Economics 50,* 327-350.

Longstaff, F.A., Pan J., Pedersen, L.H. and Singleton, K.J., 2011. “How Sovereign Is Sovereign Credit Risk?”. American Economic Journal: Macroeconomics 3, 75–103.

McConnell, M.M. and Perez-Quiroz, G., 2000. “Output Fluctuations in the United States: What Has Changed since the Early 1980’s?” *The American Economic Review 90(5),* 1464-1476.

Merton, R.C., 1974. “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates”. *The Journal of Finance 29,* 449-470.

Naifar, N., Shahzad, S.J.H. and Hammoudeh, S., 2017. “The Impact of Major Oil, Financial and Uncertainty Factors on Sovereign CDS Spreads: Evidence from GCC, other Oil-Exporting Countries and Regional Markets” *ERF Working Paper n°1129*

van Norden, S. and Vigfusson, R., 1998. “Avoiding the Pitfalls: Can Regime-Switching Tests Reliably Detect Bubbles?” *Studies in Nonlinear Dynamics & Econometrics* 3, 1-22.

Pan, J. and Singleton, K.J., 2008. “Default and Recovery Implicit in the Term Structure of Sovereign CDS Spreads”. *Journal of Finance 63(5),* 2345-2384.

Remolona, E.M., Scatigna, M. and Wu, E., 2008. “The Dynamic Pricing of Sovereign Risk in Emerging Markets: Fundamentals and Risk Aversion”. *The Journal of Fixed Income 17(4),* 57-71.

Sharma, S. and Thuraisamy, K., 2013. “Oil Price Uncertainty and Sovereign Rrisk: Evidence from Asian Economies”. *Journal of Asian Economics(28)*. 51–57.

Shi, S. 2013. “Specification Sensitivities in the Markov-Switching Unit Root Test for Bubbles”. *Empirical Economics 45(2),* 697-713.

Smith, A., Naik, P.A. and Tsai, C.-.L., 2006. “Markov-Switching Model Selection Using Kullback-Leibler Divergence”. *Journal of Econometrics 134(2),* 553-577.

Tang, D., and Yan, H., 2010. “Market Conditions, Default Risk and Credit Spreads”. *Journal of Banking and Finance 34*, 743-753.

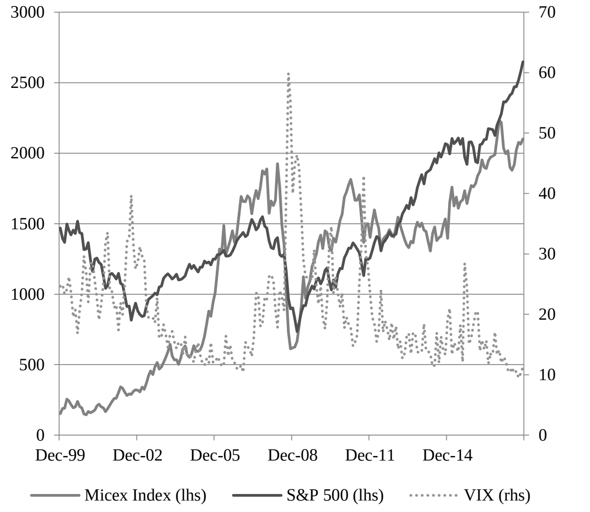
Wu, L. and Zhang, X., 2008. “A No-Arbitrage Analysis of Macroeconomic Determinants of the Credit Spread Term Structure”. *Management Science 54,* 1160-1175.

Zhang, F.X., 2008, “Market Expectations and Default Risk Premium in Credit Default Swap Prices: A Study of Argentine Default”. *Journal of Fixed Income 18(1),* 37-55.

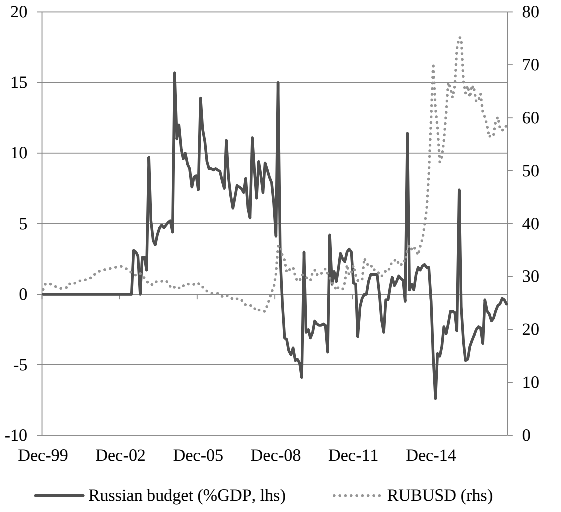
Zhang B., Zhou, H. and Zhu, H., 2009. “Explaining CDS Spreads with The Equity Volatility And Jump Risk of Individual Firms”. *Review of financial Studies 22,* 5099-5131.

Appendix A – Explanatory factors of Russian CDS spreads

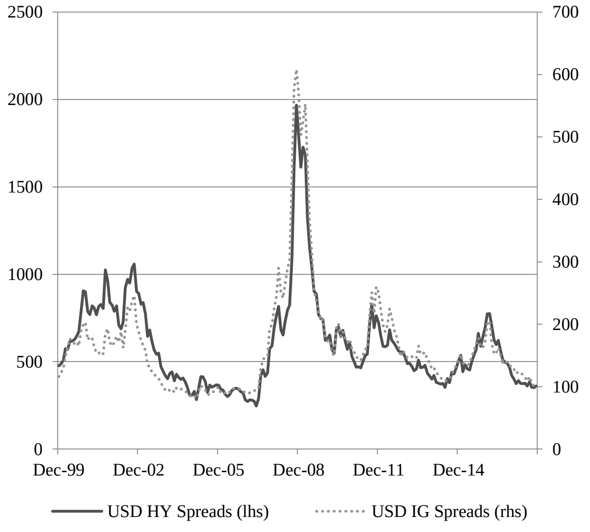
Stock Markets



Russian Budget & the Rubble



US Corporate spreads



Crude oil price and its trend

Brent and Natural Gas Index

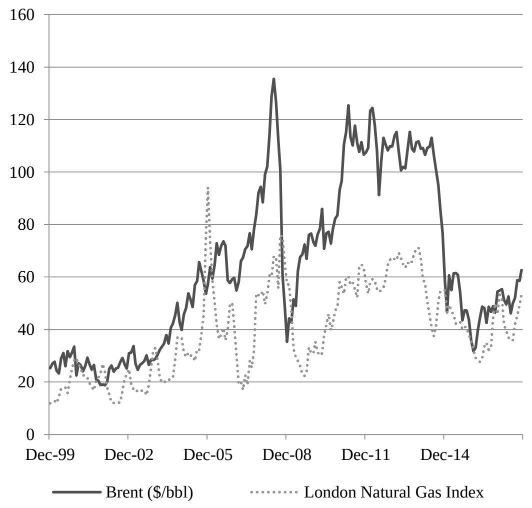
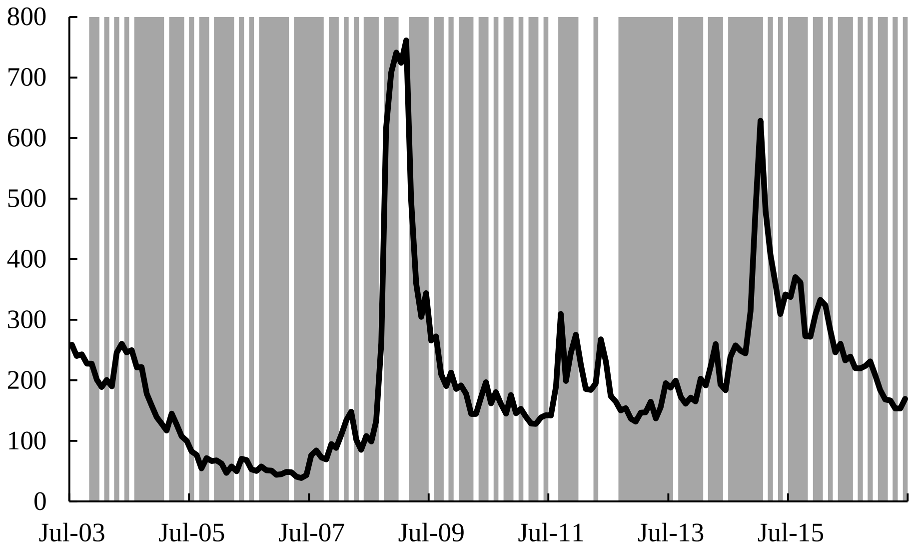


Table A - Expected Effects of Some Determinants of CDS

Explanatory factors	Expected sign
Corporate Yield	+
Forex Reserves	-
Fiscal Balance	-
Stock Mkt. (return)	
Local	- (Longstaff *et al.* 2011)
Global (euro, USA)	+ (Fender *et al.* 2012, during the crisis period)
Implied Volatility	+
Policy Uncertainty	+
Exchange Rate	+
Oil / natural gas	-

Source: authors' synthesis

APPENDIX B – SMOOTHED PROBABILITIES OF REGIME 2 AND CDS SPREADS



Shaded areas correspond with regime 2

Appendix C - Estimates of MS(2)-TVTP Model UNTIL Dec. 2015

	Regime 1	Regime 2
Government Balance	1.96E-03***	-
Russian Stock Market	-0.67***	-0.70***
USD/RUB	0.84***	1.38***
US Investment Grade spread vs Treasuries	0.30***	-
US Stock Market	-0.38***	-1.29**
VIX	0.07***	-
Intercept	-	-
σ^2	2.89E-04 ***	0.01***
Transition Matrix Parameters		
Intercept - $p_{1,2}$	-	
Oil - $p_{1,2}$	-	
Intercept - $p_{2,2}$	-	
Oil - $p_{2,2}$	-9.62*	
Log-likelihood	127.77	

****, **, and * denote respectively 1%, 5% and 10% significance.*