An investigation of oil prices impact on sovereign credit default swaps in Russia and Venezuela

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Abstract

In this paper, we study the impact of oil price returns on sovereign Credit Default Swaps (CDS) spreads for two major oil producers, Russia and Venezuela. Using daily spreads from 2008 to 2015 trough a Time Varying Transition Probabilities Markov Switching model, our results show that crude oil price is a critical determinant of CDS spreads. We highlight some differences between the two countries explained by their level of development. Moreover, global and local factors play a major role in the determination of the sovereign CDS spreads with some differences across both countries.

JEL Classification Numbers: C22, G1, H6, O16, O57, P28, Q02

Key words: Oil prices, Sovereign Credit Default Swaps, Markov-switching, Time Series modeling, Venezuela, Russia

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1 Introduction

The recent oil price collapse has brought to the fore that a debt crisis could also reach oil exporting countries. Not so long ago, they were viewed as financially sound, accumulating huge amount of petro-dollars and showing relatively good ratings by credit rating agencies. Nevertheless, those countries have recently seen their level of debt rise dramatically, leading to increasing credit default swap (CDS) spreads and thus raising the issue of a potential default. For illustration, as a result of tumbling oil prices Venezuela's 5-year credit default swap (CDS) has spiked from less than 2000 basis points (bps) on January 2014 to more than 5000 bps on January 2015. CDS are often seen as financial instruments that can potentially affect financial stability, even though there are controversial debates concerning their use and utility. Nevertheless, the appearance of those financial instruments usually acts as a prelude to a debt restructuring. Sovereign credit risk is more than ever a critical issue, since the Greek crisis and the European bailout, but the question of credit default risk in oil exporting countries has been overlooked by economists so far.

We present one of the first analysis to investigate how oil price returns and financial factors impact the changes of CDS spreads in two emerging oil exporting economies, Venezuela and Russia, on a daily basis. A critical question is whether oil price returns can increase the risk of default, through a rise of sovereign CDS. Our intuition is that the fall of crude oil prices and its high volatility at the end of 2014 has increased the instability of sovereign CDS. Indeed, as the countries studied are highly dependent on oil revenues, financial markets can doubt their ability to honor their debts. This is why understanding the role of oil price returns in oil exporting countries CDS market is essential for investors and policy makers to better understand those solvability issues. Data on financial indicators are available at higher frequencies than macroeconomic indicators, thus it provides additional information which helps identifying the determination process of sovereign credit spreads in a short time period, such as a fall of commodity prices. Indeed, the impact of oil price on sovereign CDS spreads has not been really examined in the literature, and its effect is usually ambiguous in oil exporting countries. On the one hand, oil can be seen as a secure source of revenue for those economies and is viewed as a liquid asset by credit rating agencies. Even though its price is volatile, it enables natural resource rich countries to accumulate enough foreign exchange reserves to pay their debts. Therefore, the volatility of oil price should not undermine sovereign CDS. On the other hand, oil can also be seen as a malediction, fueling conflicts, corruption, and mismanagement of natural resources,with negative macroeconomic consequences, as a shrinking manufacturing sector in an undiversified economy. This last thesis is put forward by the "natural resource curse" and the "dutch disease" literature. To address this question, we study the determinants of sovereign CDS spreads in Venezuela and Russia from 10/10/2008 to 07/02/2015. We use daily sovereign 5-year CDS, which are more liquid than the market sovereign bond, and thus enable us to obtain more accurate estimates of credit spreads. We compare a Time Varying Transition Probabilities Markov Switching model to other standard models, such as a linear and a Markov Switching models. As a lot of breaks can be seen in the data, a non linear model appears more relevant. Moreover, policy changes during the sample period are also important potential sources of regime switching. For instance, Russia's economy has been largely impacted by wars and Arab spring in Libya. Regime switching in the sovereign CDS market could result from those political events. Finally, countries with high levels of sovereign debt are vulnerable to speculative attacks. If the probability of default is high, the demand for sovereign CDS increases. For all those reasons, linear regression models could produce misleading results when regime switching exist. We therefore use a test developed by Carrasco et al. (2014) and find evidence of regime switching in our sample. It will enable us to study two kinds of regimes, one "calm regime" and one "turbulent regime". We thus refer to a Time Varying Transition Probabilities Markov Switching model of Filardo (1998) and Kim et al. (2008), where the transition probabilities are driven by the oil prices volatility index changes.

We show that oil price returns impact directly the changes of Venezuela CDS spreads. In the case of Russia, monetary interventions lead to a depreciation of the ruble to compensate the fall of oil prices. We take also in consideration the oil price volatility. We find that the volatility perceived by the market plays a major role in the determination of CDS spreads. In this paper, we make the assumption that oil price volatility does not affect directly the daily pricing of CDS spreads but the state of the economy. Indeed, if oil prices become more volatile, practitioners can interpret it as a bad signal of the state of the economy. Thus, determinants of sovereign CDS spread will not have the same impact in time of crisis than in calm periods. Investors will be more vigilant to a downturn of global and local factors. We also study the impact of stock markets on sovereign CDS in those natural resource rich countries, as financial stability is known to play a key role in the CDS market. The main results of the article can be summarized as follows: first, we show that crude oil price returns is a critical determinant of Venezuela CDS spreads. However, concerning Russia, the nominal exchange rate plays a key role, as the latter one is directly impacted by commodity prices. Secondly, in both countries oil price volatility has an impact on the state of the economy. The more oil price returns are volatile, the more the probability to be in a high volatility regime increases. Thirdly, global factors impact both countries in the same way. For example, if the US stock market (S&P500) rises, sovereign CDS spreads from Russia and Venezuela decline. Last but not least, we show that the Venezuelan stock market index (IBVC) does not impact Venezuelan CDS spreads, whereas the Russian stock market impacts Russian CDS.

This article contributes to the existing literature by focusing on sovereign CDS in two emerging natural resource rich countries, Venezuela and Russia. Indeed, most empirical studies have concentrated on developed countries, especially in the Eurozone since the Greek crisis, or on emerging countries without taking into account one of their major characteristics, price commodities. We choose to focus on those two major oil producers, Venezuela and Russia, as they have seen their CDS rise those last years, facing financial turmoil as oil price tumbled. There are very few studies examining those two countries, even though oil price has had a dramatic impact on their economy. Our study is at the crossroads of two literatures, the literature on the determinants of CDS and more broadly on sovereign risk, and the literature on natural resources, especially oil. In the past years, the literature on Credit Default Swaps has been flourishing. Many articles highlight the importance of global factors as determinants of CDS spreads. Longstaff et al. (2011) show that global risk factors, such as U.S. equity, volatility, and bond market risk premia, explain CDS spreads. Pan and Singleton (2008) have also pointed out the predominance of such factors, by developing a theoretical pricing model that decomposes spreads into expected losses from default and a risk premium. The risk premia of the sovereign CDS spreads co-move strongly over time and are related to global risk factors. Moreover, Augustin and Tédongap (2014) show that expected growth and consumption volatility in the U.S impact components in the term structure of CDS spreads for a geographically dispersed panel of 38 countries. Further evidence that shocks from the United States influence sovereign CDS spreads in emerging markets is provided by Dooley and Hutchison (2009). Finally, Wang and Moore (2012) find that the CDS markets of both developed and emerging countries are highly correlated during the US subprime crisis and mainly driven by the US economy. Moreover, some authors using financial indicators as determinants of sovereign CDS spreads, (Fontana and Scheicher 2016 ; Fender et al. 2012) distinguish the pricing behaviors between normal times and crisis times. Other studies also emphasize the role of local factors on sovereign risk. For example, Alexander and Kaeck (2008) find a time-sensitive relationship between CDS and local stock markets and Eyssell et al. (2013) include the Chinese stock market as a determinant of Chinese sovereign CDS changes. Remolona et al. (2008) find that country-specific fundamentals determine sovereign risk in emerging countries, and that global investors' risk aversion drives time variation in the risk premia. Our results are consistent with this literature, as we also find that our global risk factors (the S&P 500 and the VIX) and local factors (local stock market) explain CDS changes. A second body of literature focuses on natural resources, and more precisely on the "dutch disease". Among this literature, it has been shown that higher oil prices lead to a real exchange rate appreciation (Corden and Neary 1982; Corden 1984). If different studies attempted to see if Russia contracted the "dutch disease" (Mironov and Petronevich 2015), in our paper we find that the exchange rate seems to play the same role on CDS spreads than oil price returns. As Rautava (2004) highlights it, the exchange rate in Russia could be influenced by oil prices, even though he does not demonstrates a clear relationship between them. For that reason, we decided to use separately those two variables to better assess their respective impact on CDS in the case of Russia. Moreover, few articles have shed light on the relationship between oil price and CDS. Among them, Sharma and Thuraisamy (2013) show, by using daily time series data over eight Asian countries, that oil price uncertainty can predict CDS spreads for three countries. We fill the gap in this literature by taking into account the impact of oil price returns and volatility on the changes of CDS spreads in emerging oil exporting countries.

The rest of the paper is organized as follows. Section 2 describes the Venezuelan and Russian economies. Section 3 presents the methodology. Results are given in Section 4. Section 5 concludes.

2 Oil price and sovereign CDS spreads in Venezuela and Russia

In this section, we give some stylized facts regarding the Venezuelan and Russian economies, that will enable us to explain some of our results. Table 1 provides some descriptive statistics for CDS spreads. We also provide a theoretical background for the determinants of sovereign CDS changes.

2.1 Structure of the Venezuelan and Russian Economies

2.1.1 The Venezuelan economy

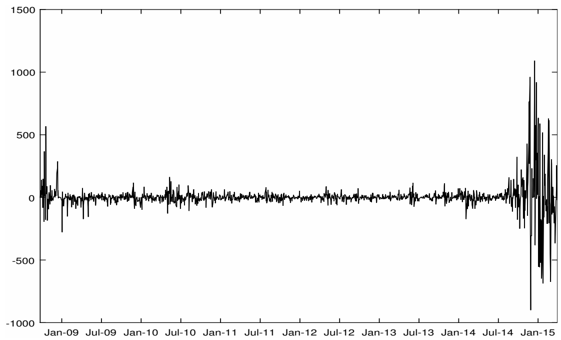
As a founding member of the Organization of the Petroleum Exporting Countries (OPEC), Venezuela plays a key role in the global oil market. It has the largest reserves in the world, with nearly 300 billion barrels of proved oil reserves. Revenues from petroleum exports account for more than 50 percent of the country's GDP and roughly 95 percent of total exports. Venezuela is heavily dependent on oil extraction, as it has mostly extra heavy oil, harder and more costly to extract. Moreover, its economy lacks major investments to maintain oil production at its current level. Figure 1, which displays the variations of CDS spreads, WTI crude oil price returns and the changes of oil price volatility index (OVX), shows that concerning Venezuela, those series present turbulent periods in 2008 and at the end of 2014. More than the 2008 crisis, the country can also have afraid financial markets by some violent reforms negatively perceived by investors. Indeed, in 2007-2008 many nationalizations were engaged: nationalization of key energy and telecommunications companies, of household fuel distributors and petrol stations, of banks. Oil revenues were also shrinking following the oil slump at the end of 2008, which started to raise issues of concern related to fiscal matters. The Venezuelan economy might also have been impacted by the death of the president Hugo Chavez in March 2013. In February 2015, the government devalued currency, but its unstable political situation and its acute economic problems (undiversified economy, skyrocketing inflation) has led to rising CDS. The cost of insuring against losses on Venezuelan government debt is now one of the most expensive government debt to insure in the world. Nevertheless, Table 1 shows that Venezuelan CDS spreads are less volatile than Russian CDS spreads. Indeed, in the case of Russia it reveals a larger variance and excess of Kurtosis.

Country	**T**	**Min**	**Max**	**Mean**	**Variance**	**Skewness**	**Kurtosis**
Venezuela	1701	-42.04	31.98	0.096	12.23	0.167	24.52
Russia	1687	-43.96	50.53	0.002	24.32	0.669	26.29

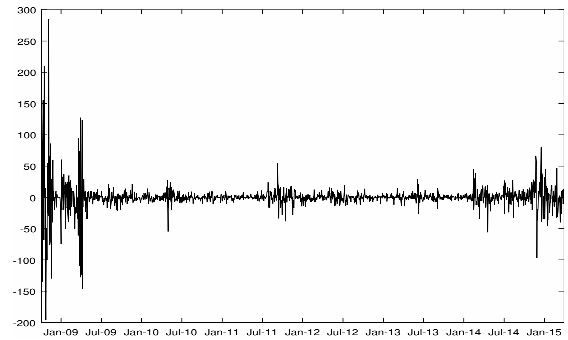
Table 1 Credit default swaps changes characteristics between the 10 October 2008 and the 2 july 2015.
Note: T is the number of observations.

2.1.2 The Russian economy

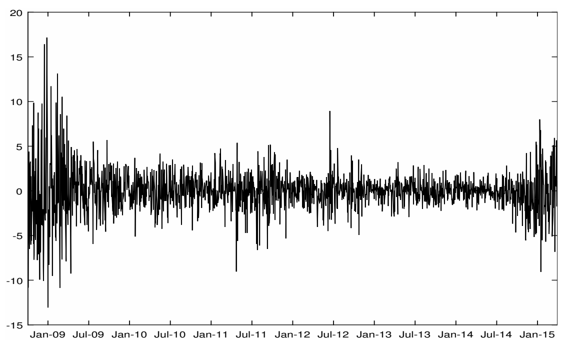
Russia is one of the world's largest producers of crude oil including lease condensate. According to the U.S. Energy Information Administration (EIA), Russia's proved oil reserves are estimated to 80 billion barrels. In 2014, Russia exported roughly 7.3 million barrels per day of petroleum and other liquids. As shown



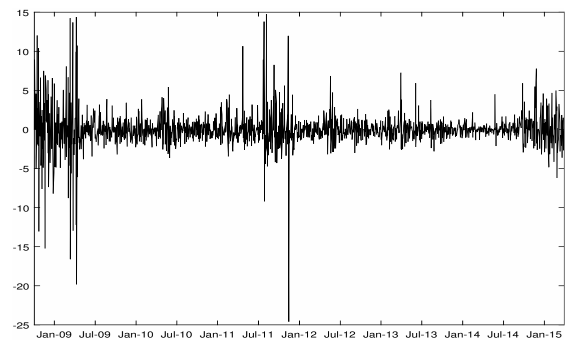
(a) Venezuela ΔCDS



(b) Russia ΔCDS



(c) WTI oil returns



(d) ΔOVX

Figure 1: Daily change of CDS spreads of Venezuela and Russia, WTI oil returns and change of OVX between the 10 October 2008 and the 2 July 2015.

in Figure 1, there are three main turbulent periods: in 2008, during 2011 and at the end of 2014 regarding Russian CDS. Russia was hit by the 2008 crisis, facing an economic recession and a steep decline in external demand. This was worsened by a negative perception of risks after the war with Georgia and by the oil price slump after its peak in July 2008. In 2011, oil prices became more volatile, that could be due to geopolitical reasons, like tensions caused by the Arab spring and the conflict in Libya. Both countries have had strong relationships since the cold war, thus the conflict may have impacted negatively Russia. The Russian economy experienced two shocks in 2014. The first one is a terms-of-trade shock, as oil prices more than halved between July and December 2014.

The second shock, more idiosyncratic, was the economic sanctions in July 2014, following geopolitical tensions with the annexation of Crimea. This was followed by massive capital outflows and a depreciation of the ruble. Indeed, the currency was extremely volatile in 2014 (it lost 46 percent of its value against the U.S. dollar). In November 2014, Russia switched to a free-float exchange rate system. As oil price and the ruble tend to be linked, the exchange rate dynamics reflect the abrupt downward adjustment in oil prices. For Rautava (2004), the Russian economy is influenced significantly by fluctuations in oil prices and by the real exchange rate through both long-run equilibrium conditions and short-run direct impacts. Those tensions and events led to a sharp increase in the costs of external borrowing for Russia. As a result, spreads on Russian CDS peaked in 2014 at 284 basis points.

2.2 Determinants of sovereign CDS spread for oil exporting countries

Following Eyssell et al. (2013), we use a Merton-type theory to justify determinants of CDS spread. This theory evaluates the firm credit risk. Merton (1974) characterizes a firm's default when, at the maturity of the debt, the value of the firm is below the value of outstanding debt. In Merton's model, the firm value is defined as a stochastic process. Gapen et al. (2008) extend this model to sovereign default. Sovereign CDS is an instrument to proxy the market views on a country's default risk and acts like an insurance against credit events. Credit spread changes should respond to changes of some global and local factors. The default is thus presented like a stochastic process directly linked to the structure of the economy. According to Merton (1974), bond and equity prices are correlated with default: high equity prices should induce low CDS prices. Spreads of a sovereign CDS should be determined by local stock market and its volatility index. If volatility is high, the sovereign CDS spread should increase. However, other country risk factors could also affect CDS spreads. As shown by Figure 1, changes of CDS spreads, WTI crude oil price returns and change of the oil price volatility index appear to be linked. At the end of 2008, we assist to an increase in the oil price volatility and Venezuelan CDS spreads volatility. We observe the same behavior at the end of 2014. Nevertheless, this correlation between oil price returns and CDS spread variations is not always respected. For example, in mid-2012 oil price plummeted from 125 dollars to 90 with an increase of the volatility, but it did not lead to an increase in CDS spread volatility. In fact, some other events may impact CDS spreads. Global factors have to be taken in consideration too. We thus select determinants following the literature on sovereign CDS: the local stock market is used to represent the country financial stability, the S&P 500 as a proxy of the financial globalization since it is considered as the main stock market. The VIX represents the implied volatility of the S&P 500 index and is commonly used as a proxy of global risk aversion. OVX is the Crude Oil Volatility Index. Of course, we take account of the asynchronicity issues, dealing with open and closing time on each markets. To conclude, we will use S&P500 returns, local stock market returns, VIX and OVX changes, WTI crude oil returns and the real exchange rate returns as determinants of CDS spread changes.[1]

3 Methodology

3.1 A general to specific approach in the linear framework

To model the dynamic of the CDS spread changes, we first start by a general-to-specific approach in a linear model to detect and eliminate statistically in-

[1]The dataset is described in the Appendix and can be available on demand.

significant variables. The approach used is an automatic model selection, Autometrics, a recent third-generation algorithm for computer-automated model selection developed by Doornik and Hendry (2007). The algorithm is implemented by Doornik (2009) and is available on OxMetrics software. The method can handle some problems like outliers and structural breaks detection with the impulse-indicator saturation (IIS) and the Step-Indicator Saturation (SIS).[2] The idea is to include impulse and step dummies for all observations in a process. Impulse and step indicators are defined respectively by $1_{\{t=j\}} = 1$ for observation $t = j$ (zero otherwise) and $1_{\{t \leq j\}} = 1$ for observations up to j (zero otherwise). More details are given in the Appendix.

The economic mechanism that operates in the real world is represented by an unknown Data Generating Process (DGP). To approximate this DGP, we specify a General Unrestricted Model (GUM) based on institutional knowledge and informations:

$$\Delta CDS_t = f(x_t) + \varepsilon_t \tag{1}$$

where ΔCDS_t is the change of the log CDS spreads, f is a linear function of x_t a vector of explicative variables and ε_t the remainder. The vector x_t is composed by lags of CDS spread changes, by different explanatory variables[3] and their own lags: the local stock market returns (rSM), the S&P500 returns (rSP), the VIX change (ΔVIX), the WTI crude oil price returns ($rOIL$), the nominal exchange rate returns (rFX). The algorithm starts with five lags for all variables. The different stages of the algorithm can be found in the Appendix. Following this methodology, we obtain the final linear model which describes best the CDS changes: it contains all the relevant variables considered in the GUM and some impulse and step indicator variables.

[2]Such methods have been largely studied in the literature with their asymptotic properties, see for example Johansen and Nielsen (2009) and Castle et al. (2011).

[3]We consider log-returns since we are interested in relative changes.

3.2 Introducing nonlinearities

A linear model is often too restrictive to model daily long time series. Indeed, the dynamics of a financial variable may be dependent on the "well-being" of the economy. It follows that the dynamic is driven by an underlying latent state which can take a finite number of values. We analyze the determinants of the Credit Default Swaps (CDS) through a dynamic mixture autoregressive framework. Such model has been introduced by Hamilton (1989) with the Markov Switching Autoregressive (MS-AR) model and became very popular to model time series of macroeconomic and financial variables. For example, Ang and Bekaert (2002) show that MS-AR model matches quite well the behavior of interest rates and Sims and Zha (2006) use a multivariate MS model to study monetary policy switches. This kind of model is particularly suitable to model sovereign CDS. As we said in Sections 1 and 2, both countries have been affected by external events. Moreover, Venezuela has been the target of speculative attacks, thus Markov Switching models regarding sovereign CDS spreads should be more relevant. It exists other non linear models of structural breaks. However, in most cases, they require a priori some information concerning the breaks. When many sources of regime switching exist, this type of model appears more appropriate, we then need to determine the number of regimes in the economy.

Markov Switching models depend on a latent state variable s_t. This variable indicates the nature of the world at time t. s_t follows a Markov chain with finite state spaces $S = 1, ..., k$, and a transition matrix P. The transition matrix P is given by

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \cdots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{pmatrix}$$

with $p_{ij} = p(\Delta_t = j|\Delta_{t-1} = i)$ the probability to be in state j at time t given to be in the state i at the time $t-1$. The simple MS(k)-AR(p) process is defined if there exist ω_{s_t} and ϕ_{i,s_t}, $i = 1, \ldots, p$ such that

$$y_t = \omega_{s_t} + \sum_{i=1}^{p} \phi_{i,s_t} y_{t-i} + \varepsilon_t \tag{2}$$

where ε_t is the error term. The model defined by Equation (2) can be generalized by adding the vector of explanatory variables x_t in the regression. Each variable can switch or not across regimes, thus, x_t can be decomposed in two vectors x_t^{ns} and x_t^s. x_t^s contains the variables which switch and x_t^{ns} the ones which do not switch. Let us define the Markov Switching Generalized model as

$$y_t = \sum_{i=1}^{l} \gamma_i x_{i,t}^{ns} + \sum_{i=1}^{m} \phi_{i,s_t} x_{i,t}^{s} + \varepsilon_t \tag{3}$$

with $\varepsilon_t \sim P(\zeta_{s_t})$ the assumed probability density function of the innovations, with its own set of parameters ζ. $\gamma = (\gamma_1, \ldots, \gamma_l)'$ and $\phi_{s_t} = (\phi_{1,s_t}, \ldots, \phi_{m,s_t})'$ are the vectors of parameters to estimate with l the number of non switching variables and m the number of switching variables.

Similarly to Filardo (1998) and Kim et al. (2008), we introduce Time Varying Transition probabilities (TVTP), where the transition probabilities are time-varying and depend on some variables. The transition matrix becomes:

$$P_t = \begin{pmatrix} p_{11}(z_t) & \ldots & p_{1k}(z_t) \\ \vdots & \ldots & \vdots \\ p_{k1}(z_t) & \ldots & p_{kk}(z_t) \end{pmatrix}.$$

z_t is an explanatory variable which follows the conditions of Filardo (1998) and Kim et al. (2008). The probabilities are defined by $p_{ij}(z_t) = \Phi(\theta_{ij} z_t)$; z_t is called the state variable vector and θ_{ij} are the parameters to be estimated. For $k = 2$, we only need to estimate θ_{11} and θ_{12}. The interpretation of these parameters is the following one. If θ_{11} is positive, the probability to stay in regime one increases if z_t is positive. In the same way, if θ_{12} is positive, the probability to switch from regime 2 to regime 1 increases if z_t is positive. $\Phi()$ is the cumulative normal distribution function. Even though the choice of the cumulative normal distribution function for the transition probabilities is common wisdom in the applied literature, any function that maps the transition parameter into the unit interval would be a valid choice for a well-defined log-likelihood function. The TVTP model is the main point of interest: it enables us to see which variables impact the probabilities of regime switch. Following the work of Hamilton (1989), this model is estimated by maximum likelihood.[4]

4 Results

4.1 The linear model

Table 2 reports the estimates of the linear model. As expected, a rise in crude oil price returns decreases the change of the CDS spread for Venezuela, as oil accounts for more than 95 percent of Venezuela's export revenues. This impact is significant at the one percent level. When oil prices are high, it means more oil revenue for the government, which it is well viewed by financial markets. Nevertheless, concerning Russia the Autometric selection method does not retain oil price returns as a determinant of CDS spreads. This finding is interesting since the Russian economy is largely dependent on oil exports. It could be explained by the fact that Russia has other important sources of revenues, like gas (Russia is the second-largest producer of gas in the world). Moreover, oil prices can impact CDS spreads through the exchange rate canal. The Russian authorities can let the ruble depreciate against the US Dollar to counter the fall

[4]See Perlin (2015) and Ding (2012) for more details.

of oil prices. There is a theoretical and empirical literature about this subject. For example, Ferraro et al. (2015) show that commodity prices can predict commodity currencies exchange rates at a daily frequency. The two countries have indeed different exchange rate systems. Russia has moved to a floating exchange rate regime those last years, whereas Venezuela has a complex multi-layered exchange rate system and currency controls still exist, since their introduction in 2003 by the former President Hugo Chavez. Concerning the other determinants, the results confirm our intuition. When the change of VIX is positive (in other words the VIX rises), thus the more the market's anxiety rises, the more CDS spreads also increase. Moreover, there is strong evidence for Venezuela that changes of CDS spread are significantly and negatively affected by the returns of the S&P 500. In the case of Russia Russia, the S&P500 and the local stock market returns play both a significant role and have a negative sign. Nevertheless, financial stability tends to decrease CDS spreads more strongly in Russia, as the estimates are higher than those of Venezuela. However, this linear model is too restrictive to fully assess the impact of oil price returns on CDS spreads and thus the probability of default of these emerging countries.

4.2 Evidences from the TVTP-MS model

Results from the TVTP-MS model are reported in Tables 3 and 4. Explanatory variables are selected independently from the linear model. We estimate four models for Venezuela. Model 1 reflects the impact of oil price returns on the change of CDS spread without other factors. In the second and third one, we include respectively local and global factors. The Model 4 includes both local and global factors. For Russia, we estimate six models. Models 1 and 2 are similar to those of the Venezuela. Models 3 and 4 are estimated with both oil price returns (Models 3.1 and 4.1) and real exchange rate returns (Models 3.2

	Venezuela	Russia
ΔCDS_{t-1}	0.105^{***} (0.01)	-
rSP_{t-1}	-0.140^{***} (0.03)	-0.329^{***} (0.04)
rSM_{t-1}	-	-0.629^{***} (0.03)
$rOIL_{t-1}$	-0.111^{***} (0.02)	-
ΔVIX_{t-1}	0.081^{***} (0.01)	0.201^{***} (0.06)
rFX_{t-1}	-	0.516^{***} (0.06)
σ	1.649 (−)	1.89 (−)
log-LL	-3147.79	-3361.03
Number of Impulse dummies	60	53
Number of Step dummies	140	136

Table 2 Linear models estimation of Venezuela and Russia CDS spreads from 10/10/2008 to 07/02/2015.
Note: Standard errors are in parentheses. ***, ** and * statistical significances at 1 percent, 5 percent and 10 percent. A '-' means that the concerning variable is eliminated by the selection process.

and 4.2). To select which variables are switching across regimes, we perform a standard test. For one explanatory variable, if the associated parameters in regime 1 and 2 are statistically different, we assume that the impact of this variable switches over time. Explanatory variables can be significant in only one regime because in turbulent periods, traders and operators are looking for some stabilization indicators and modify their behavior. Finally, we impose the unconditional variance to switch in order to define both regimes. The calm period is associated to the regime with the smallest variance (regime 1), regime 2 is called the turbulent regime.

One practical issue is choosing valid information variables for the transition function. These variables have to be uncorrelated with contemporaneous state. The selection is done in two steps. Firstly, we test the null hypothesis of a standard MS model against a TVPMS model. This test is presented in the next section. Secondly, the parameters θ_{11} and/or θ_{12} need to be statistically significant. When several variables satisfy the tests, the final selection is made by considering information criteria. After testing different variables, we retain the OVX index to proxy the volatility of oil prices, as it represents the implied volatility of the crude oil stock market. This is fairly reasonable for many problems as long as $z_{t-1} = \Delta OVX_{t-1}$ the lagged transition variable is considered to be predetermined with respect to s_t the state. The interpretation of the coefficients associated to this variable is done in the following manner: if θ_{11} is negative, it means that when the change of oil prices volatility is positive, probabilities to stay in regime one go down.

In this Markov Switching model, the first important result is the impact of oil prices and exchange rates on CDS spreads. Oil price returns are statistically significant only in turbulent periods for Venezuela, with a negative sign: negative returns (in other words the oil price decreases) lead to an increase in CDS spreads, and thus in the probability of default. Investors keep a close look on oil price "news" when sovereign CDS appear to be in a turbulent period. In the case of Russia, oil price returns seem to have an impact on sovereign CDS spread changes in both regimes, however, this is true only in Models 1 and 2. When we add local and/or global factors, this impact decreases until it disappears in calm periods or in turbulent periods (respectively Models 3.1 and 4.1 in Table 3.4). As the literature (Rautava, 2004; Ferraro et al., 2015) does not offer clear evidence that the nominal exchange rate and oil prices are linked, but highlights that a relationship could exist especially on short-term horizons, we decided to use those two independent variables separately. We thus run the same regressions with nominal exchange rate returns instead of oil price returns. Exchange rate returns are positively significant in calm periods for Models 3.2 and 4.2 in Table 3.4. In the turbulent regime, exchange rate returns are near to be negatively significant. It means that when the ruble depreciates against the US Dollar (in other words returns are positive), changes of sovereign CDS spread increase in calm periods and decrease in turbulent periods. A depreciation of the ruble increases the probability of default in calm periods. It plays the same role as the oil price returns. If oil price goes down, revenues for the oil industry go down too. A depreciation of the exchange rate will make exports more competitive and appear cheaper to foreigners. This will increase demand for exports. However, imports are more expansive for the Russian government and it increases the sovereign CDS spread. Secondly, Russian local stock market has a significant impact on Russia's CDS spread changes but only in turbulent periods since the parameter associated in calm periods is not significant. An increase in stock market returns during 'turbulent times' (regime 2) decreases the variation of CDS. For Venezuela, the variable is not significant. This result is probably due to the development level of the two stock markets. Capitalization to Growth Domestic Product for the Russian Federation is about 45 percent against 4 percent for Venezuela.[5]

Concerning global factors, an increase in the US stock market returns during 'normal times' (regime 1) tends to lower the probability of default, and this impact is even sharper during turbulent times (regime 2). This empirical evidence is similar for both countries, showing their dependence to the global economy. The VIX also appears to be a major determinant of Russian and Venezeluan CDS (the coefficient is statistically significant at the one percent level), as a positive change of the implied volatility has a positive impact on the changes of CDS spreads. Those results are consistent with Longstaff et al. (2011), who find that global financial factors play a key role in determining sovereign CDS spreads.

Estimation results of the transition function are as we expected. In the case

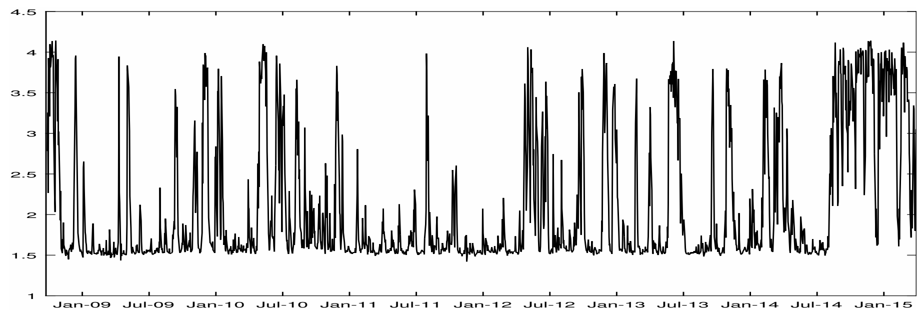
[5]Source FRED economic data

of Venezuela, when returns of the OVX decrease, the probability of switching from a turbulent state to a "non-crisis" state increases. This is illustrated by the negative coefficient attached at ΔOVX_{t-1} variable in p_{12}. If the volatility rises, returns will be positive and this probability will decrease. Similarly, a lower volatility of oil prices tends to stabilize the financial economy of Venezuela. Contrary to Venezuela, it is the probability of remaining in a "calm" state which rises for Russia when the returns of the OVX are negative. Nevertheless, a higher oil price volatility increases the chance of moving from a turbulent state to a calm one for both countries, which confirms our intuitions.

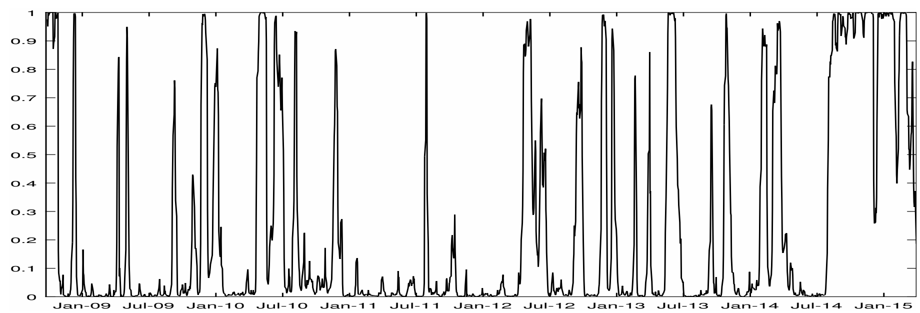
Finally, Figures 2b and 3b present the smoothed probabilities to be in the high volatility regime. They point out that our model takes in consideration the last drop of crude oil prices and its impact on CDS spread changes at the end of 2014. Moreover, the MS model for Russia detects the period of instability caused by the war in Libya around July 2011. For Venezuela, there is also a high instability level around March 2013 caused probably by Chavez's death. We can notice also that low volatility periods for Russia are expected to last at least about 50 days, compared to only 35 days for the Venezuelan economy.

4.3 Model validation

We justify our TVTPMS model with some tests. Linear and TVTPMS models have a different and distinct structure. Thus, classical test procedures have to be used cautiously. In fact, we have to test the constancy of parameters. We assume that they are constant under the null hypothesis, whereas they are random and weakly dependent under the alternative. Testing the stability of coefficients is particularly challenging. The parameters that enter in the dynamic of the random coefficients are not identified under the null hypothesis. It is the well known nuisance parameters problem: the usual tests like the Likelihood Ratio



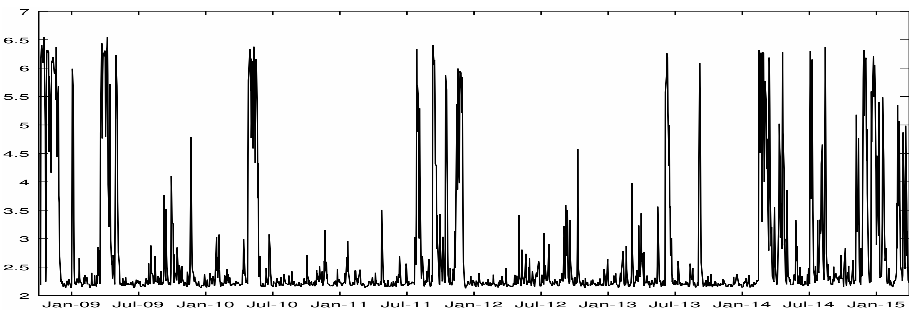
(a) Conditional standard deviation



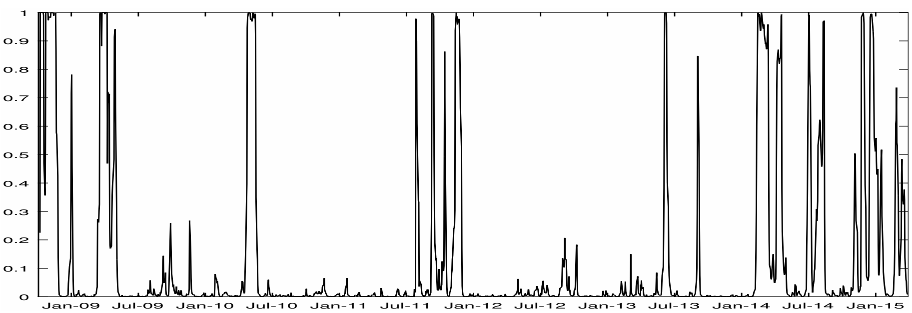
(b) Smoothed probability

Figure 2: Venezuela. Standard deviation and smoothed probability of turbulent regime.

(LR) test have a non standard distribution. To address this issue of MS models, Carrasco et al. (2014) propose an optimal test for parameter stability. We apply this test to see if MS model is better than the linear model without the step and indicator variables. If we reject the null of linearity for the MS model, it means that all the step and indicator variables represent in fact a stochastic regime switching model. This test has been used in recent empirical studies, for example Hu and Shin (2008), Dufrénot et al. (2011) and Morley and Piger (2012). To validate the TVTPMS model, we use Kim et al. (2008)'s approach. They use a LR statistic to test for endogenous switching. They propose a two-step maximum likelihood estimation procedure to deal with the problem of endogeneity in Markov-switching regression models. In this paper, size-adjusted critical values are used, taken from the Monte Carlo simulations generated with



(a) Conditional standard deviation



(b) Smoothed probability

Figure 3: Russia. Standard deviation and smoothed probability of turbulent regime.

a model under the null. AIC and BIC are also reported for the three models.

Table 5 presents those results. The MS and the TVTPMS models tested are respectively Model 4 in Table 3.3 and Model 4.2 in Table 3.4. First, if we look at information criteria, the smallest corresponds to the TVTP-MS model. It can be underlined that they are very similar for the Venezuela between the TVTP-MS and the MS models. However, as shown by Chuffart (2015), these criteria are not always efficient in some special cases. But, all the tests reject the null at least at 10 percent. That means that for the Carrasco et al. (2014) test, we reject the null of linearity and for the Kim et al. (2008) test, we reject the null of no time varying transition probabilities. We can thus conclude that our final model, the TVTP-MS is preferred to the linear and the MS models on the basis of those tests.

5 Conclusion

In this paper, we compared a Time Varying Transition Probabilities Markov Switching model to a linear and a Markov Switching models, to assess the impact of oil price returns on sovereign default risk for two major oil producing countries. The Markov-Switching with Time Varying Transition Probabilities model outperforms the other standard models. We showed that crude oil price returns have a significant influence on Venezuela's CDS spreads, but does not explain significantly Russian CDS spreads changes. Our interpretation is that oil prices impact Russian CDS spread through the exchange rate canal, as Russia has a flexible exchange rate system. On the contrary Venezuela has fixed exchange rates, so oil price changes impact directly Venezuelan CDS spreads. The evidence also suggests that the Russian local stock market returns have a significant and negative impact on Russia's CDS spreads, whereas Venezuela's CDS spreads are not related to its local stock market. This study suggests a number of policy implications for those economies. First, in order to better face oil price volatility they should more than ever diversify their economy. Some countries have managed to move from a natural resource oriented economy to an economy open to financial services (like Dubai) or to tourism (Indonesia). Second, this oil price collapse should be seen as an opportunity for those countries to reduce their oil subsidies, which usually represents a huge expense in the government budget. Further research could take into account contagion risk between countries.

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	Model 1		Model 2		Model 3		Model 4	
	R1	R2	R1	R2	R1	R2	R1	R2
Parameters								
cst	-0.087^{*} (0.05)	0.397 (0.27)	-0.085 (0.05)	0.389 (0.27)	-0.076 (0.05)	0.351 (0.25)	-0.043 (0.05)	0.286 (0.25)
$\Delta \mathrm{CDS}_{t-1}$	0.199^{***} (0.02)	-	0.199^{***} (0.02)	-	0.179 (0.02)	-	0.168^{***} (0.02)	-
rOIL_{t-1}	-0.016 (0.03)	-0.187^{*} (0.10)	-0.021 (0.02)	0.389^{***} (0.28)	0.000 (0.03)	-0.223^{**} (0.10)	-0.016 (0.01)	-0.186^{*} (0.1)
rSM_{t-1}	-	-	-0.005 (0.04)	0.037 (0.12)	-	-	-0.020 (0.04)	0.034 (0.11)
rSP_{t-1}	-	-	-	-	-0.099 (0.06)	-0.770^{**} (0.22)	-0.123^{***} (0.05)	-0.694^{***} (0.16)
$\Delta \mathrm{VIX}_{t-1}$	-	-	-	-	0.000 (0.01)	-0.052 (0.04)	0.091^{***} (0.01)	0.198^{***} (0.03)
σ^2	2.139^{***} (0.15)	17.906^{***} (2.33)	2.141^{***} (0.15)	17.848^{***} (2.35)	2.079^{***} (0.15)	16.662^{***} (2.12)	2.010^{***} (0.14)	17.241^{***} (2.08)
dof	4.339^{***} (0.57)	-	4.342^{***} (0.57)	-	4.329^{***} (0.57)	-	5.277^{***} (0.80)	-
Trans. funct.								
p_{11}								
cst_{11}	1.980^{***} (0.12)		1.980^{***} (0.12)		1.957^{***} (0.12)		1.942^{***} (0.12)	
$\Delta \mathrm{OVX}_{t-1}$	-0.011 (0.05)		-0.011 (0.06)		-0.009 (0.05)		-0.027 (0.02)	
p_{12}								
cst_{12}	-1.512^{***} (0.17)		-1.512^{***} (0.18)		-1.514^{***} (0.17)		-1.494^{***} (0.162)	
$\Delta \mathrm{OVX}_{t-1}$	-0.086^{*} (0.05)		-0.087^{*} (0.05)		-0.083^{*} (0.05)		-0.095^{**} (0.05)	
Model validation								
Log-LL	-3992.66		-3992.63		-3984.41		-3895.469	
E(R1)	41.63		41.70		39.52		36.87	
E(R2)	12.66		12.65		12.83		11.92	
LM-Autocorr(5)	5.304 (0.38)		5.394 (0.37)		5.036 (0.41)		5.109 (0.40)	

Table 3 TVTP-MS models estimation of Venezuela sovereign CDS spread between the 10 October 2008 and the 2 July 2015. Note: Standard errors in parentheses. ***, ** and * statistical significances at 1 percent, 5 percent and 10 percent. R1 and R2 are respectively regime 1 and regime 2. A '-' means that the concerning variable is eliminated by the selection process and/or that it is not switching across regimes. σ^2 is the unconditional variance, dof is the degree of freedom. Log-LL is the log likelihood. E(R1) and E(R2) are respectively the expected duration of regime 1 and regime 2. LM-Autocorr(5) is an heteroskedasticity consistent serial correlation test with 5 lags.

	Model 1		Model 2		Model 3.1		Model 3.2		Model 4.1		Model 4.2	
	R1	R2	R1	R2	R1	R2	R1	R2	R1	R2	R1	R2
Parameters												
cst	-0.055 (0.07)	0.192 (0.685)	-0.073 (0.070)	0.310 (0.67)	-0.032 (0.06)	0.310 (0.52)	-0.035 (0.06)	0.281 (0.62)	-0.020 (0.07)	0.147 (0.66)	-0.036 (0.07)	0.384 (0.51)
ΔCDS_{t-1}	0.103^{***} (0.02)	-0.134 (0.09)	0.104^{***} (0.03)	-0.397^{***} (0.06)	0.037 (0.02)	-0.110^{**} (0.04)	-0.004 (0.02)	-0.158^{***} (0.05)	0.043^{*} (0.03)	-0.431^{***} (0.06)	0.027 (0.03)	-0.427^{***} (0.00)
$rOIL_{t-1}$	-0.138^{***} (0.02)	-1.077^{***} (0.31)	-0.125^{***} (0.03)	-0.780^{***} (0.20)	-0.042 (0.03)	-0.314^{**} (0.18)	-	-	-0.052^{*} (0.03)	-0.289 (0.20)	-	-
rFX_{t-1}	-	-	-	-	-	-	0.362^{***} (0.08)	-	-	-	0.440^{***} (0.09)	-0.491 (0.37)
rSM_{t-1}	-	-	0.002 (0.04)	-1.160^{***} (0.18)	-	-	-	-	0.003 (0.04)	-0.868^{***} (0.17)	0.071 (0.05)	-0.962^{***} (0.30)
rSP_{t-1}	-	-	-	-	-0.530^{***} (0.06)	-1.465^{***} (0.26)	-0.518^{***} (0.06)	-1.717^{***} (0.26)	-0.540^{***} (0.07)	-1.478^{***} (0.31)	-0.522^{***} (0.07)	-1.693^{***} (0.28)
ΔVIX_{t-1}	-	-	-	-	0.146^{***} (0.01)	0.402^{***} (0.05)	0.150^{***} (0.01)	0.426^{***} (0.06)	0.150^{***} (0.01)	0.444^{***} (0.07)	0.150^{***} (0.01)	0.473^{***} (0.07)
σ^2	4.934^{***} (0.40)	72.369^{***} (18.05)	4.795^{***} (0.31)	55.254^{***} (7.72)	4.009^{***} (0.27)	34.066^{***} (4.50)	4.169^{***} (0.27)	43.839^{***} (6.16)	4.473^{***} (0.293)	48.708^{***} (6.849)	4.366^{***} (0.34)	47.648^{***} (9.68)
dof	4.453 (0.71)	-	4.837 (0.75)	-	4.622^{***} (0.64)	-	5.004^{***} (0.74)	-	5.947^{***} (1.10)	-	5.926^{***} (1.14)	-
Trans. funct.												
p_{11}												
cst_{11}	2.453^{***} (0.22)		2.297^{***} (0.16)		2.310^{***} (0.16)		2.272^{***} (0.15)		2.194^{***} (0.14)		2.173^{***} (0.14)	
ΔOVX_{t-1}	-0.083^{***} (0.03)		0.066^{**} (0.03)		-0.066^{***} (0.02)		-0.060^{**} (0.02)		-0.056^{**} (0.02)		-0.056^{***} (0.02)	
p_{12}												
cst_{12}	-1.283^{***} (0.19)		-1.332^{***} (0.15)		-1.412^{***} (0.15)		-1.291^{***} (0.16)		-1.168^{***} (0.15)		-1.159^{***} (0.17)	
ΔOVX_{t-1}	0.014 (0.03)		0.003 (0.03)		-0.005 (0.04)		-0.0148 (0.02)		-0.015 (0.02)		-0.018 (0.02)	
Log-LL	-4437.213		-4429.553		-4289.992		-4283.591		-4285.550		-4276.513	
E(R1)	79.19		69.95		68.97		66.20		57.12		54.47	
E(R2)	9.98		10.93		12.64		10.10		8.19		8.05	
LM-Autocorr-5	3.406 (0.64)		4.994 (0.42)		5.649 (0.34)		5.250 (0.38)		3.406 (0.64)		3.560 (0.61)	

Table 4 TVTP-MS models estimation of Russia sovereign CDS spread between the 10 October 2008 and the 2 July 2015.
Note: see note of Table 3.3.

	Venezuela		Russia	
	AIC	BIC	AIC	BIC
MS	8003.0	8077.1	8594.6	8696.5
TVTP-MS	7980.8	8067.8	8591.0	8694.4e
Carrasco et al.	3.47^{*} (0.06)		5.37^{**} (0.04)	
Kim et al.	4.170^{*} (0.078)		6.42^{***} (0.02)	

Table 5 Information criteria and specification tests for Model 4 of venezuela and Model 4.2 for Russia.
Note: Critical values have been simulated with 3000 simulations. ***, ** and * statistical significances at 1 percent, 5 percent and 10 percent. p-value in parentheses.

Appendix

A. Data and programs

All our variables come from Thomson-Reuters database. We use daily data from the 26 September 2008 to 2 July 2015. The period depends on the availability of the data since CDS spreads are new instruments. The dependent variable is the change of the log of CDS spreads at time t, and the independent variables are all expressed in terms of log-returns. We use variables from different parts of the world in the model thus, we had to synchronize the series, as the day-off and the holidays are not the same in each country. This can lead to missing information for some days. To circumvent this issue, we have decided to delete all the extra information contained in the independent variables. For example, if there is no quotation for the CDS spread and on contrary, there is a quotation available for the S&P 500 on the same day, we delete this observation. In the other case, when there is additional information for the dependent variable, we interpolate linearly the missing observation for the independent variables. The program to synchronize data is available upon demand to the authors. We compute then log returns of each variable. The estimations of the models are computed using the toolbox of Ding (2012). A main file to replicate the results and data is also available upon demand.

B. Autometrics

We give briefly the general idea of the three stages of the Autometrics algorithm (see Doornik and Hendry (2007) and Doornik (2009)).

Stage 1: the general model and indicator saturation (IIS+SIS). The first stage is to estimate and evaluate the GUM defined in Section 3.1 by Equation (1). It must have stationary regressors. It is an approximation of the Local DGP

(LDGP) which is a reduction of the DGP for relevant variables, nested within it. The general model is estimated, and diagnostic statistics are calculated for it. If any of those diagnostic statistics are unsatisfactory, the modeler must decide between developing another GUM or continuing with the simplification procedure. Secondly, inclusion of impulse and step dummies for all observations is feasible. However, the number of variables will be larger than the number of observations. To deal with this issue, a block strategy is used. Autometrics performs block additions and searches of impulse dummies for all observations in a process known as indicator saturation (IS). Doing so generates a robust regression estimator and provides a check for parameter constancy. If these tests result in a statistically satisfactory reduction of the GUM, then the new model is the starting point for the next Stage. Otherwise, the general model itself is the starting point.

Stage 2: a multi-path encompassing search. At this stage of the algorithm, a multi-path search is implemented, starting from the model at the first stage. The searches filter for relevant variables using usual Student tests and Fisher tests. At each step, the congruence is checked through diagnostic tests. If some variables are statistically insignificant, then Autometrics tries to delete those variables to obtain a simpler model. A simplification could be rejected. In this case, the algorithm backtracks along that path to the most recent acceptable model and then tries a different path. A terminal model results if the model's diagnostic statistics are satisfactory and if no remaining regressors can be deleted. The algorithm pursues multiple simplification paths and we can obtain many terminal models. An union model from those terminal models is considered and the algorithm tests this union model against all the terminal models. Finally, an other union model is created which nests all the surviving terminal models.

Stage 3: another multi-path encompassing search. Stage 3 repeats Stage

2, by applying the simplification procedures from Stage 2 to the union model obtained. The resulting model is the final model. If Stage 3 obtains more than one terminal model after applying encompassing tests, then the final model is selected by using the information criteria.