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Master’s Thesis

Pricing Models in the Energy Markets: A Quantitative and Qualitative Approach

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SUMMARY

This master's thesis offers a comparative study on the performance of the two-factor models versus one-factor models when modeling energy related commodities. The models chosen for the study have been: on the two-factor side, the Schwartz-Smith model, and in the one-factor side, the Ornstein-Uhlenbeck model and the Geometric Brownian motion model. It is also studied the convenience of the medium-term performance of the Schwartz-Smith two-factor model, when projecting commodity prices to the future.

The commodities studied in this master's thesis have been: Brent oil, WTI oil, NBP natural gas, Henry Hub natural gas, API#2 coal index and Spanish, French and German electric power spot prices.

The methodology employed in this study has been formed of three different analysis: in-sample analysis, out-sample analysis and real implementation. In the in-sample analysis models are adjusted with the 70% of the available dataset and compared between the in terms of log-likelihood scores and mean absolute errors.

The out-sample analysis is devoted to analyze the performance of the Schwartz-Smith two-factor model, previously adjusted in the in-sample analysis, comparing it with the reserved 30% of the reserved observations of the spot price, employing Monte Carlo simulations.

Finally, the he Schwartz-Smith two-factor model is adjusted for all commodities with the 100% of the dataset, and projected for a whole natural year employing Monte Carlo simulations. After that results obtained are analyzed in terms of last values and all values, computing statistical measures to compare with historical prices.

Once all analysis were done, it could be observed how the Schwartz-Smith two-factor model scored the higher log-likelihood scores in all commodities, obtaining also, the lower mean absolute errors in most of the contracts studied for each commodity, so it can be stated that the Schwartz-Smith two-factor model performs best than any of the one-factor models in every commodity.

On the future performance side, it can be concluded that the Schwartz-Smith two-factor model performs appropriately, identifying the past tendencies of the market and acting according to them.

Related to electric power commodities, it can be seen how the Schwartz-Smith two-factor model has some difficulties when modeling their prices. The peculiarity of the electric power prices, combined with seasonal patterns that depend on many complex variables, makes the model not to adjust properly.

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1

INTRODUCTION AND OBJECTIVES

1.1 MOTIVATION

Liberalization of electricity markets is now a major reality in most of the developed countries. It has been proven that, while transmission and distribution business are key natural monopolies that have to be somehow regulated by authorities, generation and retailing business experiment a decrease in its total costs when they are open to free competition. In this liberalization framework, the electricity has become itself a new commodity to trade with, but with substantial differences when comparing it with the other energy commodities already in place.

From a modern utility point of view, the management of commodities is not only restricted to electricity; energy commodities such as: oil, natural gas or coal, are constantly traded to provide power-plants the needed fuel for generating electricity, being this management a key activity in the business core of the company.

Associated with the increasing trading of energy commodities in spot markets, parallel financial markets are also being developed in order to let the market agents manage the risks undertaken in their operations. This financial markets are growing in popularity, displacing in some cases the physical markets they are linked to, adding more complexity to the daily activity.

According to what stated before, it is crucial in any quantitative, risk, or market analysis department, to have the necessary tools to interpret the market signals in order to take the appropriate strategic decisions.

The main motivation of this thesis titled *"Pricing Models in the Energy Markets: A Quantitative and Qualitative Approach"* is to develop a deep study of the main energy commodities. Although amongst the vast literature, there can be found many analysis of separate energy commodities, this master's thesis makes an original overall study of the most important ones related to the electricity value chain.

The practical motivation of this master's thesis is to add value to the current analysis methodology of spot energy markets that can take place at any modern utility energy management department. New products and new markets implemented, along with sudden changes in energy commodity prices due to the current geopolitical situation, make necessary to implement some improvements, not only on the pricing models being used now, but on the methodology itself.

From a theoretical point of view, the accomplishment of this master's thesis is motivated also by the fact of acquiring a deep understanding of how pricing models for energy commodities work along with how energy spot and forward markets work, how are they ruled and what is the behaviour of the different products and agents involved in it.

As mentioned above, electricity is the departing point of this study, but in order to understand the actual behaviour of electricity markets, oil, natural gas and coal have also to be analyzed. For doing so, Brent oil and WTI oil indexes are analyzed in an oil markets epigraph, separated from NBP and Henry Hub natural gas indexes that are analyzed in the corresponding epigraph. API#2 coal index is also studied in order to have the whole picture of the energy markets before analyzing, in a separate epigraph, Spanish, German and French electricity markets.

The analysis carried out in this thesis are of a qualitative nature, but in order to assess the properties of energy markets, quantitative measures have to be obtained. For obtaining the necessary market parameters, the most popular one-factor and two-factor models amongst the literature have been selected. On the side of two-factor models, Schwartz-Smith model has been the choice, while on the side of one-factor models, Geometric Brownian motion model and Ornstein-Uhlenbeck models are the chosen ones.

The reason behind the choice of this models is the proven ability that they have in modeling commodity prices, being for example Schwartz-Smith two-factor model developed for modeling Brent oil prices. Geometric Brownian motion model and Ornstein-Uhlenbeck model have set the base of commodity price modeling, so the choice is more than justified.

1.2 OBJECTIVES

The main objective of this master's thesis is to develop a quantitative analysis tool that is able to quantify medium-term market risk in electric power utilities. As electric power is heavily impacted by other commodities that are used as fuel for power plants, this tool will take into account those fuel commodities for the market risk assessment.

This main assessment objective can be divided in two sub-objectives, being the first one to evaluate if the Schwartz-Smith two-factor model performs better than one-factor models as Geometric Brownian motion and Ornstein-Uhlenbeck model. And secondly, if it is appropriate for making medium-term predictions in the commodities selected for this study.

To investigate the research objective for this master's thesis, three different analyses have been carried out. The first analysis, or in-sample analysis, is devoted to quantitatively compare the performance of the two-factor model versus the one-factor ones. This is made by adjusting the three models with the 70% of observations contained in the available dataset of commodity prices, and making a benchmark analysis of the different parameters obtained.

Second analysis, or out-of-sample analysis, is a concluding analysis that has the objective of assessing the generalization the pre-adjusted Schwartz-Smith two-factor model, comparing it against the reserved 30% of the observations contained in datasets employing Monte Carlo simulations.

Last analysis is devoted to study the medium-term performance of the Schwartz-Smith two-factor model, under a real test scenario, by adjusting the model with the 100% of the observations contained in the datasets and projecting the model to the future employing Monte Carlo simulations.

1.3 STRUCTURE OF THE REPORT

This report is structured in six chapters, being this first chapter the introductory one, where motivation for the master's thesis and its main objectives are explained in detail.

The second chapter contains the theoretical framework, where the main energy commodities studied are explained in terms of commodity overview, market structure and characteristics of spot and forward prices. This chapter also contains the theoretical background needed for understanding the main characteristics of the Schwartz-Smith two-factor model, the Geometric Brownian motion model and the Ornstein-Uhlenbeck model. Last but not least, the Monte Carlo simulations principles are also explained so the whole picture of the theory applied is obtained by the reader.

In the third chapter titled problem description, an introduction about the main challenges to be faced in the study of this master's thesis is found. It is followed by the list of the main commodities and indexes to be analyzed and a broad explanation of the tools employed. In this tools explanation, the whole functioning of the software employed for running the models is explained in terms of inputs needed, theory behind the running of the models and main outputs obtained. After this epigraph a detailed list of the datasets employed per commodity can be observed.

The fourth chapter, devoted to the analysis methodology, will describe in depth the three different types of analysis carried out in the study: in-sample, out-of-sample and real implementation, detailing the methodology followed and the kind of results to extract from them.

In the fifth chapter the results of the aforementioned three analysis methodologies are presented for all commodities studied, divided by indexes, and followed by a detailed study of the results obtained.

The conclusions regarding the main objectives fixed in this first chapter, will be drawn in the sixth chapter. This will be done by taking an overall view on the results obtained in the fifth chapter. This sixth chapter will also contain the future research proposals identified throughout the development of this master's thesis.

Last but not least, all the references employed in the whole master's thesis can be found listed at the end of each chapter.

2
THEORETICAL FRAMEWORK

2.1 ENERGY COMMODITY MARKETS

According to economics, a commodity market is a place where goods or services which are assumed to have a uniform quality that is independent of the supplier, are traded amongst sellers and buyers. The price at which these commodities are traded is called the equilibrium market price and is derived from the intersection between the supply and the demand curve (Baillo, 2015).

Prices for commodities can be classified in spot and forward or future prices. Spot trading is related to immediate commodity deliveries traded normally through an organized exchange. On the other hand forward or future trading can be done through an organized exchange or bilaterally through OTC contracts, and imply a future delivery of the goods traded.

While spot prices are driven by current information on supply and demand, and establish the commodity reference price, forward prices reflect the future expectations that the agents have on the commodity. This two prices are linked by the concept of inventories in the way that forward prices can be higher than spot prices if future expectations are promising but they can not be higher than spot prices plus storage costs. Having a limited storage leads to another important concept: seasonality.

A. Oil markets

Commodity overview

Petroleum, or crude oil, is a complex mixture of hydrocarbons found in the upper layer of the Earth's crust. It is a dense black liquid used since the beginning of the mankind that has had many applications during its history. Nowadays is pumped from the soil through machine-made drills and then distilled in order to obtain many different sub-products as gasoline, naptha or kerosene.

Although it may seem that petroleum is the same everywhere, its characteristics vary substantially depending where it has been extracted. The main properties that define oil are its content in sulphur and the gravity. This two properties classify oil in sweet/sour and heavy/light, being the sweet light crude oil the highest quality one, and subsequently, the more expensive. In figure 2.1 a classification of worldwide oils can be seen. (Deutsche Bank, 2011).

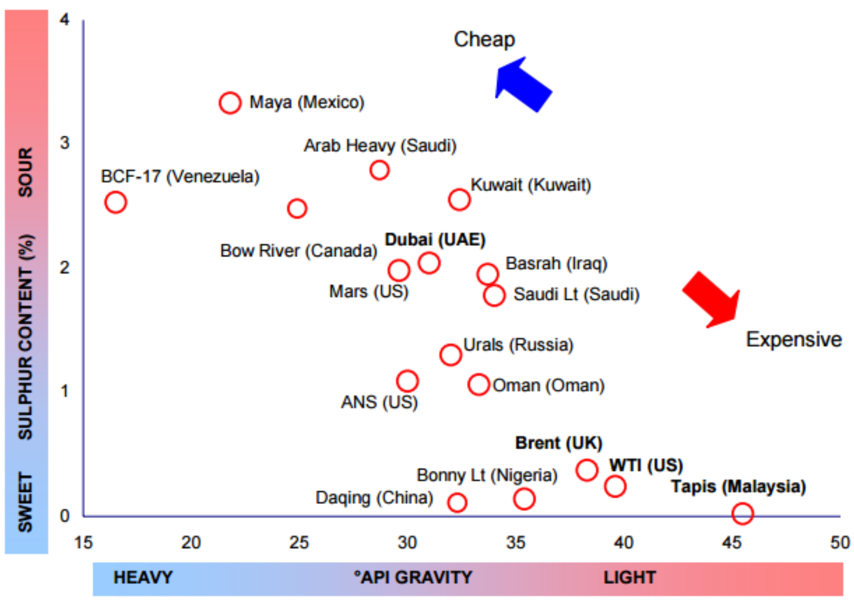

Figure 2.1 - Classification of worldwide oils (Deutsche Bank: A user guide to commodities - 2011)

Market structure

Oil markets are considered to be global markets as agents trade worldwide to benefit from global operational differences, similarities and opportunities. According to the IEA in 2013 (IEA, 2014) Saudi Arabia became the largest oil producer worldwide, followed by the Russian Federation and the United States.

Regarding imports, USA is also the largest net importer of this commodity, followed by China and India. On the exporter side, Saudi Arabia, Russian Federation and Nigeria are the top net exporters.

Spot and forward prices

Crude oil futures and options are mainly traded at NYMEX (New York Mercantile Exchange) and ICE (Intercontinental Exchange). In the United States, West Texas Intermediate (WTI) crude oil is used as the reference or benchmark index for the operations. On the other hand in Europe and worldwide, Brent oil is employed as the reference crude oil index. Spot prices are provided by agencies like Platts, and are based on current transactions.

B. Natural gas markets

Commodity overview

Natural gas is a gaseous fossil fuel consisting primarily of methane (about 90% in volume), but including significant quantities of ethane, heavier hydrocarbons like propane or butane, as well as carbon dioxide and nitrogen. As crude oil, natural gas can be distinguished in sweet and sour depending on its hydrogen sulphide content. Other factors taken into account when determining natural gas quality are Wobbe index and higher heating value (Deutsche Bank, 2011).

When transporting natural gas around the world, it is normal to see it in the form of LNG (Liquefied Natural Gas). Gas is liquefied in order to reduce, as much as possible, its volume to ship it to its destination. Natural gas can also be transported through pipelines.

It is also important to mention existence and recent revolution of the shale gas in the United States. Shale gas is natural gas trapped in shale formations that is usually extracted by the hydraulic fracturing (fracking) technique. This controversial technique is employed in a large part of the world (mainly USA) and banned in other (France and Germany).

Market structure

The natural gas market can also be defined as a global market. The main characteristic of this market is that, as it is a very capital intensive activity, it is a market with only a few relevant global suppliers. Amongst main producers United States, Russian Federation and Qatar can be found. Regarding top net exporters, the list is headed by Russian Federation, Qatar and Norway. On the other hand top net importers are Japan, Germany and Italy.

Spot and forward prices

Natural gas spot and forward prices are mainly traded in dollars per million BTU at two places in the world, USA and Europe. Regarding the United States of America, future contracts with different maturities are traded at NYMEX for delivery via the Henry Hub at Erath Louisiana. Henry Hub is the most liquid hub in the USA where also spot prices for natural gas are negotiated.

Regarding continental Europe, natural gas was traditionally traded through long-term oil-linked contracts in order to ensure both security of demand and security of supply, only additional volumes were traded through european hubs. Due to the development of the european natural markets and hubs, the way in which natural gas is traded is changing from oil-linked contracts to market negotiation. The most important hubs in Europe are: NBP in the UK, TTF in the Netherlands and ZEE in Belgium.

C. Coal markets

Commodity overview

Coal is a sedimentary rock composed mainly of carbon hydrogen and oxygen, its use as a fossil fuel became widely extended during the industrial revolution and the development of steam machines and motors. As many other commodities, coal can be classified in function of its main properties and components: carbon, ash, sulphur content and water. This components determine the hardness of the rock as well as the efficiency when burning it. The main four classifications of coal are: anthracite, lignite, bituminous coal and sub-bituminous one.

Regarding the value chain of coal, it is important to mention that there are two main methods of extracting coal: open pit and underground mining. The selection of the method to employ depends on the geological location of the source. According to experts, it is stated that, although it is not a renewable source, there is coal available for the next couple of centuries.

As coal is a rock it can only be transported by truck, train or vessel being one of the most expensive process in the value chain. This fact makes main points of coal consumption be placed near extraction points or main logistic points as harbours.

The main use of coal nowadays is electric power generation, so once that it is transported from the extracting point to the final destination, it is burnt in coal power plants and electricity is generated transferring the heat generated, when burning the coal, into steam turbines connected to generators.

It can be said that, although coal consumption for coal-fired power plants is still growing in some developing countries as China and India, the main tendency of the consumption is to be decreased. This decrease pattern goes together with the fact that coal is one of the most air polluting fuel in terms of CO_2, NO_x and SO_2. Even though many efforts are being taken to convert coal into a clean technology, renewable sources are being called to lead the so called decarbonisation of the industry.

Market structure

The three main top coal producers worldwide are China, USA and India. The main differences of characteristics in coal, as well as the local coal consumption markets, make that top producers are not necessarily to be the top exporters.
This exportations of what is called seaborne coal have a serious impact on coal prices. Seaborne coal export markets are dominated by Australia and South-Africa due to the quality of their coal.

In terms of net export Indonesia is the leader country although the quality of their coal is classified as low. Regarding the atlantic markets (USA and Europe) Colombia is one of the main actors in the market, being consumed the total amount produced in these two countries.

Spot and forward prices

As stated above, coal prices are decided in bilateral contracts amongst worldwide producers and consumers. Its price is proportionally dependant on the quality, being 6500 kcal/kg the standard for trading. Although many companies located in many countries participate in this global market, it can be stated that Asian transactions are the ones that highly influence the spot market.

Regarding futures or forward prices, in NYMEX exists the possibility to trade future contracts of 1550 tons, establishing the price in US Dollars per ton. The main index traded is the API#2 that obeys to the arithmetic average of the McCloskey Coal Information Services. This information services track the price of shipments of coal that is then used for power generation, having a wide overview of the global market, and being able to fix a price.

D. Power markets

Commodity overview

Electricity is one of the main commodities used worldwide, as it has been observed, most of the other energy commodities are used to produce electricity. The early start of the electricity generation began with the first power station located in Pearl Street, Manhattan, NY. Since then, its use not in households only but in industrial processes, has extended broadly, being its price a key factor in worldwide economies.

As a main difference from other commodities, electricity cannot be distinguished amongst countries or qualities, and its main characteristic that makes it unique is that it can not be stored. This storage issue makes that all electricity that is produced has to be consumed instantaneously.

Until the early 90s' vertically integrated companies dominated the electricity industry. Most of the times one state owned company had the monopoly to generate, transport, distribute and supply electricity to all customers, having the only mandate to do it at the lowest cost possible.

With the liberalization of the electricity sector, first in Chile and then in UK and Norway, many changes modified the paradigm that it was taking place. Leaded by the idea that competition would lower electricity prices, the electricity business was splitted into four different businesses. Because of the economies of scale that clearly presented the businesses of transporting and distributing energy (network businesses) they remained as regulated businesses. On the other hand generation, of which the price depended mostly, and supply were opened to fair competition.

This liberalization wave make electricity markets appear and study and analysis on prices became a major issue for a wide part of the industrial sector.

As stated above the price on electricity is highly dependent on generation technologies. In Europe the generation mix is led by fossil-fuels like coal and gas (48% share), nuclear (32% share), hydro (14% share) and renewables (8% share). Due to a political commitment from the EU Commission renewable generation technologies are called to displace thermal conventional ones, but up to date, these are still leading the mix (Deutsche Bank, 2011 and IEA, 2014).

Market structure

Although electricity is a worldwide commodity, markets are mainly local because of history and transmission issues (losses and investment). In free competitive markets generators sell their produced electricity in pool markets where suppliers buy them on provision of demand and on the behalf of their supplied clients.

The locality of markets is slowly changing as the benefits of interconnected systems are proven. Interconnections amongst many countries, and common bidding platforms in Europe are now a major reality due to the energy packages and the target model. For the first time in history, same prices in same hour were obtained for the vast majority of Europe.

Spot and forward prices

Spot prices are obtained by matching submitted supply and demand bids with an specific algorithm for clearing the market. The electricity market is a marginal market, so price is determined by the variable costs of the last unit that is available for supplying an extra MWh of demand. Even though the European Internal Energy Market is now a reality in terms of day-ahead and intraday market, prices are still cleared by market operators or PXs around the world. For the Spanish and Portuguese case the spot market is operated by OMIE, the French and German spot market is operated by EPEX.

Regarding futures markets, they work as in any other commodity. Organised markets, where different products regarding electricity can be traded, are placed around the world. The typical products traded are for MWh of electricity during peak hours, valley hours and plateau hours. Prices are also distinguished between summer and winter seasons, as well as, labour days or weekends.

Regarding this last paragraph, it is important to mention that one of the most important characteristics of electricity prices is seasonality. As electricity can not be stored, prices increase and decrease dependently on temperature and labour days. As seen, electricity is one of the most complex commodities, this makes experts state that electric systems and markets are one of the most perfect creations of the mankind.

2.2 REFERENCE MODELS

A. Introduction to the theory and dynamics of commodity prices

As stated in the beginning of the chapter, a commodity is a good or service which is assumed to have a uniform quality that is independent of the supplier. As physically produced, commodity prices depend mainly on cost of production and current expected scarcity, what in other words mean, supply and demand. Another characteristic that differentiates commodities from regular assets is the seasonality phenomenon in prices.

Seasonal patterns in commodity prices are a visible fact in many of them. This price patterns are characterized to be predictable and regular along the time, and are mainly caused by temporal changes in supply and demand. This changes are related to temperature, workable days and the possibility of commodity storage amongst many others.

When talking about commodities, as well as about other financial tradable assets, spot or current prices can be related to futures prices by what is known as the term structure (Dominice Goodwin, 2013). This term structure reflects the expectations of market participants about future changes in the price of commodities. Formally,

$$F_{o,T} = S_o e^{(r-q)T} \qquad [2.1]$$

where $F_{o,T}$ is the current price for the T maturity futures contract, S_o the current spot price of the commodity, r the continuously compounded interest rate and q the periodic continuously compounded yield rate.

One of the main characteristics of this equation is the slope. If futures price is above the expected future spot price, it could be said that a contango market condition is being faced. On the other hand, when the futures price is below the expected future spot price, it can be stated that a normal backwardation market condition is happening. This slope directly depends on the market feelings about the preference of holding the asset or holding the futures contract.

These studies about the dynamics of commodity prices led to two main theoretical currents of modeling prices. This modeling currents can be divided into convenience yield models and risk premium models.

Convenience yield models base their terms structure in linking the futures price to the spot price taking into account the comparison between the net cost/benefit of holding the asset, versus holding the future contract.

This can be observed in the equation 2.2 that defines the model,

$$F_{o,T} = S_o e^{(r+u-y)T} \qquad [2.2]$$

where the new variables u and y reflect the cost of storage and the convenience yield, defined as the benefit or premium associated with holding an underlying product or physical good, rather than the contract or derivative product, respectively.

On the other side of price modeling, risk premium models obtain futures prices by discounting a risk premium to the expected spot price. This can be observed in equation 2.3 as follows,

$$F_{o,T} = E_o[S_T]e^{(-rp)T} \qquad [2.3]$$

where $E_o[S_T]$ represents the expected spot price and rp the risk premium used for discounting.

B. Mean-reversion models

Going further in the modeling of commodity prices and the study of their dynamics, another important characteristic is the mean reversion. Mean reversion is given by the changes in the term structure over time from contango to backwardation, and vice versa, around a mean given by an equilibrium price (Dominice Goodwin, 2013).

This dynamics characteristic can be explained by the fact that, assuming constant supply, when the current market price is lower than the average price, the commodity becomes really attractive for purchase, increasing the demand and, therefore, increasing the price too. On the other hand, when the spot price is higher than the average price, the demand decreases decreasing as well the price. The overall conclusion of this property is that, whatever causes the spot price to be higher or lower than the average price, short-term deviations are always going to revert to its average or mean price.

Mean-reversion is modeled under the Ornstein-Uhlenbeck process, that can be defined as an stochastic process based on the Wiener process or random walk. This Wiener process is a random movement process along time, characterized by having a probability distribution function which follows Normal distribution with mean zero and standard deviation σ.

The Ornstein-Uhlenbeck process modifies the Wiener process to revert the random movement to a certain central location (average price), being the reverting movement faster, when it is far from the central location, and slower when it is near.

This behaviour is modeled under the following stochastic differential equation, that applied to prices stands as follows,

$$dS_t = \kappa(\overline{S} - S_t)dt + \sigma W_t \qquad [2.4]$$

where the differential of the spot price dS_t in period t is given by multiplying the speed of reversion κ, times the difference between the average or mean central spot price and the spot price in period t, times the time differential plus the Wiener process W_t characterized by the volatility of prices. In order to reflect the volatility of prices in the model, the Wiener process is assumed to be a N(0,1) so when it is multiplied by the volatility of prices, it reflects the random walk process adapted to the prices being modeled.

C. Geometric Brownian Motion models

Another way of modeling commodity prices is employing the Geometric Brownian Motion models. Also derived from the Wiener process, Geometric Brownian Motion stochastic process is, indeed, a Wiener process modified by a new term called drift or expected growing rate. This drift parameter directly multiplies the Wiener process to make it grow at the specified speed (Postali and Picchetti, 2006).

The stochastic differential equation that Geometric Brownian Motion processes satisfy is,

$$dS_t = \alpha S_t dt + \sigma S_t W_t \qquad [2.5]$$

where the new constant terms introduced are the drift or growing rate α and the percentage volatility σ. It can be observed in the identity how the first part $\alpha S_t dt$ controls the trend of the trajectory, and the second part $\sigma S_t W_t$ controls the random noise that is produced.

Geometric Brownian Motion models present very useful solutions when modeling different assets due to its simplicity and easy implementation, but also embeds high volatility in predicted prices, as well as, high level of uncertainty.

D. Schwartz-Smith two-factor models

Since the aforementioned models were developed, many other models have tried to model prices according to their dynamics. One-factor models were evolving giving birth to multiple factor models (Dominice Goodwin,2013).

In 1990 Gibson and Schwartz developed the first two-factor model to adjust oil prices. They assumed that the spot prices could be modeled employing a Geometric Brownian Motion process, and the convenience yield a mean-reverting process.

Later on, in 1997, Schwartz went further on developing a three-factor model for modeling gold, copper and crude oil. For this model he modeled the spot price and the convenience yield as in 1990, but introduced a new factor for the interest rate. The conclusion of this new development was that the three-factor model did not perform better than the two-factor model developed in 1990 although it performed substantially better than a one-factor model, being this only factor the spot price modeled as a mean-reverting process. From this, it was also concluded that the interest rate was not a key aspect to model introducing a new factor, but that the two-factor models were the the line for further developments.

These studies give birth to what is known as the Schwartz-Smith two-factor model. Developed in 2000 form modeling crude oil prices, Schwartz-Smith two-factor model assumed that spot prices had two main components to model: one long-run component and a short-run component. This model was firstly employed and tested in oil prices, but since then, it has become the most popular model to approach commodity prices.

In order to summarize the complexity of the Schwartz-Smith two-factor model, it has to be said that it introduced a new way of thinking when developing pricing models. Schwartz-Smith assumes that spot prices can be decomposed in a long-term equilibrium price ξ_t, that will follow a Geometric Brownian Motion process, and in a short-term deviation from this equilibrium price χ_t, that will follow a Mean-reverting process towards zero (Schwartz-Smith, 2000).

This approach can be seen in the main equations that were proposed,

$$ln(S_t) = \chi_t + \xi_t \quad [2.6]$$

$$d\xi_t = \mu_\xi dt + \sigma_\xi dz_\xi \quad [2.7]$$

$$d\chi_t = -\kappa\chi_t dt + \sigma_\chi dz_\chi \quad [2.8]$$

As it can be seen in [2.7] for the long-run factor, and [2.8] for the short-run one, these both equations reply exactly the structures defined for the Geometric Brownian motion process and the Mean-reverting process (assuming it reverts towards the central or average price zero, so $\overline{S}$ =0) respectively. Terms dz_{ξ} and dz_{χ} are the increments of the Wiener process which are also assumed to be correlated through the $\rho_{\chi\xi}$ that will be explained later on, and to conclude, the addition of both short-run and long-run components will result in the logarithm of the spot price.

The process defined in their theory allows short-term spot price deviations that will not last on time, as they revert towards the equilibrium spot price, and also allows a long-run spot price dynamics that will extend along time. Although convenience yield is not taken into account in this model, Schwartz-Smith argues in favour of this new structure stating that short-run/long-run components or factors are more intuitional than spot prices and convenience yield.

To continue explaining the model structure and functioning, for the sake of clarification, it is important to explain that this model estimates prices, from spot and future prices for different maturities, employing seven parameters extracted from the development of equations [2.7] and [2.8] plus the elements of the measurement covariance matrix in a risk-neutral process. The current value of the two factors contained in [2.6] is also needed to run the model.

It is expected that all parameters and factors regarding the model are known, but normally this parameters are not known, and factors not directly observable, so they have to be estimated employing both the maximum likelihood estimation and the Kalman filter technique. These parameters can be found in table 2.1.

κ	Mean-reversion coefficient
σ_{χ}	Volatility for the short-term deviations
λ_{χ}	Risk premium for the short-term deviations
μ_{ξ}	Equilibrium price level drift rate
σ_{ξ}	Equilibrium price leve volatility
μ_{ξ}^{*}	Equilibrium price level drift rate ($\mu_{\xi}^{*} = \mu_{\xi} - \lambda_{\xi}$, being λ_{ξ} the long-term component risk premium) taking into account a risk-neutral process.
$\rho_{\chi\xi}$	Correlation coefficient for both Wiener processes ($dz_{\xi}dz_{\chi} = \rho_{\chi\xi}dt$)
S_{n}^{2}	Diagonal elements of the measurement covariance matrix. Sub index n denotes the number of future contracts, with different maturities, employed for the price estimation

Table 2.1 - Model parameters (Schwartz-Smith - 2000)

In order to conclude, the model uses the relationship between spot and different maturities futures contracts, to estimate the required parameters and factors that conform the model. The logic behind this is that short-term deviation parameters will be estimated by taking the differences in prices between long-term maturities and short-term ones, giving the model the possibility to adapt to changes that will not last in the future (deviations).

On the other hand, equilibrium price level parameters will be estimated taking the differences on prices from the longer-term maturities contracts, interpreting that this differences on prices are the expectations that the market have on prices in the long-term (equilibrium price).

2.3 MONTE CARLO METHOD

A. Definition

Named because of the famous *"capital of casinos"* in Monaco, the Monte Carlo method is one of the most popular non deterministic methods used in optimization and numerical integration.

It constitutes also the analysis methodology most commonly used amongst many risk assessment departments. It is devoted to quantify risks that will influence later the strategical decisions concerning the whole business activity of a company.

In order to obtain a proper definition, Weisstein (Eric W. Weisstein, 2015) defines the Monte Carlo method as any method which solves a problem by generating suitable random numbers and observing that fraction of the numbers obeying some property or properties. This approach is often used for obtaining numerical solutions to problems which are too complicated to be solved analytically.

For applying the Monte Carlo theories, the Monte Carlo simulation is the most common technique. This technique relies on simulating one system for a large number of scenarios, assuming that each scenario simulated will only produce a single result or future situation for the system. Once all possible results are obtained, are assembled into a probabilistic distribution in order to be able to predict, inside a confidence interval, which results or future situations are going to be more likely to happen.

B. Example

In order to clarify the Monte Carlo method and simulations, an example about rolling two dices and obtaining a particular sum is presented as follows (Gold Sim, 2015 and Hyperphysics 2015).

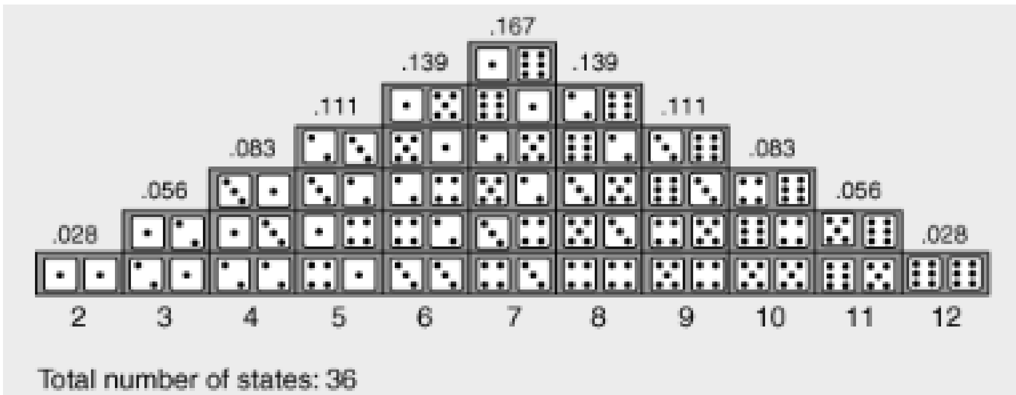

Figure 2.2 - Dice example representation (HyperPhysics - Georgia State University - 2015)

As it can be seen in the figure 2.2, there are 36 six possible states or combinations to get all 11 possible results. From this graph, the probabilities of getting a determined sum can be computed by dividing the number of possible states with which the desired sum is obtained, between the total possible states, so for obtaining the probabilities to strike seven, the division between 6 and 36 has to be made, obtaining then a 16,7% of probabilities.

As stated above, instead of computing the probabilities using analytic methods, the Monte Carlo simulations can be applied to obtain these results. To do this, the dice has to be thrown a large amount of times (simulating the system) and if it is done 100 times and 20 times a 6 is obtained, it can be then stated that there is a 20% of probabilities of striking 6.

As it can be derived from the example above, the result will be obviously more accurate as much simulations are made, to see this fact the comparative figure 2.3 is shown.

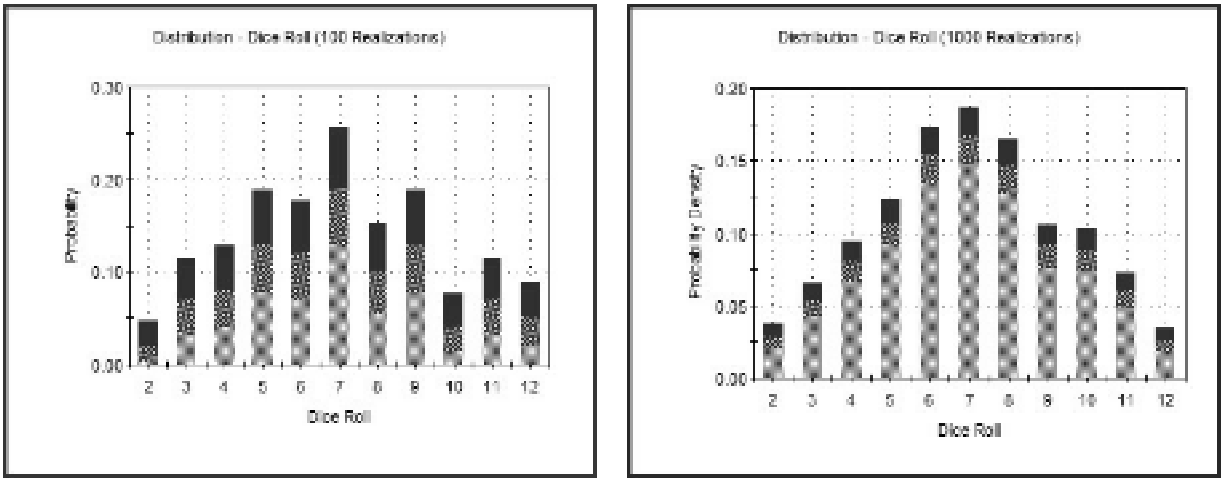

Figure 2.3 - Probability distribution of dice game: 100 simulations vs. 1000 simulations (Gold sim - 2015)

As it can be seen in the left chart, if only 100 simulations are done results are not that accurate as in the right chart with 1000 simulations. This happens due to the fact that when more simulations are done, the more likely is to really capture the nature of the system simulated.

2.4 CONCLUSIONS

In order to conclude, from all the topics reviewed above, it is important to highlight some important concepts as well as making some aclaratory points to them.

As it can be extracted when reading the part of the chapter related to commodities and markets, commodities are, at first sight, indispensable assets in the development of nowadays society. Oil, coal, natural gas and power are classified as energy commodities that are universally traded around the world, being for some developed and undeveloped economies, a significant part of the GDP. The importance that commodities have gained through the last decades, has made the society to put high amount of efforts to try to understand them and predict their prices.

This leads to the development of commodity pricing models, it has been seen the evolution in the modeling techniques, from one-factor models to two-factor models, going through the three factor ones. Although it may be thought that a model that contains three factors will adjust better the dynamics of prices that a model that only contains one, it has been proved that far from that, the correct performance of a model does not rely on the number of factors included, but on the design of them. Other issue to be taken into account is the importance of keeping the compromise between complexity of the model and results obtained.

Facing the prediction of future spot prices employing the parameters obtained from the different models, the Monte Carlo simulations technique is of a wide importance for analyzing the obtained data. Assembling results obtained from simulating the system under many different future scenarios in probability distributions, is a key point for having a broader view on the behaviour of prices in the future.

Just to conclude, as the main aim of this work is not developing new models or improve existing ones, but their use in analyzing prices of energy commodities, their explanation has been reduced to the essential. To this point, many information on how the models work and the mathematics behind them can be found amongst the varied existing literature.

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3
PROBLEM DESCRIPTION

3.1 DESCRIPTION OF THE PROBLEM

As stated in the first chapter of this master's thesis, the main objective of this research project is to analyze the dynamics and behaviour of spot prices in the main energy commodities. In order to achieve this main objective, raises the necessity of developing a reliable quantitative analysis tool that is able to cope with this main objective.

When talking about the different models in the second chapter: Schwartz-Smith, Geometric Brownian motion and Ornstein-Uhlenbeck, it was concluded that independent of the factors, the performance of a pricing model depends mainly on its design, so it can be possible that for a commodity with storage capacity and a more or less stable price dynamic, a one-factor model performs better than a two-factor one.

In order to have this idea in mind, the quantitative tool for analyzing price dynamics should incorporate these three models, and taking a benchmarking approach, be able to give results that are valid to assess their performance.

Taking into account the variety of energy commodities and markets to be analyzed, this study classifies them depending on their nature: oil, natural gas, coal and electric power. For modeling the behaviour of prices, Matlab software has been employed using a modified code that is able to adjust the three models at the same time, generating the needed quantitative parameters to asses their performance and to analyze the most important features of each commodity. In this sense, the modelling tool itself could be thought to be the most important element of this study, but it is not going to perform well in the inputs provided are not adequate.

All these issues are studied in depth in this third chapter, where all the tools employed are described so the results exposed later are understable and coherent.

3.2 COMMODITIES TO ANALYZE

A. Oil

- Brent
- WTI (West Texas Intermediate)

B. Natural Gas

- NBP (National Balancing Point)
- Henry Hub

C. Coal

- API#2

D. Electric Power

- OMIE
- EPEX Spot Germany
- EPEX Spot France

3.3 SOFTWARE EMPLOYED

A. Original code

As pointed out in the problem description, the software employed in this analysis has been Matlab. The code employed has been developed by Dominice Goodwin for his master's thesis: *"Schwartz-Smith Two-Factor Model in the Copper Market: before and after the New Market Dynamics"* (Dominice Goodwin, 2013) and is able to adjust Schwartz-Smith, Geometric Brownian motion and Ornstein-Uhlenbeck models at once.

Although in the reference it can be found a detailed analysis of copper prices employing the tool, the code itself is also available at Matlab Central, the software platform for sharing material.

Validation and calibration of the models

Before entering into detail, the first important thing to check is if the code is well structured, as well as the models are optimally calibrated, so the results obtained from them are valid. In order to do so, the author, employing the same oil data than in the Schwartz-Smith paper: *Short-term variations and long-term dynamics in commodity prices*, compares the obtained results to the ones exposed in the paper. The result of the test is satisfactory, so the code is valid and the models calibrated.

Inputs

As in any other model, the first important things to set are the inputs. As explained in chapter two, Schwartz-Smith two-factor model estimates its parameters employing the commodity spot price data and different maturity futures data.

Because of the developing of financial markets and the peculiarities of some commodities being traded bilaterally rather than in organized exchanges, futures data is often more likely to be obtained than spot data.

In these situations, shortest-maturity futures data has been taken as a proxy of spot data. For obtaining accurate results, the futures prices introduced should include observations from the shortest-term maturity, to the longest-term available.

As an example, for WTI crude oil, spot and two years in advance monthly futures were available, so in order to reflect long-term and short-term market expectations of prices: Spot, 3M, 9M, 12M, 15M, and 24M were introduced as inputs, being the M contracts future contracts that expire in the M months after the date of contracting.

In order to indicate the software the maturity and number of contracts that are being introduced, a number of contracts and maturity fields have to be fulfilled. As the models annualize the introduced data, depending on the type (daily, monthly, weekly…) a annualization field has also to be fulfilled. For this study daily data has been employed for all commodities, so the annualization rate or dt, has been set to 1/360. Note that the data is annualized for a proxy of the trading days in a natural year for spot and futures prices.

Running the model

Once all data has been introduced and input parameters set, the model is run. As it can be seen when analyzing the code, the main model that the code is adjusting is the Schwartz-Smith two-factor model. The tool also has a separate piece of code to run the Kalman filter in order to estimate together with the maximum likelihood function all parameters and factors needed.

As explained in chapter two, the Schwartz-Smith two-factor model assumes that the spot price is composed of a long-term equilibrium level component, following a Geometric Brownian motion process, and a short-term deviations from this equilibrium one component, following an Ornstein-Uhlenbeck process, so what the code does in order to adjust Geometric Brownian motion model and Ornstein-Uhlenbeck model, is to impose a constraint restricting to zero long-term parameters (μ_ξ, σ_ξ and μ_ξ^*) when adjusting Ornstein-Uhlenbeck model, and the same with short-term ones (σ_χ and λ_χ) when adjusting the Geometric Brownian motion model. This way the code is able to isolate and adjust both models from the Schwartz-Smith two-factor model.

Outputs

The main outputs that the model is generating are obviously all the model's parameters and factors, but in order to test their adequacy or good performance, the code is also generating many statistical and error measurements.

The parameters produced are the ones listed in chapter two, table 2.1. All these estimated parameters go along with their computed standard error, what allows directly to observe the statistical significance of the estimation.

Another important output are the log-likelihood scores given by the maximum likelihood estimation of each model with each dataset. This scores are capable to explain statistically the ability of the different models to explain the observed data.

Last but not least, the errors between the predicted prices and the observed prices are analyzed in terms of mean absolute error, standard deviation of error and mean error.

The study carried out in this thesis has a similar structure, regarding the models, than the study carried out by Schwartz-Smith in their paper. For the sake of clarification, a brief review has been done on the main parameters, statistics and errors, so for further information on the deep mathematics, theory and computations of the model, the reader can take a look at the two main references used. (Schwartz-Smith, 2000 and Dominice Goodwin, 2013)

B. Modifications

The code itself only provided the adjustment of the three models in terms of parameters, factors, statistics and errors. Although it is a good starting point, some modifications had to be introduced in order to get the desired results for carrying out the original proposed analysis for the targeted commodities.

This particular analysis proposed, introduced in chapter one and explained in depth in chapter three, needed the implementation of a Monte Carlo simulations tool that would be fed with the parameters obtained from running the models.

Following the Monte Carlo explanation described in chapter two, the matrixes contained in the transition equation and the measurement equation, obtained from the State-Space form representation of the Schwartz-Smith two-factor model, were computed and implemented in a Monte Carlo simulations code. The process is explained as follows,

$$x_t = c + Gx_{t-1} + \omega_t,\ t = 1,\ 2,\ 3,\ \ldots,\ n_t \qquad [3.1]$$

$$y_t = d_t + F_t^{'} x_t + v_t,\ t = 1,\ 2,\ 3,\ \ldots,\ n_t \qquad [3.2]$$

The aforementioned transition and measurement equations described in depth in Schwartz-Smith, 2000, describe the evolution of the state variables and the relationship between state variables and observed prices, respectively.

Components ω_t and v_t, that correspond to serially uncorrelated normally distributed disturbances, have been passed through the random function in Matlab. Doing this, many price paths have been obtained always respecting the characteristics and parameters obtained by running the models.

Once being able to simulate or generate as many price paths (simulating the system under many different scenarios) as wanted, it was important to obtain results. As explained in chapter two, probabilistic results and statistical results are the best way to obtain a quantitative approach to Monte Carlo simulations.

Three main quantitative approaches were implemented in the code to analyze Monte Carlo results. The first one was to compute percentiles 5th and 95th of all price paths in order to draw a confidence interval for analyzing possible spot price violations. Later on, statistical values like mean, standard deviation and aforementioned percentiles were computed for the last price contained in all price paths. To conclude, same statistical values than before were computed but combining them with simple observations as the máximum and minimum price obtained. This last code implementation was focused in all values regarding all price paths.

All this results obtained were employed in several posterior analysis explained further in chapter four.

As mentioned along this report, the main aim of this study is to analyze commodities spot price, nevertheless it could be also interesting to carry out the same analysis but for forward or futures price.

This possibility is contemplated in the paper (Schwartz-Smith, 2000) by, once obtained all model's parameters, introduce them in the equations described in the epigraph 3.1 *Valuing Futures Contracts* of the paper. The same happens for valuing European options on futures contracts, which can be found on following epigraph *Valuing European options on futures contracts* 3.2 of the paper.

3.4 DATASETS

In this next epigraph the datasets employed as inputs for the models are presented. As it can be seen in the charts that follow the data is classified by commodity, indicating the dates when the observations took place, the contracts employed, the number of total observations employed and the computation of the 70% and the 30% of these total observations. These computations were made following the strategy of the analysis, that will be explained in depth in chapter four.

In order to highlight some important issues regarding the data, it has to be mentioned that this data has been provided by the Quantitative and Market Analysis unit within Endesa S.A.

Another important issue is the period of the observations, it has been taken daily for all commodities understanding that modeling daily prices was the best option to be able to take all price dynamics.

Last but not least, holiday days as christmas or non-trading days have been deleted from the datasets.

Oil

Commodity	Dates	Contracts	Observations	70% of Obs.	30% of Obs.
Brent	18/01/2011 - 24/04/2015	Spot, M3, M9, M15, M24	1101	770	331
WTI	02/01/2008 - 24/04/2015	Spot M5, M7, M11, M12	1843	1290	553

Table 3.1 - Dataset employed for analyzing oil commodities

Natural Gas

Commodity	Dates	Contracts	Observations	70% of Obs.	30% of Obs.
NBP	14/04/2008 - 24/04/2015	Spot, 2M, 5M, 7M, 9M, 12M	1790	1253	537
Henry Hub	25/08/2008 - 24/04/2015	Spot, M3, M6, M9, M12, M15	1680	1176	504

Table 3.2 - Dataset employed for analyzing natural gas commodities

Coal

Commodity	Dates	Contracts	Observations	70% of Obs.	30% of Obs.
API#2	01/01/2010 - 22/06/2015	Spot, M3, M6, M9, M12, M15	1419	993	426

Table 3.3 - Dataset employed for analyzing coal commodities

Electric Power

Commodity	Dates	Contracts	Observations	70% of Obs.	30% of Obs.
OMIE	01/01/2010 - 31/12/2014	Spot, M3, M6, M9, M12, M15	1296	907	389
EPEX Spot Germany	01/01/2010 - 21/05/2015	Spot, M3, M6, M9, M12, M15	1397	997	420
EPEX Spot France	01/01/2010 - 21/05/2015	Spot, M2, M4, M6, M9, M11	1397	997	420

Table 3.4 - Dataset employed for analyzing electric power commodities

3.5 REFERENCES

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4
ANALYSIS METHODOLOGY

4.1 IN-SAMPLE ANALYSIS

In this fourth chapter the methodology employed in this study will be explained in detail. It is divided in three sections, each one devoted to a different analysis methodology. All methodologies are oriented to achieve a specific objective and the sum of them make the whole integral commodity analysis. To illustrate the reader, this testing methodology is often called as backtesting, out-of-sample testing and forward testing (Jean Folger, 2015).

First the in-sample analysis is devoted to assess the performance of the three models in each commodity. The out-of-sample analysis will be executed to analyze the generalization capacity of the models. To conclude, the third analysis will use the three models from a company's risk department perspective, that means, will make future predictions on commodity prices.

In order to begin, the in-sample analysis has been one of the most recurrent methodologies for traders in financial institutions. It gives the analyst the key to understand what has happened in the past, being able to analyze how the model would have performed during a specific time period. Although knowing the past is important to be able to predict the future, in-sample analysis or backtesting presents many risks to be held on its own when drawing any conclusion, as conclusions would only be valid for the past but not for the future.

In this study, the in-sample analysis has taken a benchmarking approach. As stated in chapter three, the modeling tool is able to compute Schwartz-Smith two-factor model, Geometric Brownian motion model and Ornstein-Uhlenbeck model at the same time, so the benchmarking comparison amongst them has been possible.

In order to complete the backtesting and the out-of-sample testing, data was divided into a 70% of the observations and a 30% of them. The 70% of the data was employed in backtesting while the remaining 30% was reserved for the out-of-sample analysis.

The backtesting carried out in this thesis contains qualitative and quantitative analysis. It assesses the performance of the three models in each commodity by taking into account the parameters obtained together with their standard errors, a qualitative interpretation of the obtained graphs and a benchmarking comparative of the log-likelihood scores that result from running all three models. For the qualitative analysis, the graphs present three variables: the observed price (spot price introduced as input), the estimated price (equilibrium price level plus short-term deviations) and the equilibrium price (equilibrium price level).

4.2 OUT-OF-SAMPLE ANALYSIS

Out-of-sample analysis or testing is the complementary tool to the backtesting or in-sample analysis (Inoue-Kilian, 2002). Even though is still dealing with past experiences, it allows the analyst to assess if the adjusted model performs accurately, being able to predict the dynamics of the remaining data sample.

As stated by Folger (Jean Folger, 2015), the logics behind the out-of-sample analysis is to it provide a way to test the idea on data that has not been a component of the input of the model. As a result, the idea will not have been influenced in any way by the out-of-sample data and traders will be able to determine how well the system might perform on new data.

The out-of-sample analysis carried out in this study is used, as stated above, to test the models on data that has not been included in the inputs of the models and, as a consequence, is not affected by them. This analysis has been combined with a Monte Carlo simulations in order to test, within a definite confidence interval, if the model would have been able to predict the 30% of the reserved data for the study.

The 5000 simulated Monte Carlo price paths have been extended for the same number of observations than the ones comprised in the 30% reserved observations, so they could be tested against this remaining 30% of the spot price.

From the quantitative analysis point of view, the confidence interval has been defined by computing the Monte Carlo 5^{th} - 95^{th} percentiles. As stated above, the main focus of this analysis has been based on the study of the the possible spot price violations of the defined percentiles. This study allows to state that if the spot price is above or under the confidence intervals for a large number of observations, then the model has not been able to capture the dynamics of the commodity prices. For assessing this fact, the number of observations that spot prices violate confidence intervals have been computed in percentage of the total out-of-sample observations.

4.3 REAL IMPLEMENTATION

For the real implementation analysis, a risk and market analysis approach has been taken. This approach is the result of the wish of giving this study a more practical implementation, taking a compromise between an academical thesis and a practical and business thesis.

The real implementation analysis or forward testing is based on the idea of providing analysts or traders with another view of the performance of a determined model. This new performance, based on the adjustment of the models with the 100% of the dataset, is done at future, giving a more live prediction with results ready to use in making decision processes.

The methodology followed in this analysis has been firstly, to use all the dataset available as inputs for running the models and obtaining new, and more up to date, parameters and factors. Then, with these new parameters, the same Monte Carlo price paths simulations than in out-of-sample analysis have been implemented.

The logics behind this methodology is to be able to simulate the system under many different and real scenarios in order to observe and analyze the future behaviour of the prices of the different commodities. As in the out-of-sample analysis 5000 price paths have been generated and extended for a whole natural year (365 days) in terms of observations.

This analysis is mainly oriented to obtain quantitative results, although some qualitative predictions could be made. Again, for analyzing the outputs of the Monte Carlo simulations, the tools described in chapter three have been used. The study has been divided in two: last values analysis and all values analysis. This classification has brought some light on the assessment of future performances, having a broader view for the decision making process.

In the last values analysis, the last prices of all price paths have been assembled in a probabilistic distribution, studied by computing statistical measures as: mean, standard deviation, 5^{th}, 50^{th} and 95^{th} percentiles.

In the all values analysis, the same than for the last values analysis has been done but taking all values of the generated price paths. The statistical measures computed have been the same than for last values analysis but introducing some simple indicators as the maximum and minimum price registered.

Once all steps have been presented, in order to sum up the whole methodology process, the next figure explaining the data and the analysis taken is presented,

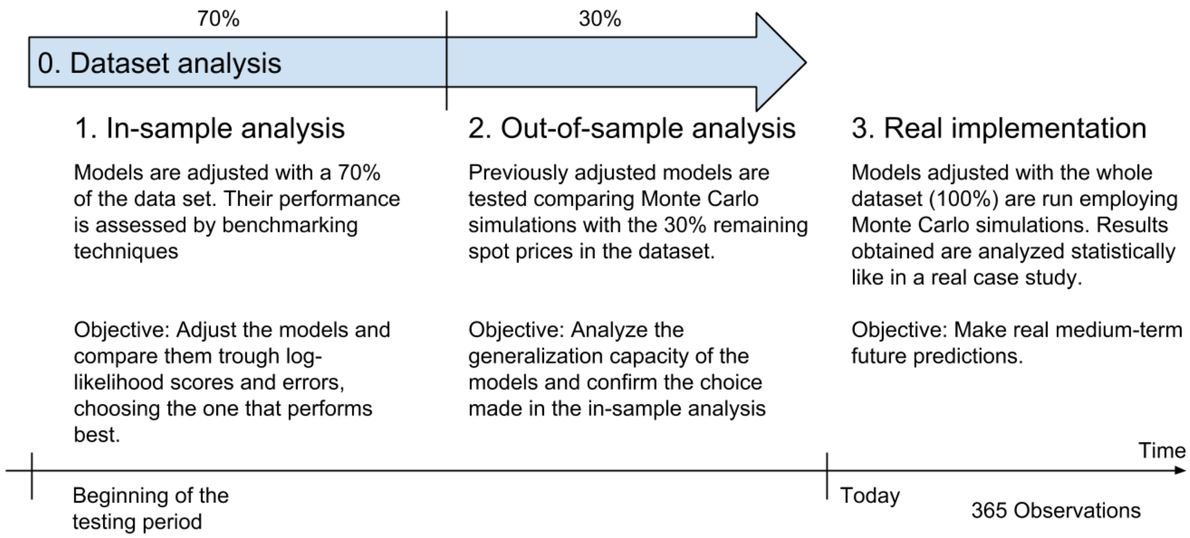

Figure 4.1 - Methodology employed for analyzing commodities price dynamics

4.4 REFERENCES

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Inoue-Kilian. 2002. *In-sample and Out-of-sample tests for predictability: which ones we should use?.* European Central Bank working paper number 195

5
EMPIRICAL RESULTS

5.1 OIL COMMODITIES

A. Dataset

Brent

In this first commodity study, Brent and WTI oil commodities are going to be analyzed. In figures 5.1 and 5.2 it can be seen both spot prices plotted, for each dataset employed.

Regarding figure 5.1, the dataset plotted corresponds to Brent oil prices from 18/01/2011 to 24/04/2015, being composed of 1101 observations. As it can be seen for almost 900 observations (3 years and a half) the oil price is fluctuating between 100 and 120 $/BBL with a clear dynamic, almost with no sharp increase or decrease.

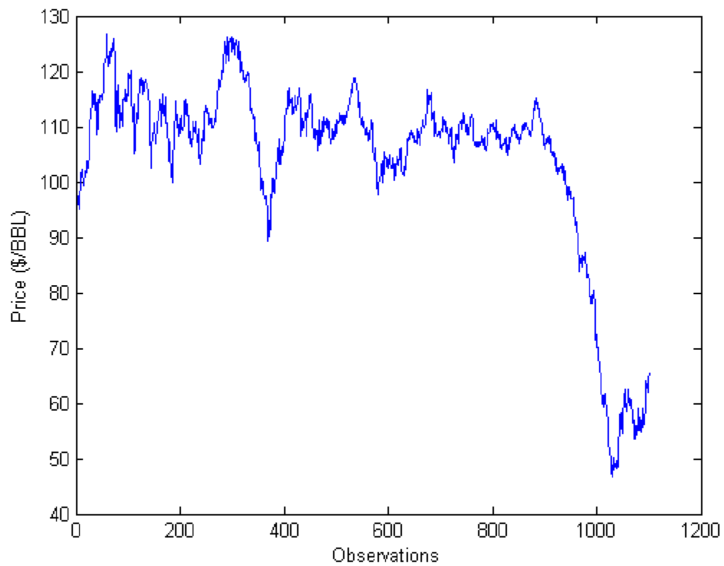

Figure 5.1 - Brent spot price dataset

This prices obeyed to the pre-oil-crisis situation, where highest oil prices took place in history. In September 2014, what is known as the oil crisis started (Krauss Clifford, 2015), moving prices in less than half a year, from 110 $/BBL to less than 50 $/BBL. This oil downturn caused by the increase in world oil production while the demand decreases, is caused by many different geopolitical facts, being the most important the Saudi Arabia's willing to continue to produce the same share of oil barrels independently of their price. Some experts link this movement to the intentions of oil producers to sell their production before the change to renewable technologies, and others conclude that it is because of the will of expelling competitors out of the market.

WTI

Regarding WTI dataset employed, it is composed of 1843 observations going from 02/01/2008 to 24/04/2015. When looking at figure 5.2, where the spot price for WTI dataset is plotted, it can be seen that the price shape for WTI is quite different from the Brent one. This is firstly due to the temporary scope of the WTI dataset chosen. While the WTI dataset starts in January 2008, the Brent one does not start until January 2011. This fact explains the sharp price decrease contained in WTI, and not in Brent, that was caused by the outbreak of the financial crisis in September 2008.

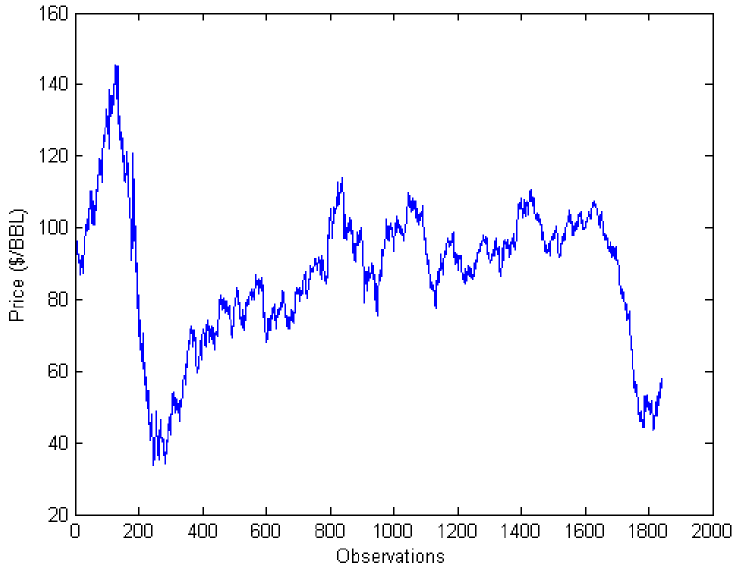

Figure 5.2 - WTI spot price dataset

Apart from the aforementioned sharp decrease in WTI, both commodities follow a relatively close path, being Brent higher in prices around 110 $/BBL and WTI around 90 $/BBL. Although WTI oil is better in quality (lightness and sulphur content) the difference in prices can be explained for many reasons, being the main one, the triumph of Brent oil as a worldwide trading index over WTI (Energy and Capital, 2012).

The expectation of the depletion of Brent oil fields, as well as the increasing flowing of northern oil into Cushing OK, together with dollar monetary politics, complete the number of reasons why the WTI price is slightly lower than Brent.

Even though WTI and Brent are different commodities and indexes, their markets are directly linked. This fact can be seen in WTI being also influenced by the September 2014 oil downturn.

B. In-sample analysis

<u>Brent</u>

Regarding figure 5.3 related to Schwartz-Smith two-factor model adjusted to Brent oil, it can be observed how the equilibrium price presents a downward slope starting from 105 $/BBL and ending in 90 $/BBL. This fact reveals that the market expects the Brent price to decrease in the long-term, to be established around more stable past values of 85 $/BBL.

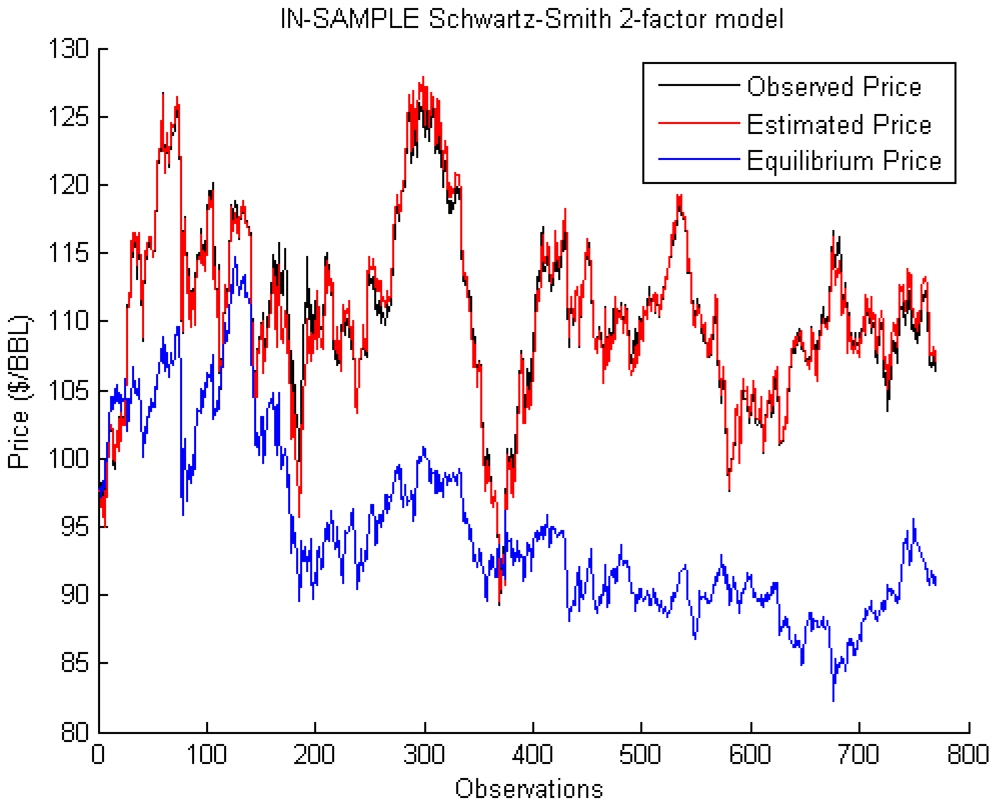

Figure 5.3 - Observed spot price vs. estimated spot price and equilibrium spot price for Brent oil

Short-term deviations reflect the market expectations of higher prices around 125 $/BBL to be of a temporary nature based on a short-term scarcity. This deviations are usual in oil prices due to the will of controlling prices by OPEC (Brad Plumer, 2015). OPEC's countries decide to produce a closed amount of oil in order to control prices when supplying global demand. If OPEC's expectations of demand are to decrease, a short-term scarcity is created in order to maintain prices at same level. This, creates the fluctuations in prices seen in figure 5.3.

WTI

When analyzing WTI Schwartz-Smith results in figure 5.4, it can be seen how, compared with Brent oil, the long-term equilibrium prices remain stable around 100 $/BBL with almost no overall slope, what reflects the firm convincement of the market that future WTI spot prices will be around that level. It is also significative the sharp increase of the long-term equilibrium price around the 100 observation. This is linked to the expectation that pre-financial-crisis high prices were also going to stay in the long-term.

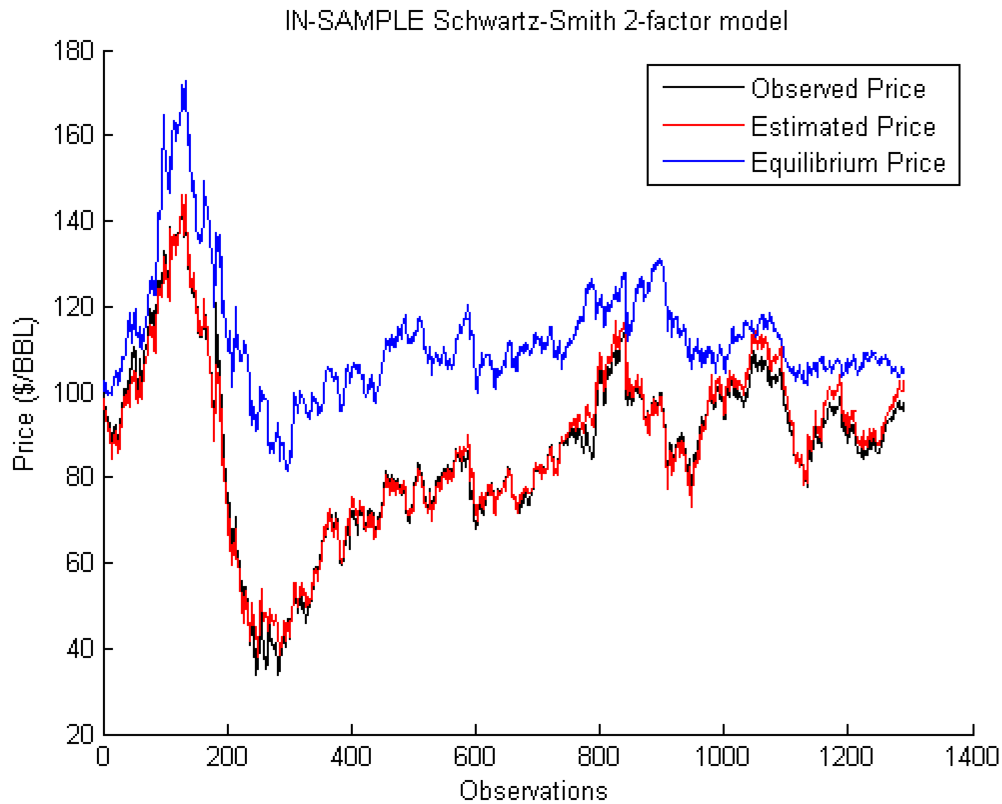

Figure 5.4 - Observed spot price vs. estimated spot price and equilibrium spot price for WTI oil

Regarding short-term deviations, it can be seen how a significant part of the 2008 crisis downturn is expected not to remain in the long-term, diminishing with the stabilization of long-term prices until the convergence at the 100 $/BBL is reached.

Parameter analysis

With the parameter analysis, a quantitative study is taken in order to explain the price dynamics for oil commodities. In this study, the Schwartz-Smith two-factor model parameters have been taken as they give a broader view in terms of short-term and long-term components of the aforementioned dynamics.

	Brent		WTI			Brent		WTI	
Parameter	S&S	SE	S&S	SE	Parameter	S&S	SE	S&S	SE
κ	0,3794	0,0006	0,4475	0,2225	$\rho_{\xi x}$	0,2966	0,0000	0,0984	0,5340
σ_x	0,3007	0,0000	0,3626	0,1063	S_1	0,0010	-	0,0160	-
λ_x	0,0328	0,0038	0,1045	0,1784	S_2	0,0003	-	0,0003	-
μ_ξ	-0,0850	0,1628	0,0242	0,2598	S_3	0,0003	-	0,0030	-
σ_ξ	0,2615	0,0000	0,2929	0,0271	S_4	0,0000	0,0000	0,0000	0,0000
μ_ξ^*	-0,0507	0,0014	-0,067	0,0575	S_5	-	-	-	-

Table 5.1 - Maximum likelihood parameter estimates and their standard errors associated for Brent and WTI oil

Regarding the parameters obtained for both commodities, represented in table 5.1, it can be observed how, in terms of standard error, Brent oil parameters present higher statistical significance than WTI ones. This fact is due to the more stable price dynamics present in the dataset for Brent. Approximately equal increases and decreases on prices lead to an adjustment of the model with lower parameter estimation errors. On the other side, WTI dataset present unequal variations on prices, with larger variations at the beginning, lower at the middle and medium ones at the end.

The degree of adaptation of the model to these variations can be seen, in table 5.1, in terms of the speed of mean-reversion. As commented before, thanks to having a more stable dynamic with lower and more expanded variations, Brent oil presents a lower mean-reversion coefficient, while WTI, with higher spikes in shorter timeframes, presents a higher coefficient.

This fact can also be explained in terms of short-term and long-term volatilities, were both coefficients present higher values for the WTI dataset than for the Brent one. It is important to mention that the aforementioned stability in dynamics is only analyzed for the datasets used as input for the models.

Regarding the performance of the three models when adjusted to the datasets, it is observable through the log-likelihood scores in table 5.2, that Schwartz-Smith two-factor model dominates the study.

The dominance of the Schwartz-Smith model over the Geometric Brownian motion model and the Ornstein-Uhlenbeck model is quite evident as the Schwartz-Smith two-factor model combines the characteristics of the other two unifactorial models, being able to catch short-term dynamics on prices and long-term ones.

	Brent	WTI
S&S Two-factor model	15418	17597
Geometric Brownian motion	11316	10557
Ornstein-Uhlenbeck	11354	12849

Table 5.2 - Log-likelihood scores for all models and commodities studied

It is also important to analyze the obtention of higher log-likelihood scores in the Ornstein-Uhlenbeck model than in in the Geometric Brownian model. This can be explained by the term structure implemented in the Geometric Brownian motion model.

The Geometric Brownian motion model term structure is simply a straight line with a time-zero intercept at the logarithm of the spot price, what makes in other words, trying to fit a straight line with constant slope through a whole time series. Another important feature of the Geometric Brownian motion model is the low performance of modeling transitions between contango and backwardation over time, playing an important role in fitting better long-time data than short-time data.

On the other hand, the term structure in the Ornstein-Uhlenbeck model suggests a mean reversion on prices around a straight line with zero slope and zero-time intercept (equilibrium price level) allowing transitions between contango and backwardation but not changes in the equilibrium price. This fact makes the Ornstein-Uhlenbeck model to perform better when fitting shorter-time data.

The aforementioned properties can be observed in terms of mean absolute errors displayed for WTI dataset in table 5.3, where the Ornstein-Uhlenbeck model is able to adjust, with zero error, the 9M futures, and Geometric Brownian Motion larger-maturity 15M futures.

Contract Maturity	Mean Absolute Error			Standard of Error			Mean Error		
	S&S	GBM	OU	S&S	GBM	OU	S&S	GBM	OU
3M	0,0126	0,0449	0,0149	0,0144	0,0598	0,0191	-0,0070	-0,0208	-0,0069
9M	0,0000	0,0202	0,0000	0,0000	0,0257	0,0000	0,0000	-0,0016	0,0000
15M	0,0023	0,0000	0,0102	0,0029	0,0000	0,0128	-0,0007	0,0000	-0,0017
24M	0,0000	0,0244	0,0218	0,0000	0,0295	0,0283	0,0000	-0,0079	-0,0030

Table 5.3 - Term structure fit for WTI

For Brent dataset adjusting errors presented in table 5.4, these model properties are less observable as both models adjust with zero error the same 11M futures contract. Aside from this, it is significant how both models adjust better medium-term contracts rather than shortest or longest-time ones. This fact can also be observable at the Schwartz-Smith paper. (Schwartz-Smith, 2000)

Contract Maturity	Mean Absolute Error			Standard of Error			Mean Error		
	S&S	GBM	OU	S&S	GBM	OU	S&S	GBM	OU
5M	0,0007	0,0083	0,0082	0,0009	0,0104	0,0103	0,0001	0,0000	-0,0001
7M	0,0001	0,0054	0,0054	0,0001	0,0067	0,0066	0,0000	-0,0001	-0,0001
11M	0,0003	0,0000	0,0000	0,0003	0,0000	0,0000	0,0000	0,0000	0,0000
12M	0,0000	0,0012	0,0012	0,0000	0,0016	0,0015	0,0000	0,0000	0,0000

Table 5.4 - Term structure fit for Brent

What can be also observed is that independent of the futures contract adjusted, Schwartz-Smith two-factor model adjusts the data better than the other two benchmarking models.

C. Out-of-sample analysis

Brent

In this out-of-sample testing analysis, the reserved 30% of the real Brent spot price observations are plotted against the 5000 simulated price paths. The key of this analysis is to observe the possible violations of the computed 5th-95th percentiles of the simulated price paths, to determine if the pre-adjusted model is able to capture new real spot data introduced.

Regarding the Brent oil prediction testing, presented in figure 5.5, it is seen how the Schwartz-Smith two-factor model is able to capture the majority of the new real spot price data introduced. As it is seen, around observation 250, the price violates the 5th percentile for some time until it gets back again into the defined acceptance interval.

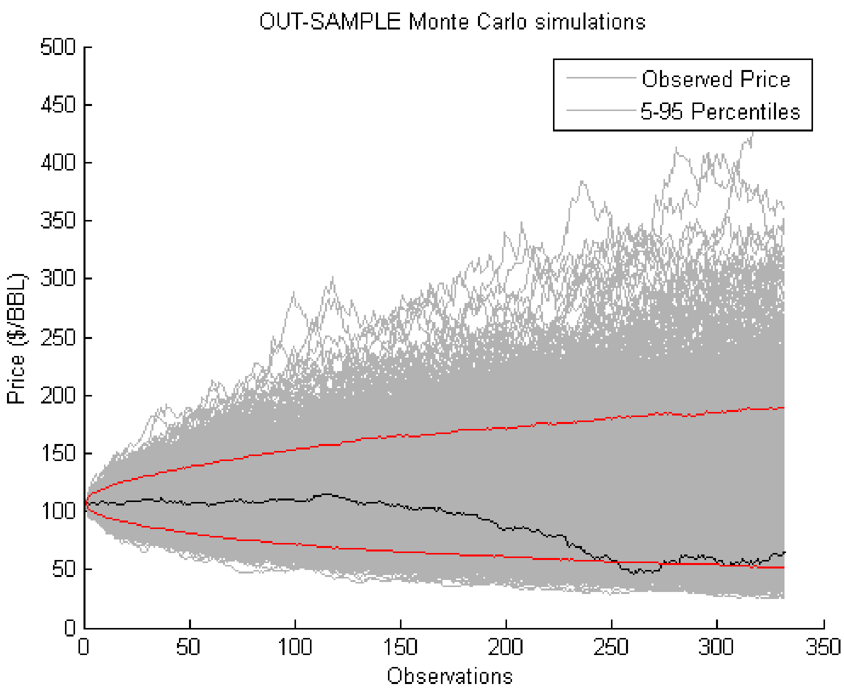

Figure 5.5 - S&S simulated price paths (with 5-95 percentiles highlighted) vs. observed spot price

The observations where this violation takes place, coincides with the September 2014 oil downturn. This downturn represents a structural break in Brent oil prices that is almost impossible to capture with any model.

WTI

Concerning the WTI oil prediction, it can be seen that the spot price is mostly always inside the 5th-95th percentiles defined interval. Although an equal downturn, regarding to Brent prices, is experienced in WTI prices, 99% of the obtained observations fall inside the 90% confidence interval determined.

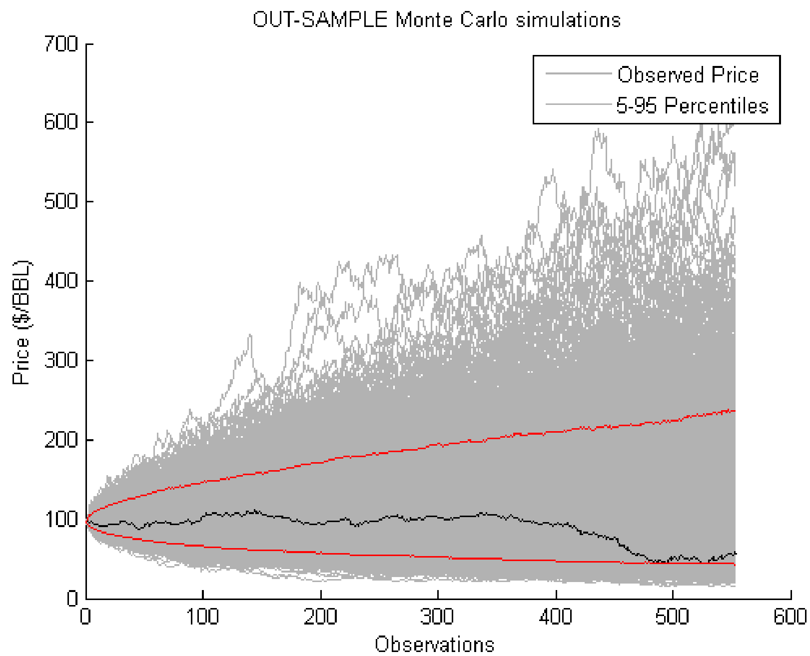

Figure 5.6 - S&S simulated price paths (with 5-95 percentiles highlighted) vs. observed spot price

The explanation for fact this relies both in the input data of the model and in the experienced downturn. As commented before, the downturn experienced in 2014 by WTI oil prices is smaller than in Brent, this makes the model be able to catch it. Regarding the input data, it is important to mention that, as explained before, the WTI dataset presents an unstable dynamic that makes the model achieve higher long-term volatilities that, when simulating, are translated in a broader defined interval that is able to catch more volatile prices. In other words, WTI model is prepared for sharp decreases in prices while Brent one is not.

In order to quantify and assess the performance of the Schwartz-Smith model in both datasets, the percentage of observations that the spot price violates the 5th-95th interval, in terms of all observations employed for the analysis, is presented in table 5.5 as follows. As a conclusion the results show what has been stated above.

Violation of 5th-95th percentiles in % of total studied observations		
Commodity	Brent	WTI
95th Percentile	0%	0%
5th Percentile	8%	1%

Table 5.5 - Violation of 5th-95th percentiles in % of total studied observations

As it can be observed in table 5.5, 92% of Brent observations fall into the 90% confidence interval drawn by 5^{th}-95^{th} percentiles of the Schwartz-Smith two-factor model simulations, while 99% do for WTI.

For the sake of clarification, Geometric Brownian motion model and Ornstein-Uhlenbeck model violations results, have been omitted as they were significantly worse than Schwartz-Smith two-factor ones.

This conclusion repeats all over every out-of-sample analysis found in this master's thesis, proving the generalization capacity of the Schwartz-Smith two-factor model and the better performance of two-factor models against one-factor ones.

D. Real implementation

Last values analysis

Regarding the real implementation of the models for the future, it is important to mention that for this analysis, Schwartz-Smith two-factor model was adjusted for the 100% of the dataset, what particularly means that the last downturn in oil prices commented along this epigraph, was also taken into account for both commodities, changing then the estimated parameters from those obtained for the in-sample analysis.

Forward testing: last values analysis		
Commodity	Brent ($/BBL)	WTI ($/BBL)
Mean	62,18	72,79
Standard deviation	17,75	29,41
5th Percentile	37,95	34,95
50th Percentile	59,45	67,64
95th Percentile	94,98	128,8

Table 5.6 - Forward testing: last values analysis

From the results of the analysis of the last values contained in all 5000 price paths simulated, shown in table 5.6, it can be observed that predictions for the end of the next natural year follow the results commented in previous analysis.

As it can be seen in table 5.6 taking a look at the percentiles computed, the simulated final prices oscillated, around a median of 59,45 $/BBL, in a 90% confidence interval of 37,95 and 94,98 $/BBL.

Results for last simulated values of WTI prices reflect a similar but broader behaviour than Brent prices. Schwartz-Smith two-factor model expects a 90% confidence interval of the last values to be between 34,95 and 128,80 $/BBL.

All values analysis

Table 5.7 shows all the values obtained in the Monte carlo simulations for the entire year. For next year, Schwartz-Smith two-factor model predicts that the maximum and the minimum for the year will take values of 193,09 and 14,59 $/BBL. As can be deducted maximum and minimum depend on the volatility parameters estimated in the model. This values reflect the less probable prices that commodities can take, nevertheless, its utility is proved as an interval definition of possible prices.

Whole year observations for WTI oil prices will take its maximum and minimum price in 271,24 and 15,58 $/BBL, respectively.

Forward testing: all values analysis		
Commodity	Brent ($/BBL)	WTI ($/BBL)
Mean	63,95	65,16
Standard deviation	13,41	21,51
Maximum	193,09	271,24
Minimum	14,59	15,58
5th Percentile	52,75	47,59
50th Percentile	63,52	64,01
95th Percentile	76,51	86,40

Table 5.7 - Forward testing: all values analysis

Regarding the analysis of percentiles, Schwartz-Smith two-factor model expects a 90% confidence interval of prices to be in between 52,75 and 76,51 $/BBL for Brent oil, and in between 47,59 and 86,40 for WTI oil.

This results reflect that the model is not expecting for the next year sharp increases in prices as the one occurred in the pre-crisis scenario, with prices around 140 $/BBL.

For a more intuitive view on what commented before about volatilities and average prices, Brent and WTI oil simulated paths are presented in figures 4.7 and 4.8.

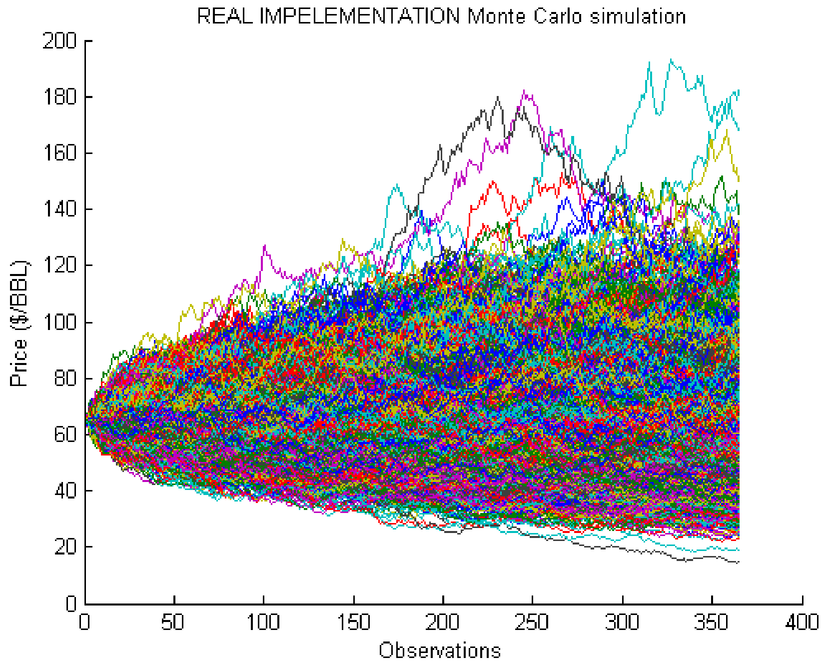

Figure 5.7 - S&S-Medium-term forward testing for Brent oil

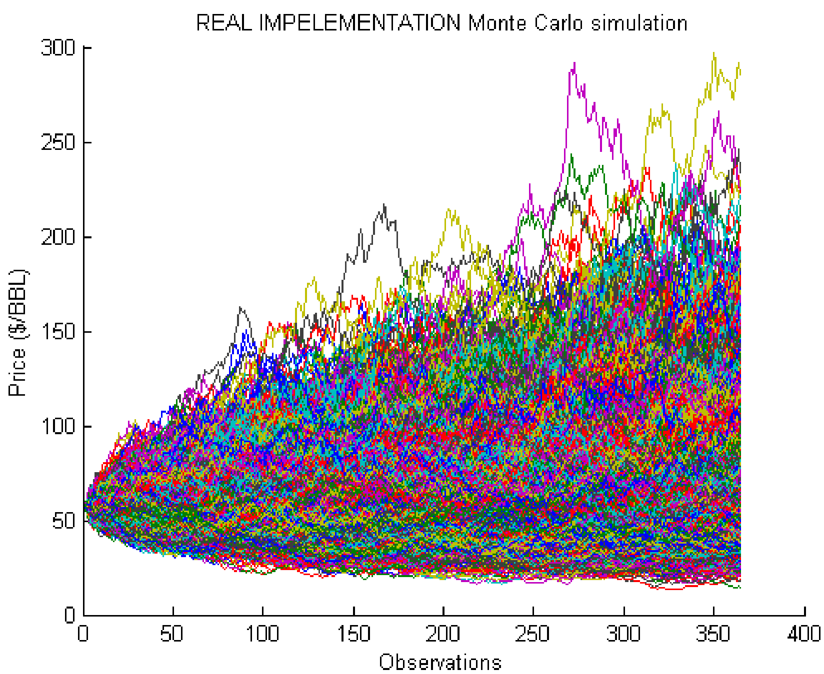

Figure 5.8 - S&S-Medium-term forward testing for WTI oil

5.2 NATURAL GAS COMMODITIES

A. Dataset

NBP

In Figure 5.9 it can be seen the plotted spot price contained in NBP employed dataset. This dataset contains NBP 1790 daily quotations of spot price and monthly futures, starting from 14/04/2008 and ending in 24/04/2015.

Traditionally natural gas prices have been always related to crude oil prices, this fact can be seen in the beginning (Sept. 2008) and end (Sept. 2014) of NBP prices in figure 5.9. Even though Brent oil and NBP natural gas are priced differently, it can be observed how the curves repeat the same downturns related to 2008 financial crisis, and 2014 oil crisis.

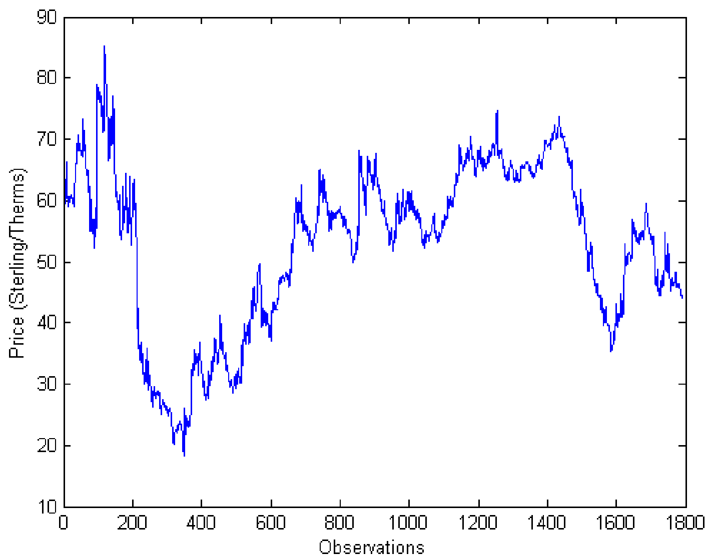

Figure 5.9 - NBP spot price dataset

As it can be observed, the dataset presents a more or less stable dynamic apart from the breakdowns mentioned above. The increases and decreases on prices are more or less stable in quantity and time differentiation, probably due to a fact of low storability suffered by the natural gas industry.

This low storability makes the commodity present higher prices in colder seasons and lower prices in hotter ones, leading to a clear seasonal pattern.

Henry Hub

In figure 5.10 the spot price contained in dataset for Henry Hub is plotted. This dataset comprises 1680 Henry Hub daily prices from 25/08/2008 to 24/04/2015. As it can be seen at first sight, prices present a more spiky but less volatile characteristics, thanks to the liquidity of the Henry Hub market.

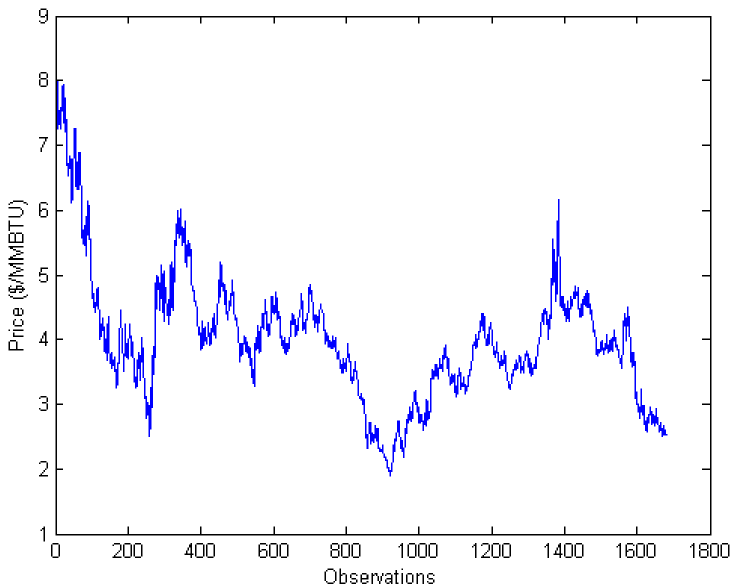

Figure 5.10 - Henry Hub spot price dataset

Comparing this dataset to the NBP one in figure 5.9, it can be seen how, affected by 2008 financial crisis, both curves decrease. After reaching the lowest peak, they start to raise again observing how Henry Hub curve decouples from NBP curve as it increases before going down again.

This change in natural gas tendency is due to the shale gas revolution that is still taking place in the USA. Natural gas trapped into shale formations on the underground is extracted through a well developed and cheap technique called fracking. Fracking has allowed the increase of volumes extracted and so the decrease on prices having a deep impact on hubs around USA and specially the Henry Hub.

This revolution has also introduced a new fact unknown until then: natural gas prices in USA have completely decoupled from oil prices in the world; this new revolution has beaten the extended tradition, making possible the decrease in natural gas prices, increasing then the competitivity of American industry.

B. In-sample analysis

NBP

With respect to adjusted NBP prices in figure 5.11, it can be observed how, despite the movement caused by 2008 financial crisis, the long-term equilibrium price fluctuates between the band of 30 and 60 sterling/therms throughout all the observations.

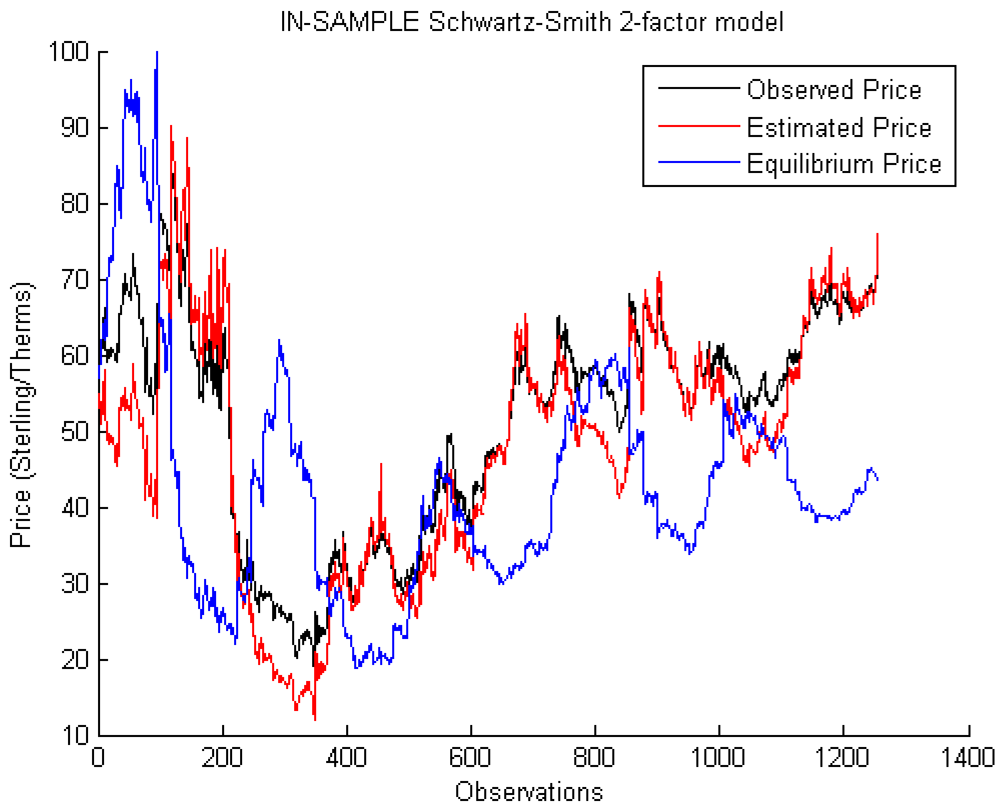

Figure 5.11 - Observed spot price vs. estimated spot price and equilibrium spot price for NBP natural gas

As it is seen in figure 5.11, when analyzing deeper the long-term equilibrium prices, the market interprets that the 2008 crisis downturn on prices is going to be of a permanent nature, but when reaching the bottom, expectations on recovering pre-crisis prices appear and long-term prices increase again. After that, it can be seen how the long-term prices stabilize around the aforementioned interval, describing as permanent, the seasonality effect explained at the beginning of the epigraph.

On the other hand, short-term deviations present an opposite behaviour to long-term equilibrium prices. Looking at figure 5.10 it is seen how they try to adjust long-term prices to the seasonal pattern, confirming again that this changes are of a temporary nature.

Henry Hub

Plotting the adjusted prices of Henry Hub in figure 5.12, it can be observed how the paths oscillate around the band of 3 and 6 $/MMBTU. It is significant how the global slope is negative, revealing the market expectations to the decrease in prices.

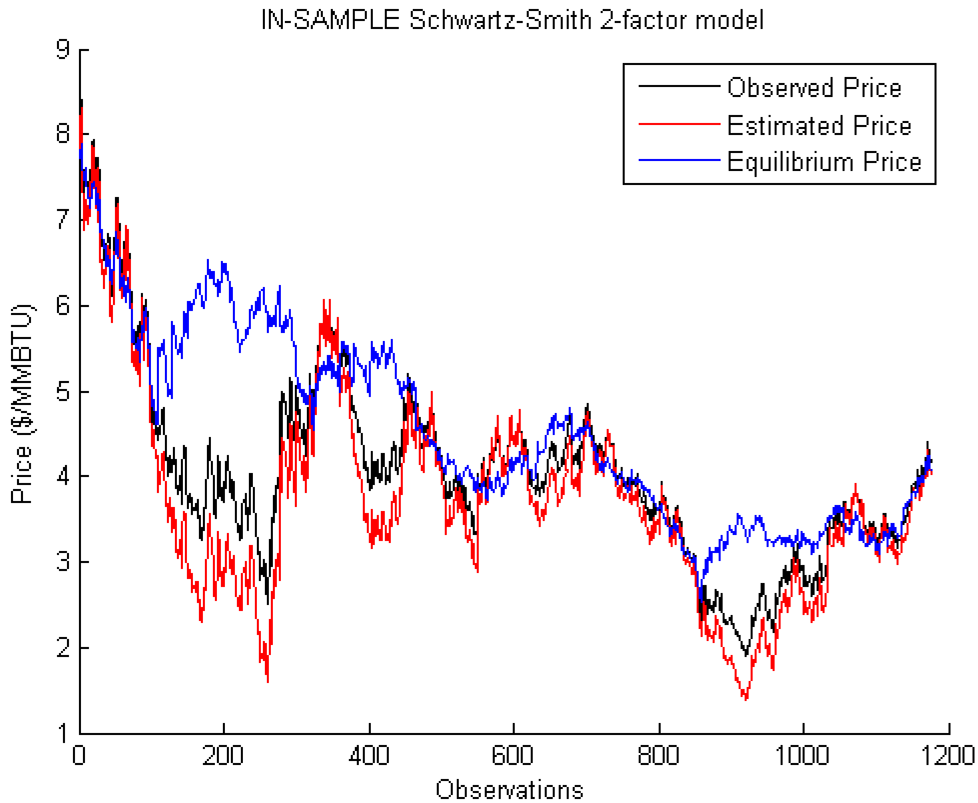

Figure 5.12 - Observed spot price vs. estimated spot price and equilibrium spot price for Henry Hub natural gas

As it can be deducted, fracking revolution is behind this negative slope in long-term equilibrium prices. Fracking has a double effect in prices: first, as it increases the supply of natural gas, it forces prices to go down, and second, it mitigates scarcity what has a smoothing effect on seasonality patterns (Fladmark and Grimstad, 2013).

Regarding short-term deviations, they adjust long-term prices in a very accurate way. They detect that downturn in prices, caused by 2008 crisis, are going to be of a temporary nature, while detecting and adjusting normal uncertainty when prices are stable. Finally they also detect that the lower prices due to a record in inventory levels that were preceded by a warm winter, around observation 900, are also of a temporary nature. (IEA, 2012)

Parameter analysis

When talking about the parameters estimated in table 5.9, it can be seen how NBP parameters are estimated, in terms of standard error, with higher statistical significance than Henry Hub parameters. Besides from this, it can be seen how mean-reverting coefficient is larger in NBP than in Henry Hub. This fact goes in line with higher volatilities also in NBP than in Henry Hub, as prices are more volatile due to deviations in supply and demand, sudden changes in those variables force the prices to adapt faster around the equilibrium price level.

This volatilities can also be interpreted in terms of market liquidity. It is widely known that Henry Hub is the most liquid natural gas market in the world, so a lower value in long-term and long-term volatilities, than the one NBP is shown in table 5.9, is expected.

	NBP		Henry Hub			NBP		Henry Hub	
Parameter	S&S	SE	S&S	SE	Parameter	S&S	SE	S&S	SE
κ	1,7129	0,0012	1,6018	0,3169	$\rho_{\xi x}$	-0,7628	0,0007	0,0106	0,4256
σ_x	1,2190	0,0023	0,7695	0,1356	S_1	0,0016	-	0,0043	-
λ_x	-0,4663	0,0587	0,3613	0,112	S_2	0,1253	-	0,0635	-
μ_ξ	0,0652	0,0379	-0,1963	0,1896	S_3	0,1002	-	0,0654	-
σ_ξ	0,6269	0,0019	0,3425	0,0111	S_4	0,0000	0,0000	0,0000	0,0000
μ_ξ^*	0,0030	0,0221	0,1443	0,0239	S_5	0,1298	-	0,0700	-

Table 5.8 - Maximum likelihood parameter estimates and their standard errors associated for NBP and Henry Hub natural gas

Regarding the performance of the Schwartz-Smith two-factor model, and its two benchmark models: Geometric Brownian motion model and Ornstein-Uhlenbeck model, in terms of the log-likelihood scores shown in table 5.9, it can be seen that again Schwartz-Smith takes the lead by far followed by the two benchmark models.

For these commodities, specially Henry Hub, Ornstein-Uhlenbeck and Geometric Brownian motion provide similar log-likelihood scores what indicates that both of them can be applied with almost same results, leaving to the analyst the choice between both of them.

	NBP	Henry Hub
S&S Two-factor model	8346	10554
Geometric Brownian motion	5112	7589
Ornstein-Uhlenbeck	4838	7622

Table 5.9 - Log-likelihood scores for all models and commodities studied

Regarding mean absolute errors for NBP shown in table 5.10, it can be observed how Ornstein-Uhlenbeck model is able to fit shorter-term maturity contracts (2M) better, while Geometric Brownian motion perform best in longer-term ones (9M). Again all three models are able to fit better intermediate contracts than extremes ones.

Contract Maturity	Mean Absolute Error			Standard of Error			Mean Error		
	S&S	GBM	OU	S&S	GBM	OU	S&S	GBM	OU
2M	0,0000	0,1870	0,0026	0,0001	0,2373	0,0038	0,0000	-0,0307	0,0002
5M	0,0953	0,1725	0,0603	0,1204	0,2161	0,0778	-0,0347	-0,0370	-0,0177
7M	0,0729	0,0804	0,1504	0,1002	0,1129	0,1928	0,0025	0,0037	0,0216
9M	0,0000	0,0002	0,1661	0,0000	0,0003	0,2041	0,0000	0,0000	0,0205
12M	0,1016	0,0825	0,1399	0,1285	0,1024	0,1694	-0,0186	-0,0231	0,0081

Table 5.10 - Term structure fit for NBP

For Henry Hub natural gas errors, in table 5.11, it can be seen how progressively Geometric Brownian motion model fits better longer-term maturity data than shorter-term maturity one, as the mean absolute errors increase when the maturities of the contracts decrease.

In an overall perspective, in line with the log-likelihood scores presented, Schwartz-Smith model is able to fit most of the futures contracts better than the other two benchmarking models.

Contract Maturity	Mean Absolute Error			Standard of Error			Mean Error		
	S&S	GBM	OU	S&S	GBM	OU	S&S	GBM	OU
3M	0,0006	0,0785	0,0685	0,0010	0,1068	0,1005	0,0000	-0,0124	-0,0079
6M	0,0471	0,0586	0,0482	0,0628	0,0752	0,0648	-0,0098	-0,0059	-0,0059
9M	0,0470	0,0374	0,0265	0,0654	0,0479	0,0343	-0,0029	0,0051	0,0026
12M	0,0000	0,0359	0,0439	0,0000	0,0471	0,0584	0,0000	0,0067	0,0039
15M	0,0574	0,0398	0,0508	0,0692	0,0477	0,0608	-0,0107	-0,0075	-0,0089

Table 5.11 - Term structure fit for Henry Hub

C. Out-of-sample analysis

NBP

In figure 5.13, it can be observed how the spot price path is contained within the 90% confidence interval defined by the selected percentiles. Although it is, it can be seen how it separates the mean, approaching more to the 5th percentile, what indicates that lower prices tail in the normal distribution are fatter.

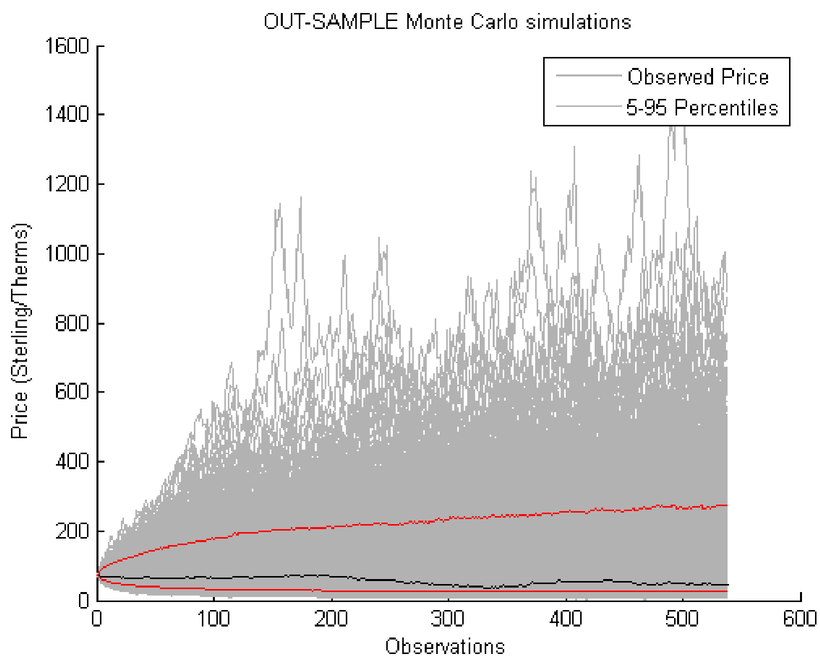

Figure 5.13 - S&S simulated price paths (with 5-95 percentiles highlighted) vs. observed spot price

As it can be seen in figure 5.13, the spot price path goes closely together with 5th percentile. This is an appreciation made by the display of the figure. Due to the aforementioned high volatility in long term prices, the cone formed by the 5th-95th interval is established between the 30 Sterling/Therms and the 200 Sterling/Therms what makes the model able to catch almost any sharp increase on prices but not a huge downturn on them, although the model is able to catch the linked 2014 oil price downturn.

Henry Hub

The first thing it can be seen in figure 5.14 is the ability of the adjusted model to catch all reserved Henry Hub spot data. The shape of the plotted cone confirmed by the determined percentiles is narrower when comparing it to the NBP one in figure 5.13. As explained this is due to the lower long-term volatility that Henry Hub adjusted model has, limiting the possible cached values to those in between 1 and 7 $/MMBTU.

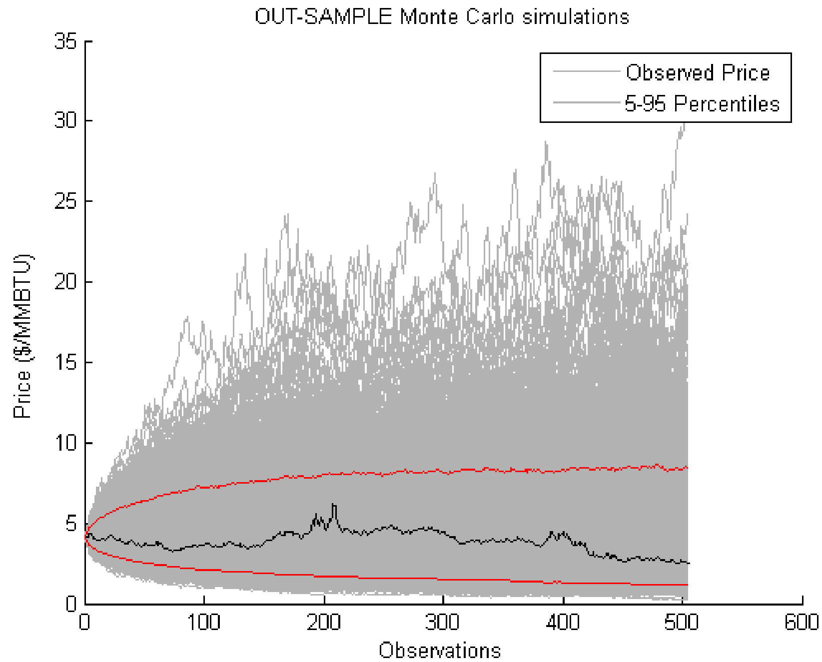

Figure 5.14 - S&S simulated price paths (with 5-95 percentiles highlighted) vs. observed spot price

This observed lower long-term volatility is again thanks to the liquidity of the market in which almost all American natural gas is traded. The difference in volatilities of NBP and Henry Hub is also explained by the decoupling phenomenon explained at the beginning of the epigraph. In order to quantify the defined percentiles violation, the percentage of violating observations are computed in table 5.12.

Violation of 5th-95th percentiles in % of total studied observations		
Commodity	NBP	Henry Hub
95th Percentile	0%	0%
5th Percentile	0%	0%

Table 5.12 - Violation of 5th-95th percentiles in % of total studied observations

D. Real implementation

Last values analysis

In order to make use the models in a more real-business approach, the same methodology than for oil commodities has been used. 5000 Monte Carlo simulated price paths, for a whole natural year, with the Schwartz-Smith two-factor model adjusted for the 100% of the dataset, have been analyzed to obtain results for the entire year and for the end of the year. Again, the analysis of the last values of all simulated price paths has been studied separately from all the values obtained. Reflecting the former the analysis on prices for T=365, and the latter for observations throughout the whole natural year.

As prices for both commodities not only stand for different currencies (GBP and $), but also in the quantity of energy priced (Therm vs. MMBTU), for the sake of clarification both of them will be analyzed separately.

Forward testing: last values analysis		
Commodity	NBP (Stirling/Therm)	Henry Hub ($/MMBTU)
Mean	45,31	2,22
Standard deviation	25,52	1,01
5th Percentile	16,84	0,98
50th Percentile	39,38	2,02
95th Percentile	94,02	4,12

Table 5.13 - Forward testing: last values analysis

For the Schwartz-Smith two-factor model results shown in table 5.13, applied together with the Monte Carlo simulations, taking a look at the percentiles it can be expected with a 90% of confidence that the prices will be between 16,84 and 94,02 GBP/Therm interval, centered in a median of 39,38 GBP/Therm.

For the Henry Hub prices in the same simulations methodology, it can be predicted that the last values in a natural year will be between a 90% confidence interval of 0,98 and 4,12 $/MMBTU, a similar value to the historical ones reflecting the ongoing tendency to continue falling for the year.

All values analysis

When studying all the the Schwartz-Smith predictions for the entire year simulated, shown in table 5.14, it can be observed how maximum and minimum simulated prices obtained for Henry Hub, are extreme prices in comparison with actual prices, but not unimaginable prices (specially the maximum) according to what has been seen in the in-sample analysis. Not the same for NBP, where maximum and minimum prices are too way distant from what has been observed along the study.

Forward testing: all values analysis		
Commodity	NBP (Stirling/Therm)	Henry Hub ($/MMBTU)
Mean	45,64	2,41
Standard deviation	20,29	0,86
Maximum	390,65	14,16
Minimum	5,00	0,32
5th Percentile	29,17	1,65
50th Percentile	44,15	2,35
95th Percentile	67,07	3,36

Table 5.14 - Forward testing: all values analysis

Regarding the percentiles analysis, it can be seen that along the year, the 90% confidence interval of NBP prices will be situated in between 29,17 and 67,07 GBP/Therm, centered in a median of 44,15 GBP/Therm. For Henry Hub prices, the 90% confidence interval of the values of all observations within a natural year, will be situated in between 1,65 and 3,36 $/MMBTU, a much more reasonable analysis than the maximum and minimum one.

As in the oil commodities, a visual idea on what has been commented until now can be seen in figures 4.15 and 4.16, where all simulated price paths are plotted for both NBP and Henry Hub commodities.

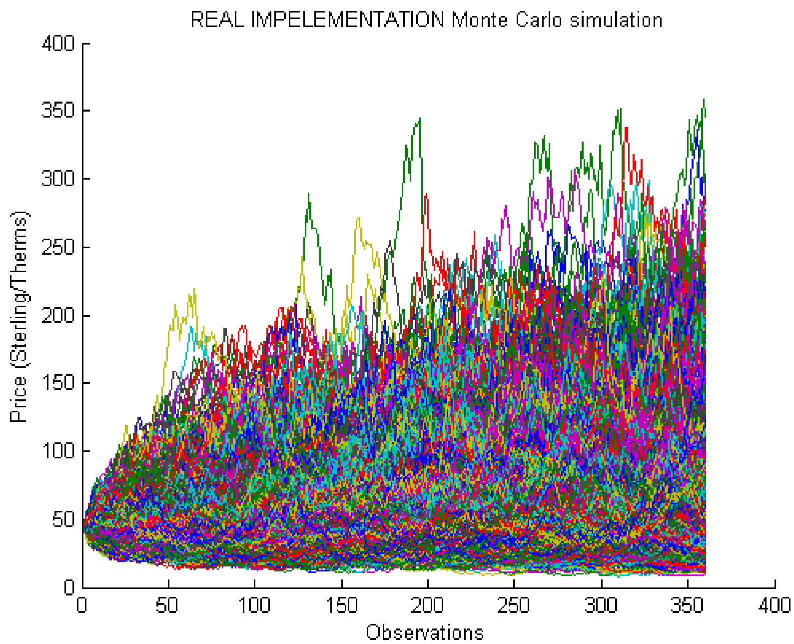

Figure 5.15 - S&S-Medium-term forward testing for NBP natural gas

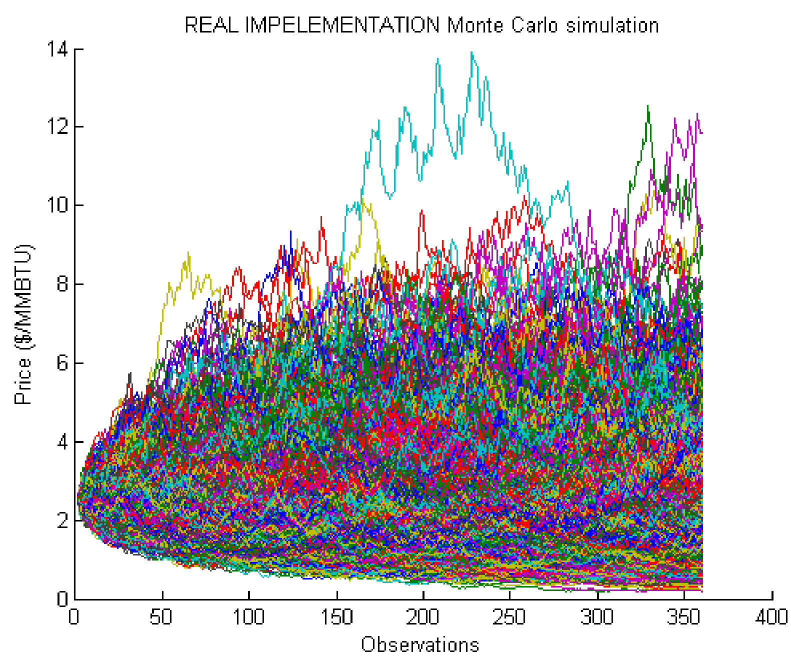

Figure 5.16 - S&S-Medium-term forward testing for Henry Hub natural gas

5.3 COAL COMMODITIES

A. Dataset

API#2

In this new epigraph the API#2 coal index is analyzed. The dataset employed for carrying out this study comprises 1419 observations from 01/01/2010 to 22/06/2015 and its contained spot price can be observed in figure 5.17.

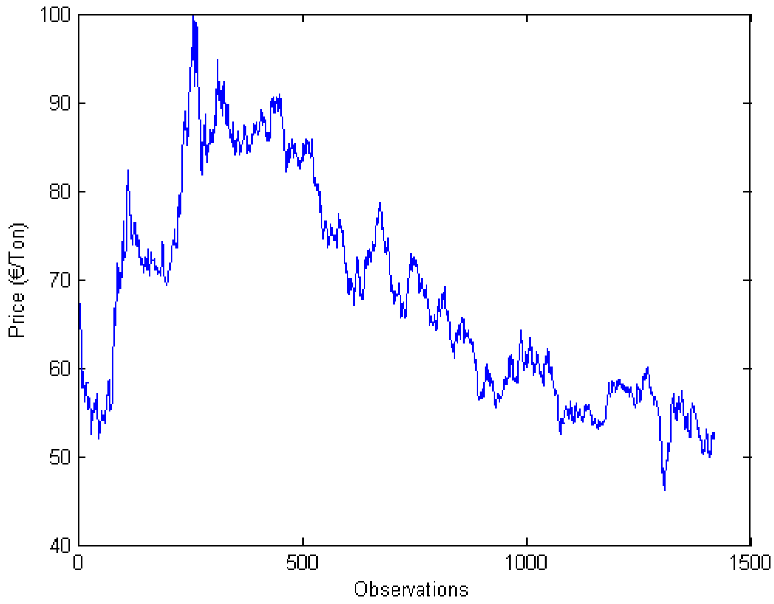

Figure 5.17 - API#2 spot price dataset

When analyzing the plotted spot price, it can be seen an irregular dynamic at the beginning, having a sharp increase up to the 100 €/Ton. This price outbreak was caused by a severe flood in Australia in December 2010 (main coal exporter to Europe) (Garry White, 2010). After that it can be seen how the prices recover their initial price, having a more or less stable dynamic with downwards slope.

As an introduction, the API#2 index is the benchmark price reference for coal imported into northwest Europe. It is calculated as an average of the Argus cif ARA assessment and the IHS McCloskey NW Europe Steam Coal marker.

Traditionally coal prices have not been influenced by any other commodity, but their price has a higher impact in electricity prices around the world. This heavy impact is due to the vast amount of coal-fired power plants installed around the world, which often are marginal technologies in their market, fixing their variable costs the spot price for the electricity. Even though they are not linked to any other commodity, the shakes in the surrounding markets due to external effects, have also been suffered in coal markets.

So after this introduction, it is statable that coal markets are driven by purely supply and demand interactions amongst agents in the markets. Business cycles around coal, cause the same effect as in oil or natural gas: seasonality.

As analyzed by Jason West (Jason West, 2012), coal as a psychic rock could be thought to be storable, and it is, but because of the nature of the business, coal acquires some special peculiarities. Coal-fired power plants have been usually placed in locations near coal extraction points, but the penetration of South-African, Colombian and Russian cheaper coal has made that made the business cycle to change, making shipments of coal a key issue.

Although producers store significant amounts of coal, the shipment facts make the commodity to present seasonality patterns. As it can be observed in figure 5.17, thermal coal prices tend to peak in July in preparation for the demand growth for imports to Europe in winter as well as the easing of the monsoon in India where the major ports begin to re-open. The lowest prices for thermal coal generally occur in the northern winter. As with the crude oil and natural gas markets, the behavior of thermal coal is affected by both seasonality and business cycles.

B. In-sample analysis

API#2

In figure 5.18 can be seen the adjusted prices of API#2 index in the Schwartz-Smith two-factor model.

When looking at figure 5.18, it is seen how the long-term equilibrium price for all the observations stands in the 60 €/Ton level. This long-term equilibrium prices show almost no slope, what indicates that the market expects future prices around the aforementioned level. Around observation 600 a sharp decrease in long-term equilibrium level with an immediate increase can be seen. This fact is probably due to a failure in the adjustment the model, as there is no qualitative explanation for that sharp movement.

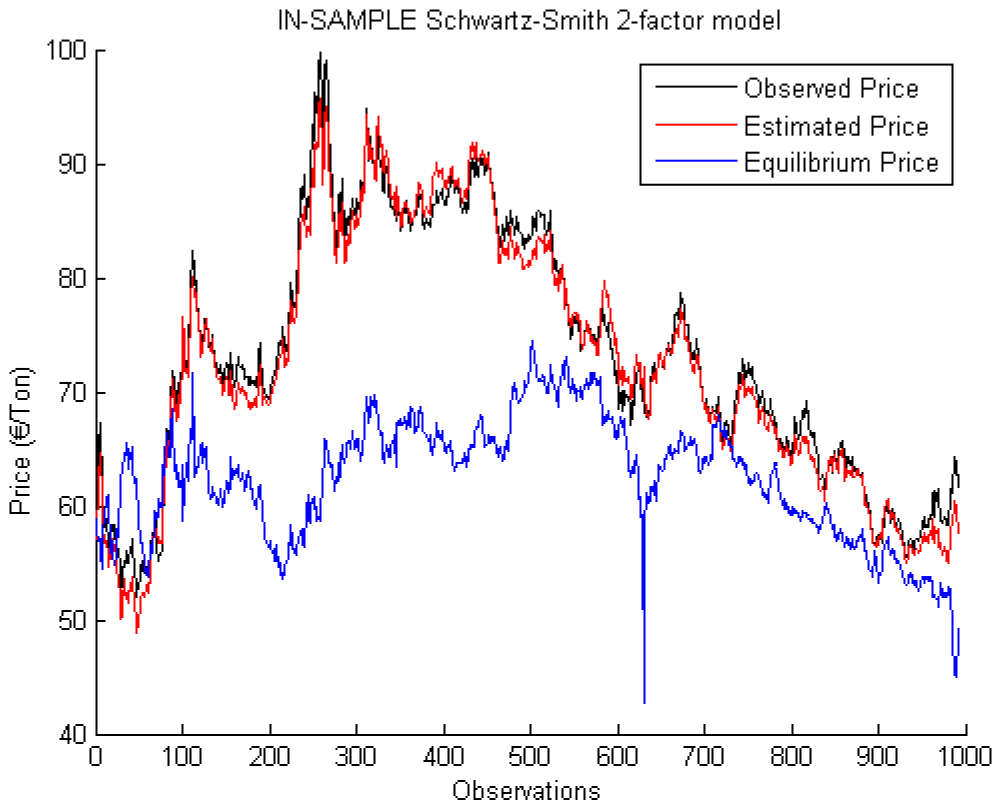

Figure 5.18 - Observed spot price vs. estimated spot price and equilibrium spot price for API#2 coal index

Regarding short-term variations, it can be observed how they capture perfectly the events that make the price oscillate in the short-term as the floodings commented one. At the end of the observations it can be seen how spot prices decrease gradually, being reduced the spread between short-term and long-term price components until they almost converge at the aforementioned equilibrium level.

Parameter analysis

When analyzing the results obtained for the parameters estimated, exposed in table 5.15, it can be concluded at first sight that the parameters have been estimated with a proper statistical significance in terms of standard error.

Parameter	S&S	SE	Parameter	S&S	SE
κ	0,5461	0,0387	$\rho_{\xi x}$	-0,7929	0,0125
σ_x	0,3865	0,0075	S_1	0,0086	-
λ_x	-0,1363	0,0771	S_2	0,0043	-
μ_ξ	0,0396	0,1302	S_3	0,0053	-
σ_ξ	0,3507	0,0066	S_4	0,0000	0,0000
μ_ξ^*	0,0123	0,0093	S_5	0,0081	-

Table 5.15 - Maximum likelihood parameter estimates and their standard errors associated

Analyzing long-term and short-term volatilities, it can be seen that the coefficients obtained are quite similar. This can be observed in figure 5.18 when comparing the whole volatility of short-term deviations along the observations, and the volatility that equilibrium price levels show throughout the observations.

In order to asses the three models performance in coal prices, log-likelihood parameters are shown in table 5.16. As it can be observed Schwartz-Smith two-factor model scores the best results followed by Ornstein-Uhlenbeck and Geometric Brownian motion in las position. It is also important to mention that a larger difference between Ornstein-Uhlenbeck and Geometric Brownian motion models scores has been found, compared with the scores obtained for other commodities.

	API#2
S&S Two-factor model	16971
Geometric Brownian motion	13659
Ornstein-Uhlenbeck	14989

Table 5.16 - Log-likelihood scores for all models and commodities studied

The performance assessment can also be done in terms of the mean absolute errors for all contracts studied. In table 5.17 it can be seen how for all contracts, both the Geometric-Brownian motion and the Ornstein-Uhlenbeck model, perform better in medium-term maturities than for extreme in time ones. The Schwartz-Smith two-factor model performs substantially better in every contract studied than the two additional benchmarking models.

Contract Maturity	Mean Absolute Error			Standard of Error			Mean Error		
	S&S	GBM	OU	S&S	GBM	OU	S&S	GBM	OU
3M	0,0061	0,0206	0,0153	0,0078	0,0265	0,0217	0,0008	-0,0026	0,0012
6M	0,0024	0,0102	0,0076	0,0033	0,0134	0,0105	-0,0004	-0,0013	-0,0003
9M	0,0033	0,0000	0,0000	0,0051	0,0000	0,0000	0,0001	0,0000	0,0000
12M	0,0000	0,0088	0,0061	0,0000	0,0116	0,0082	0,0000	-0,0004	0,0001
15M	0,0050	0,0159	0,0095	0,0081	0,0199	0,0117	-0,0008	-0,0023	0,0001

Table 5.17 - Term structure fit for API#2

C. Out-of-sample analysis

API#2

As it is seen in figure 5.19, all spot price observations fall within the 90% confidence interval defined by the 5th-95th percentiles computed for Schwartz-Smith two-factor model Monte Carlo simulations.

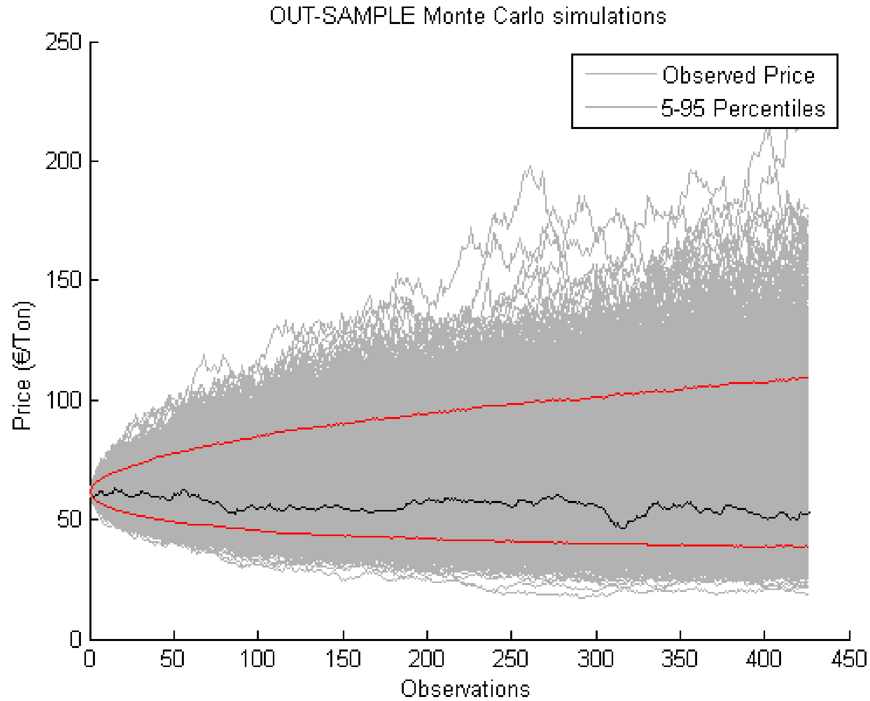

Figure 5.19 - S&S simulated price paths (with 5-95 percentiles highlighted) vs. observed spot price

Observing the cone formed by the defined percentiles, it can be seen how the model is able to catch final prices within an interval of 110 and 40 €/Ton due to the long-term volatility obtained. As it can be seen the spot price goes practically by the middle of the cone allowing the model to catch sharp increases and decreases in prices caused by oversupply and over demand issues.
In order to quantify the violations of the defined percentiles, in table 5.18 the percentage of violating observations is computed.

Violation of 5th-95th percentiles in % of total studied observations	
Commodity	API#2
95th Percentile	0%
5th Percentile	0%

Table 5.18 - Violation of 5th-95th percentiles in % of total studied observations

D. Real implementation

<u>Last values analysis</u>

For the real implementation analysis the same methodology than in other commodities' epigraphs has been employed. Once the model has been adjusted with the 100% of the dataset, 5000 price paths have been simulated thanks to a Monte Carlo simulation implementation. The price paths have been extended for a natural year, and statistical analysis has been done based on everly last values in every single path and for all values contained in all price paths.

When coming to the last values analysis in table 5.19, it can be observed how the Schwartz-Smith model situates the 90% confidence interval for prices obtained in the simulations in between 19,07 and 136,82 €/Ton, centered in a mean of 51,18 €/Ton.

Forward testing: last values analysis	
Commodity	<u>API#2 (€/Ton)</u>
Mean	61,43
Standard deviation	39,64
5th Percentile	19,07
50th Percentile	51,18
95th Percentile	136,82

Table 5.19 - Forward testing: last values analysis

In table 5.20 all values analysis can be found; predicting that the maximum price for all the predicted year will stand for 513,15 €/Ton, while the minimum will stand for 5,17 €/Ton, at first sight very unreachable prices.

Last but not least, the 90% confidence interval of all predicted prices will be in the 37,96 - 81,83 €/Ton interval, centered in a median of 55,75.

Forward testing: all values analysis	
Commodity	API#2 (€/Ton)
Mean	57,29
Standard deviation	27,28
Maximum	513,15
Minimum	5,17
5th Percentile	37,96
50th Percentile	55,75
95th Percentile	81,83

Table 5.20 - Forward testing: all values analysis

Once exposed all statistical values values, it can be observed how the confidence intervals, due to the long-term volatilities, place prices in a very broad interval. It seems that even if an oversupply, like the one is being faced right now, or a good implementation of the ETS, are not going to drive prices to this extreme values. The volatilities experienced may be derived of adjusting the models with a big part of a structural break in prices (2012 floodings in Australia) what could give non accurate impressions of the future behaviour of coal prices.

As in other epigraphs, the figure with all simulated price paths is shown as follows. This can provide the reader with a quick impression of how the future prices will display.

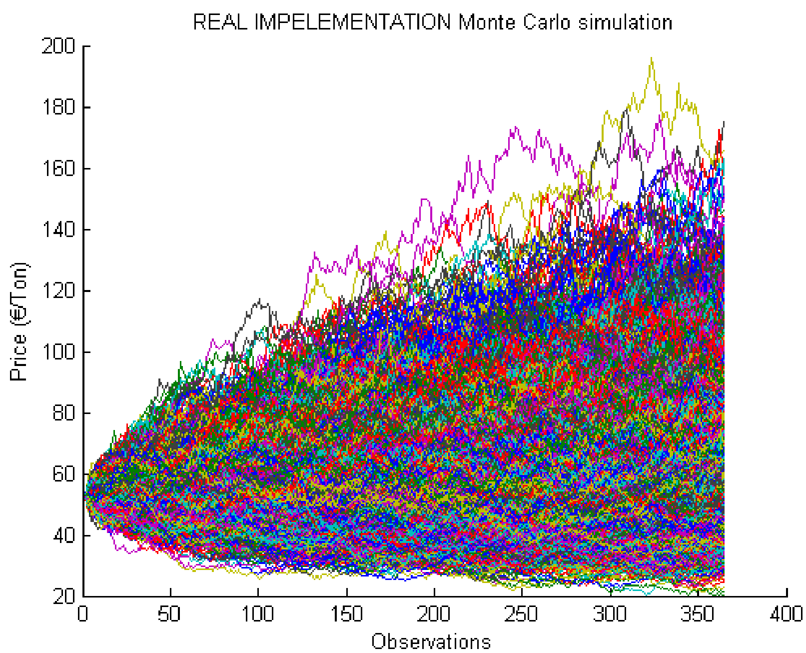

Figure 5.20 - S&S-Medium-term forward testing for API#2 coal index

5.4 ELECTRIC POWER COMMODITIES

A. Dataset

OMIE

In this next epigraph, Spanish spot power prices are going to be analyzed. Although the conclusions are based on the analysis of the futures traded at OMIP, all analysis will be made in the day-ahead price or spot price. The dataset employed for adjusting Spanish power spot prices, contains 1296 daily average observations of different maturity monthly futures going from 01/01/2010 to 31/12/2014, it can be seen plotted in figure 5.21.

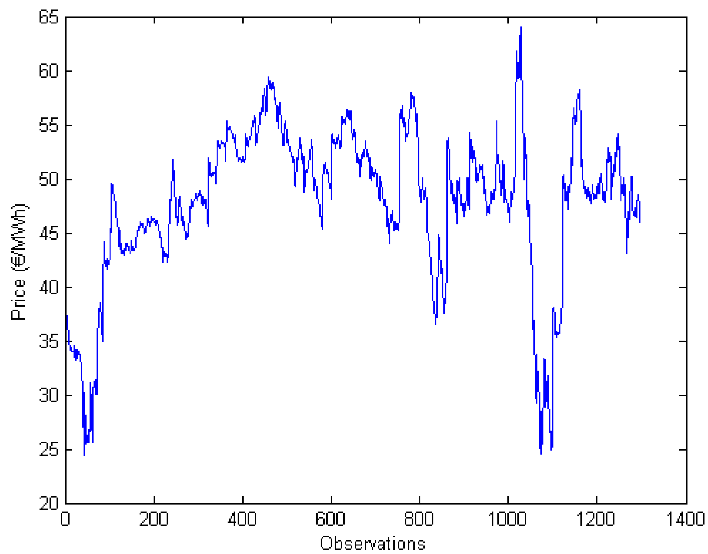

Figure 5.21 - Spanish power spot price dataset

Looking at the figure 5.21, it can be seen how the spot price presents a non regular trend with high increases and decreases on prices around an average level of 45-50 €/MWh. It is also known the high seasonality that electricity prices present almost anywhere, the fact that electricity cannot be stored makes that all electric power that is generated has to be consumed at that same time. As demand increases (or decreases) more electricity has to be generated by different units of different technologies and at different prices. The electricity market is a marginal market where the price is fixed with the marginal price of the last unit available for producing an extra MWh. It is important to mention as well the two deep decreases on prices found around observations 25 and 1100. This is due to the important wind generation penetration, with almost no variable cost, into the spanish system, lowering its average price by forcing it to be zero at some hours (OMIE, 2015).

EPEX Germany

EPEX Germany spot price dataset is composed of 1397 daily observations taken from 01/01/2010 to 21/05/2015. In the plotted figure (4.22) it can be observed how, again, the spot price trend follows a non stable dynamic, not only presenting sharp increases and decreases, but also presenting a downward slope. According to last observations, it can be seen how the prices established around the 35 €/MWh level.

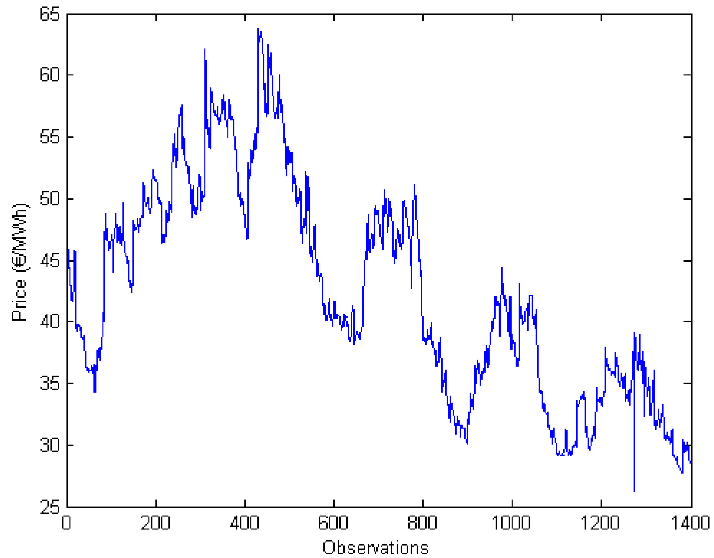

Figure 5.22 - German power spot price dataset

The aforementioned non regular dynamic is due mainly to seasonality. It can be clearly observed from observation 600 to observation 1200 (almost two years) how the prices peak high in winter seasons and then decrease again in the milder ones. As it can be seen in the Spanish case, the average normal prices decrease up to 15 €/MWh from winter season to summer one.

The downward slope experienced in the spot price trend is caused again by the penetration of renewable technologies in the German mix, combined with a decrease of demand caused by the financial crisis. Since 2002 (Fraunhofer, 2015) Germany has increased their installed solar PV generation from 0,30 GW installed up to 30,19 GW in 2015. The European Commission commitment to decrease CO_2 emissions, as well as, the Fukushima accident, have decreased the installed generation in coal and nuclear technologies in order to welcome solar and other renewable ones.

The allowance of negative prices along with the fact that solar PV panels have almost no variable costs, has made Germany to have some hours with zero prices and also with negative prices, what has decreased the total average over the years as it can be seen in figure 5.22.

EPEX France

EPEX France spot dataset is composed of of 1397 daily observations taken from 01/01/2010 to 21/05/2015. As it can be seen in figure 5.23 the trend the spot price is following presents the aforementioned seasonality, being for the French case study, really deeper the price valleys caused by seasons. It can also be observed a slight downwards slope, being the average price inside the 35-40 €/MWh.

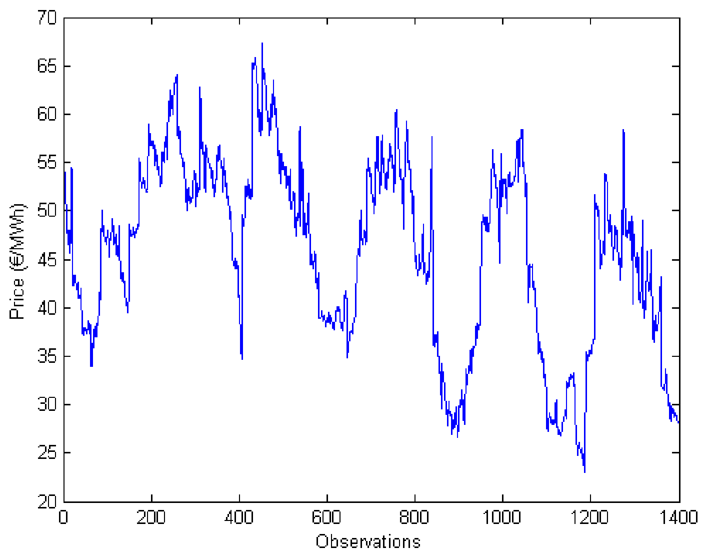

Figure 5.23 - French power spot price dataset

As it has been explained, seasonality is a common phenomenon in electricity prices, but what is relevant to comment in the French case study, are the shallow decreases that prices experience in the summer season. The fact behind this shallow decreases is the fact that France produces up to the 77% (Nuclear World Association, 2015) of its own energy consumption from Nuclear power plants. Nuclear technology is characterized for having low variable costs that are bid to the market at around 30-35 \$/MWh, so in summer when a low demand is presented, nuclear becomes the marginal technology fixing the electricity market at those prices. When winter starts, demand increases what shifts the marginal technology from nuclear to CCGT, fixing the market at the natural gas variable cost of around 60 €/MWh.

The downward slope is again explained by the penetration of renewable sources in the system combined with the decrease in demand caused by financial crisis. Being more conservative, in terms of observable downwards slope, than in Germany, renewable energy accounted for 19,5% of total energy generated for the year 2014. (RTE, 2015)

B. In-sample analysis

OMIE

In figure 5.24 it can be seen the Spanish power spot prices adjusted for the Schwartz-Smith model. For the data adjusted, it can be seen how long-term equilibrium model presents a slight upward slope in a level of around 35 €/MWh. The aforementioned slope is due to the selected data, that observing it in a broader scope in figure 5.21, it grows until it stabilizes around the 800 observation.

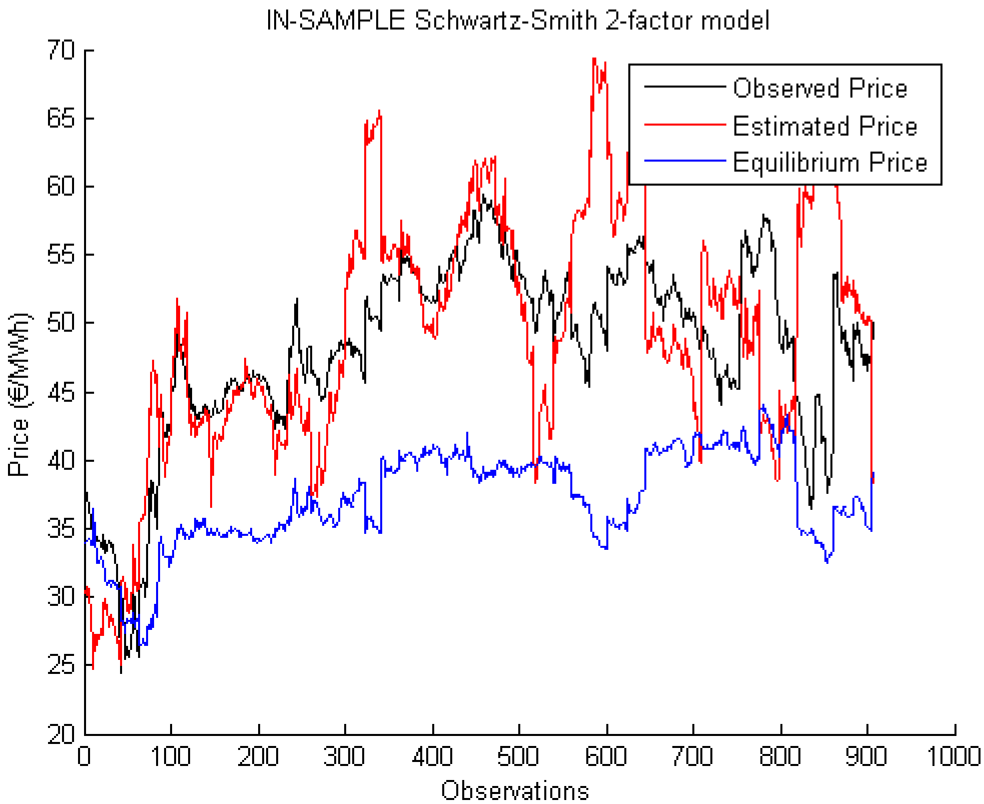

Figure 5.24 - Observed spot price vs. estimated spot price and equilibrium spot price for Spanish power

Regarding the short-term deviations, it can be seen how they attempt to catch temporal deviation on prices (seasonality) doing it properly in some observations and not so properly in another ones. The model is able to interpret seasonal movements within the Spanish electric power prices, to an overall extent, but as they are they cannot be smoothed through storability, these seasonal patterns are depending entirely on temperature and working days, not having a regular behaviour. (Lucia and Schwartz, 2001). Differentiations on daily prices (peak, off-peak, plateau) combined with transmission constraints and other particularities of electricity, makes the model not to adjust to electricity prices properly.

EPEX Germany

Observing figure 5.25, the long-term equilibrium prices go in line with what commented in the dataset analysis. The model detects how the initial increases of price are of a temporary nature fixing the equilibrium price level at 35 €/MWh. After observation 500, it is seen how this level decreases up to 20 €/MWh in latest observations due to the increasing penetration of solar PV panels in the electricity market.

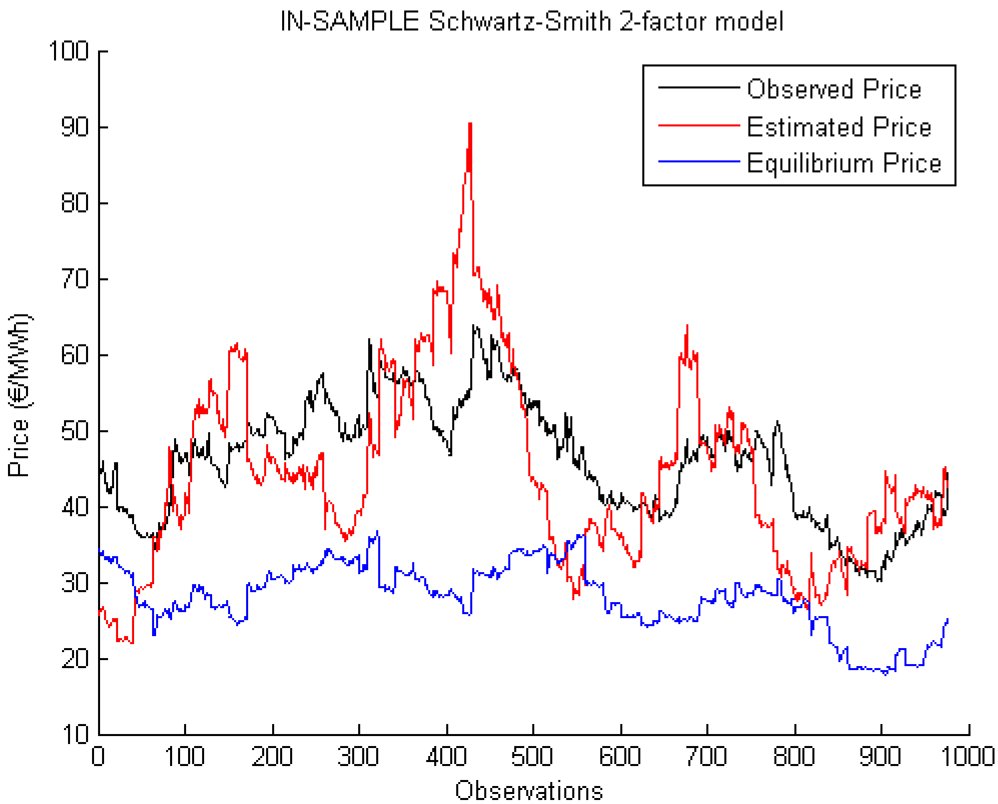

Figure 5.25 - Observed spot price vs. estimated spot price and equilibrium spot price for German power

Regarding short-term variations, a similar behaviour than in Spanish power prices is observed. The model tries to catch, throughout short-term deviations, the temporary seasonal increases and decreases.

It is seen how prices try to adapt with yearly increases and decreases in short-term deviations, converging with long-term equilibrium prices in summer season and peaking high in winter season.

Again, seasonality patterns in electric prices denote a complexity that Schwartz-Smith two-factor model is not able to catch perfectly.

EPEX France

In figure 5.26, the Schwartz-Smith two-factor model adjusted prices for French power spot prices are presented. As it can be seen, long-term equilibrium prices present significant increases and decreases along all studied observations. This fact is due to the deepness of the valleys that seasonality causes on prices, commented in the French dataset analysis epigraph. Another important fact is that long-equilibrium prices do not present any downwards or upwards slope, fixing the price in an average of 35 €/MWh.

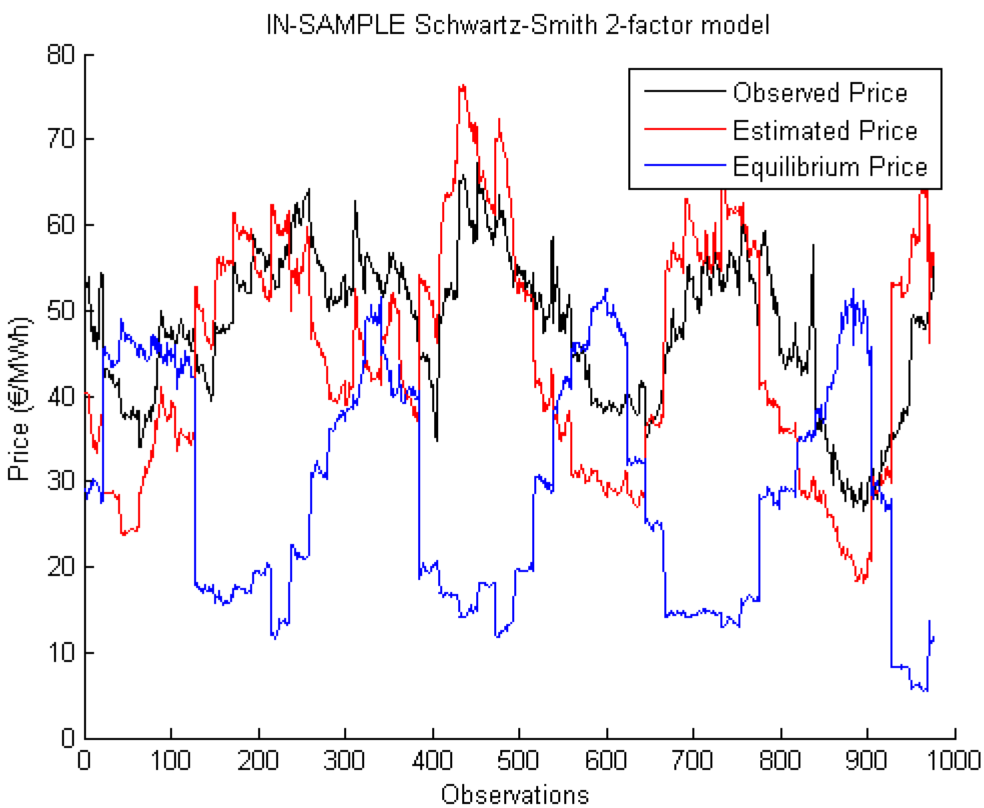

Figure 5.26 - Observed spot price vs. Estimated spot price and equilibrium spot price for French Power

It is also seen how short-term deviations try to predict the spread between long-term equilibrium prices and the real spot price, but as the former is not able to adjust prices in a more stable way, the short-term deviations also present dysfunctionalities, even though they reasonably catch spot prices.

Parameter analysis

The first thing it can be seen when analyzing the results obtained for the parameters estimated by the Schwartz-Smith two-factor model, shown in table 5.21, is that Spanish and French power parameters are estimated with higher statistical significance than German power.

The parameter that is repeatedly worst estimated for all three commodities is the long-term drift component of the two-factor model. This fact goes in line with what analyzed in past the epigraph, where it could be saw how long-term equilibrium model failed to behave in a more stable way.

	OMIE		EPEX GER		EPEX FRA			OMIE		EPEX GER		EPEX FRA	
Param.	S&S	SE	S&S	SE	S&S	SE	Param.	S&S	SE	S&S	SE	S&S	SE
κ	2,6272	0,0820	2,5491	1,9898	1,1015	0,0628	$\rho_{\xi x}$	-0,7573	0,0173	-0,7870	0,3826	-0,9792	0,0018
σ_x	0,8637	0,0148	1,0274	2,2406	2,4037	0,0803	S_1	0,0046	-	0,0003	-	0,0003	-
λ_x	-0,7530	0,0706	-1,5750	2,1898	-1,5071	0,1579	S_2	0,0503	-	0,1350	-	0,1793	-
μ_ξ	0,2519	0,1228	0,3333	2,7671	-0,0388	0,1837	S_3	0,0562	-	0,1341	-	0,2025	-
σ_ξ	0,2994	0,0056	0,4221	0,2434	1,5945	0,0581	S_4	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
μ_ξ^*	-0,0424	0,0099	-0,1180	0,4999	-0,9301	0,0597	S_5	0,0676	-	0,1348	-	0,2448	-

Table 5.21 - Maximum likelihood parameter estimates and their standard errors associated

The model for the Spanish power shows the highest value of mean-reversion speed, caused by the sharp increases and decreases in the short-term predictions seen in figure 5.24.

Regarding short-term and long-term volatilities, the French model leads the rank with the highest volatilities, as it could be expected in line with the analysis made, while the Spanish model is the less volatile one, not in the short-term, but also in the long-term. This fact could be interpreted in terms of generation mix, being the Spanish more linear in price changes than the French one. The market is also important, being OMIP one of the most liquid markets in Europe when trading futures.

Concerning the assessment of the performance of the Schwartz-Smith two-factor model, compared with the other two benchmarking models, seen in terms of log-likelihood scores in table 5.22, again Schwartz-Smith takes the lead thanks to the combination of the two other benchmarking models presented in its tho factors.

	OMIE	EPEX GER	EPEX FRA
S&S Two-factor model	8948	6763	4583
Geometric Brownian motion	7769	5714	2122
Ornstein-Uhlenbeck	7828	5814	3042

Table 5.22 - Log-likelihood scores for all models and commodities studied

It is also important to mention how for Spanish and German power, both Geometric Brownian motion and Ornstein-Uhlenbeck scores are almost the same, being able to obtain the same results with each of them.

For this two commodities differences between the performance of the models are not so significant, while for the French power they are. This reflects the difficulties of the models to adapt the prices, as it using Schwartz-Smith will not provide significant benefits than employing any other benchmark model.

The performance of the three models can also be analyzed in terms of mean absolute errors. Observing the Spanish power errors in table 5.23, it can be seen how the Ornstein-Uhlenbeck model is able to model shorter-term maturity futures (6M), than longer-term ones, which are adjusted better by Geometric Brownian motion model (9M and 12M).

Contract Maturity	Mean Absolute Error			Standard of Error			Mean Error		
	S&S	GBM	OU	S&S	GBM	OU	S&S	GBM	OU
3M	0,0007	0,0398	0,0528	0,0013	0,0523	0,0717	0,0000	-0,0015	-0,0010
6M	0,0386	0,0374	0,0014	0,0503	0,0480	0,0022	0,0012	0,0005	0,0001
9M	0,0417	0,0227	0,0408	0,0560	0,0294	0,0553	0,0051	0,0017	0,0015
12M	0,0000	0,0346	0,0396	0,0000	0,0471	0,0529	0,0000	-0,0053	-0,0048
15M	0,0482	0,0282	0,0378	0,0673	0,0359	0,0510	0,0071	0,0009	0,0025

Table 5.23 - Term structure fit for Spanish power

The same happens to German power errors shown in table 5.24. It can be observed how the lowest error for Ornstein-Uhlenbeck model is achieved in the 3M contract, while for Geometric Brownian motion model it is the 15M.

Contract Maturity	Mean Absolute Error			Standard of Error			Mean Error		
	S&S	GBM	OU	S&S	GBM	OU	S&S	GBM	OU
3M	0,0000	0,0398	0,0001	0,0000	0,0492	0,0002	0,0000	-0,0037	0,0000
6M	0,1204	0,0981	0,0924	0,1348	0,1214	0,1111	0,0096	0,0244	0,0252
9M	0,1076	0,1539	0,1509	0,1341	0,1708	0,1705	0,0046	0,0167	0,0156
12M	0,0000	0,0999	0,1060	0,0000	0,1230	0,1304	0,0000	0,0018	0,0000
15M	0,1108	0,0016	0,0400	0,1344	0,0025	0,0480	0,0112	0,0000	-0,0019

Table 5.24 - Term structure fit for German power

For the French power errors found in table 5.25 it can be seen how Geometric Brownian motion model adapts best intermediate maturity contracts, while Ornstein-Uhlenbeck model errors increase with the increase of the maturity of the contracts.

Contract Maturity	Mean Absolute Error			Standard of Error			Mean Error		
	S&S	GBM	OU	S&S	GBM	OU	S&S	GBM	OU
2M	0,0000	0,2222	0,0000	0,0000	0,2495	0,0000	0,0000	-0,0518	0,0000
4M	0,1596	0,1303	0,1365	0,1792	0,1639	0,1581	-0,0085	-0,0182	0,0093
6M	0,1674	0,0012	0,1641	0,2025	0,0024	0,1868	0,0057	0,0001	0,0231
9M	0,0000	0,1998	0,1660	0,0000	0,2579	0,2112	0,0000	-0,0324	-0,0036
11M	0,1852	0,2844	0,1566	0,2448	0,3188	0,2031	-0,0049	-0,0621	-0,0263

Table 5.25 - Term structure fit for French power

It can also be stated how the difference in errors between the three models in the three commodities is not that evident, not being the Schwartz-Smith model the one that fits best the data in every contract, going in line with the log-likelihood scores commented before.

C. Out-of-sample analysis

OMIE

The first thing it can be observed in figure 5.27 is that almost all spot price reserved observations fall within the 90% confidence interval defined. As it can be seen due to the long-term volatility parameter obtained as well as the long-term drift, when adjusting the Schwartz-Smith model for the 70% of the dataset, the shape of the cone formed by the defined percentiles is regular, increasing its 95th percentile with the observations, and remaining stable the 5th one.

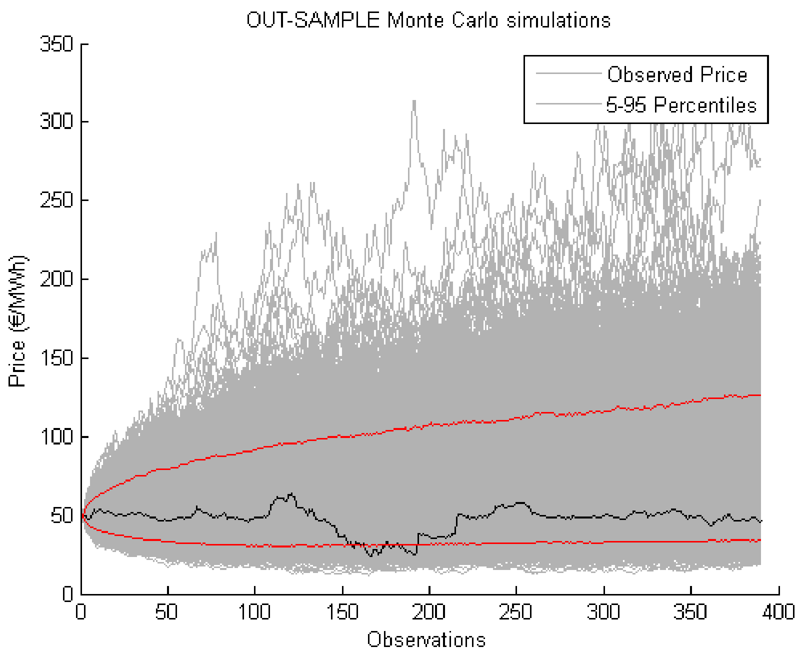

Figure 5.27 - S&S simulated price paths (with 5-95 percentiles highlighted) vs. observed spot price

As commented , the model is able to catch the whole series until observation 150, when the spot price violates the 5th percentile for going up again in observation 200. This violation coincides with the sharp decrease caused by a very windy month, explained at the beginning of the chapter, where hourly zero prices were taking place, lowering the whole daily media.

For the rest of the series, after the price recovers it equilibrium price, the model catches every observation, as they are inside the cone's 45 - 110 €/MWh interval.

EPEX Germany

Regarding the German model predictions shown in figure 5.28, it can be seen how the almost all spot price observations are contained in the defined interval, but how they are separated from the mean. The relevant fact in this analysis, in line what stated in the parameter analysis, is the long-term volatility we see when projecting the model to the future. Comparing with the Spanish one, the German model, knowing that its long-term volatility is higher, it gives for the end of the observations a wider percentile (30 - 150 €/MWh) interval of prices.

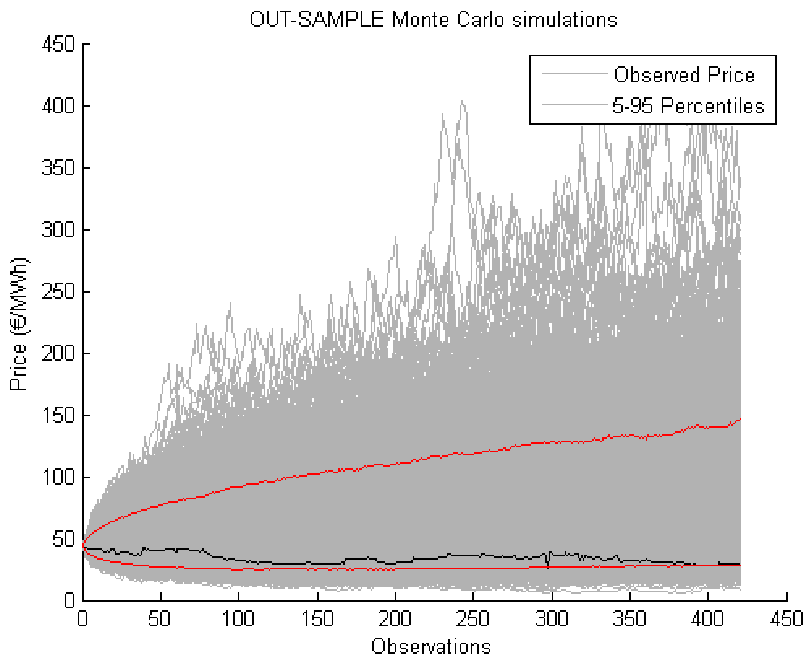

Figure 5.28 - S&S simulated price paths (with 5-95 percentiles highlighted) vs. observed spot price

As it can be observed, the observations that violate the 5^{th} interval are the latter ones (around observation 400) that coincide with the higher coefficient of solar technology installed capacity. This, combined with the summer season, decrease prices under the defined 5^{th} percentile, as the prices reach the level of 25 €/MWh.

EPEX France

The most surprising results are obtained when projecting to the future the Schwartz-Smith model adjusted with the French electric power data. As it can be seen in figure 5.29, Monte Carlo simulated price paths are peaking at about 80.000 €/MWh, what firstly can not be possible due to the unreachable price cap imposed of 3.000 €/MWh (Cepeda and Finon, 2013). This results are obtained because of the high level of long-term volatility obtained when adjusting the model, that highly increases prices as the observations pass.

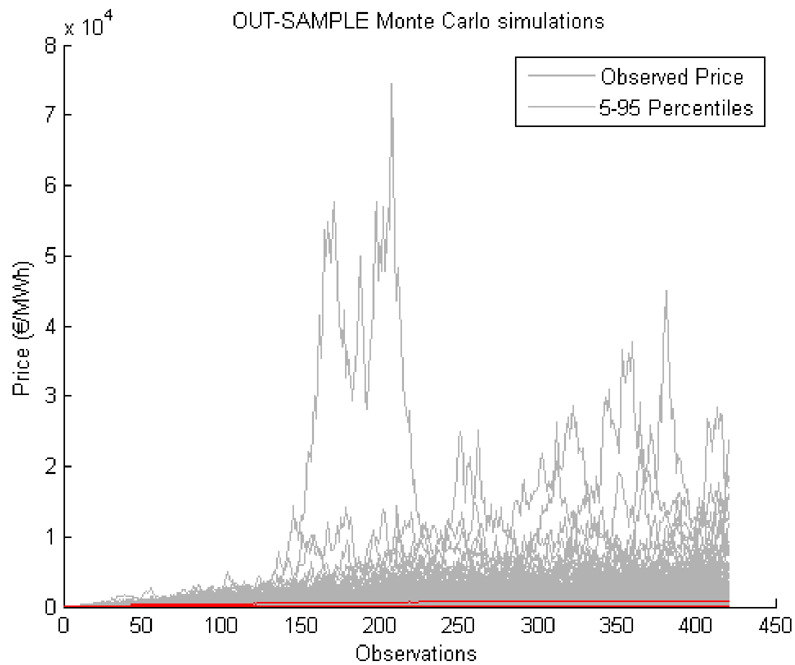

Figure 5.29 - S&S simulated price paths (with 5-95 percentiles highlighted) vs. observed spot price

Although it cannot be seen in the figure, the model is able to capture the whole reserved data. This is also linked to what commented before, making the volatility of the model define a 5^{th}-95^{th} interval from 1 to 1.300 €/MWh, being difficult not to catch every single price.

As a conclusion in table 5.26 the percentages of defined percentiles violations is computed in terms of total observations studied.

Violation of 5th-95th percentiles in % of total studied observations			
Commodity	OMIE	EPEX GER	EPEX FRA
95th Percentile	0%	0%	0%
5th Percentile	7%	2%	0%

Table 5.26 - Violation of 5th-95th percentiles in % of total studied observations

As it can be observed, all models are able to catch almost all testing data within the defined interval. The characteristics of the volatilities and the long-term drifts obtained make possible that prices fall below the 5^{th} percentile always in moments where high penetration of renewables is combined with low-demand summer seasons.

It is also important to mention, that apart from French model, all models define their 95^{th} percentile under the established market price caps, but regarding the 5^{th} percentile, it does not take into account that in France and Germany negative prices happen.

D. Real implementation

Last values analysis

In this next epigraph the Monte Carlo simulated price paths, taking into account that the Schwartz-Smith two-factor model has been adjusted for the 100% of the dataset, are analyzed in terms of last values (T=365).

As it can be observed in table 5.27, the Spanish power system is the one to expect higher prices for the end of next year, being comprised in a 90% confidence interval of 23,81 and 123,74 €/MWh. As it can be seen in terms of the standard deviation, the Spanish model adjusted with all available data, has a larger standard deviation that the German one, changing what could be seen in last epigraph.

Forward testing: last values analysis			
Commodity	OMIE (€/MWh)	EPEX GER (€/MWh)	EPEX FRA (€/MWh)
Mean	61,80	42,10	47,45
Standard dev.	33,53	23,34	96,54
5th Percentile	23,81	16,28	4,35
50th Percentile	54,42	36,87	25,45
95th Percentile	123,74	85,77	157,43

Table 5.27 - Forward testing: last values analysis

Related to German system prices in a year, it can be concluded that they will be placed, within a 90% confidence interval, between the range of 16,28 and 85,77 €/MWh, reflecting in the lower value the growth expectation of renewables installed capacity, that will decrease prices in the future. Regarding the analysis of the defined percentiles, it can also be seen how prices will be situated centered in a 36,87 €/MWh median.

On the other hand French prices reflect the aforementioned volatility in terms of standard deviation, expecting prices for next year in between the 4,35 and 157,43 €/MWh 90% confidence interval. As it can be seen the high standard deviation makes the analyst expect lower prices that are not very likely to happen in the French markets. Values will situate around a median of 25,45 €/MWh, what denotes a summer season effect added to the increasing penetration of renewables.

All values analysis

Analyzing all the values obtained for the Monte Carlo simulations, it can be seen how they are in line with last values ones but in a smaller scale due to the average effect.

In table 5.28 it can be seen how the model expects Spanish prices to be within a 90% confidence interval of 30,23 and 94,37 €/MWh, again all these results are influenced by a high value of the volatility, translated into the standard deviations obtained.

Maximum price is expected to reach 468,40 €/MWh what would be impossible due to the existent price cap of 180 €/MWh in the Spanish market, while the minimum is expected to be 5,40 €/MWh, only achievable if having a constant windy day with zero prices in almost all hours.

Forward testing: all values analysis			
Commodity	OMIE (€/MWh)	EPEX GER (€/MWh)	EPEX FRA (€/MWh)
Mean	56,04	35,99	43,18
Standard dev.	27,58	17,58	60,96
Maximum	468,40	278,39	4859,58
Minimum	5,40	4,48	0,19
5th Percentile	30,23	20,16	11,97
50th Percentile	52,47	33,90	34,70
95th Percentile	94,37	58,99	104,41

Table 5.28 - Forward testing: all values analysis

German system prices are expected to be in an 90% confidence interval of 20,16 and 58,99 €/MWh. Maximum value will be situated in 278,39 €/MWh, while probable minimum for the year is expected to be in 4,48 €/MWh. The median is situated in 33,90 €/MWh, dividing 100% of the values into two, going in line with the expected growing penetration of solar PV panels. Again it is important to mention the clear decrease on prices that the model is expecting due to the penetration of renewables combined with the decreasing demand.

French system prices observed in table 5.28 are again affected by volatility, obtaining a standard deviation for all values of 60,96 €/MWh. This will situate future spot prices in the the 90% confidence interval between 11,97 and 104,41 €/MWh. Maximum and minimum are also affected by volatility, situating in 4859,58 €/MWh the first, and in 0,19 €/MWh the second.

As it can be concluded from the whole electric power commodities analysis, although Schwartz-Smith two-factor model is able to cope with regular seasonality as seen in other commodities, it is not able to work properly with electric power commodities. The fact that seasonality in prices is not just based in regular changes in supply and demand, but also based in the discrete changes between marginal technologies and constraints in the transmission system, combined with the actual impossibility of storage, make electricity price dynamics a very complex dynamic that is not able to be caught by the model.

In order to have a clearer view on what commented before about the real implementation analysis, in figures 4.30, 4.31 and 4.32 it can be seen all simulated price paths for all the three commodities.

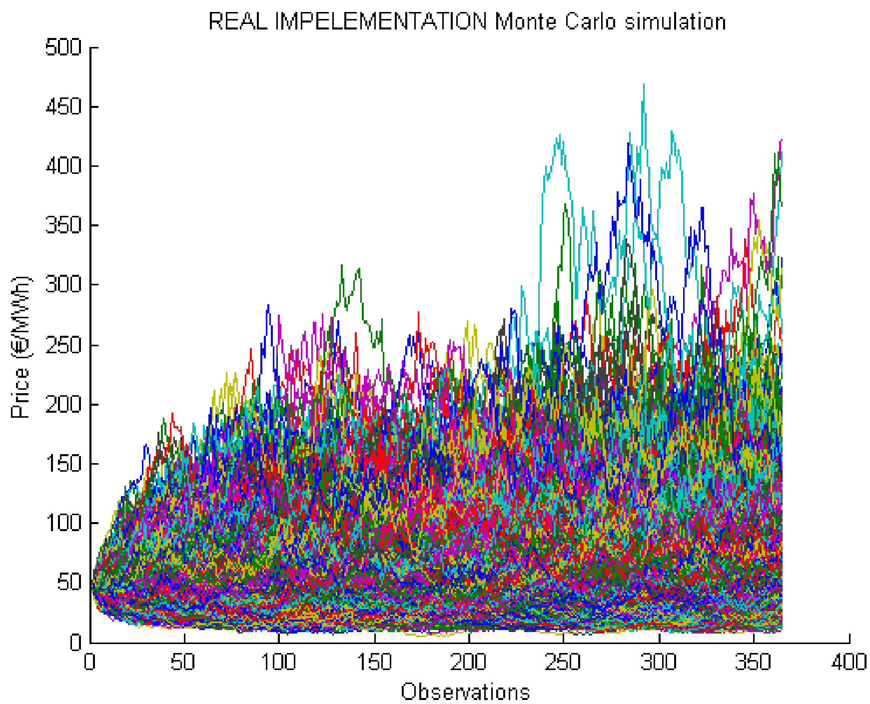

Figure 5.30 - S&S-Medium-term forward testing for Spanish power

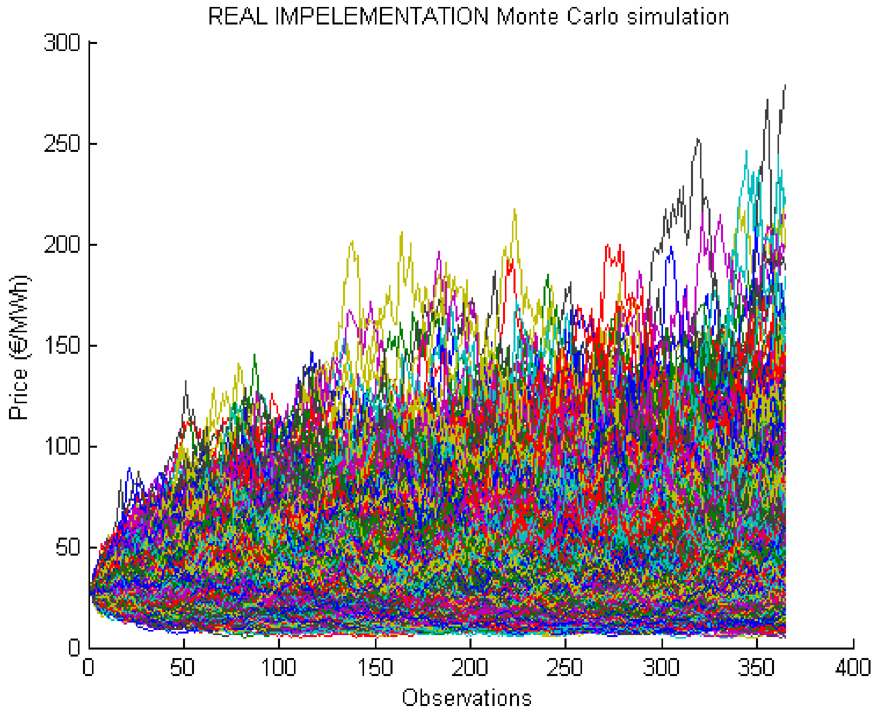

Figure 5.31 - S&S-Medium-term forward testing for German power

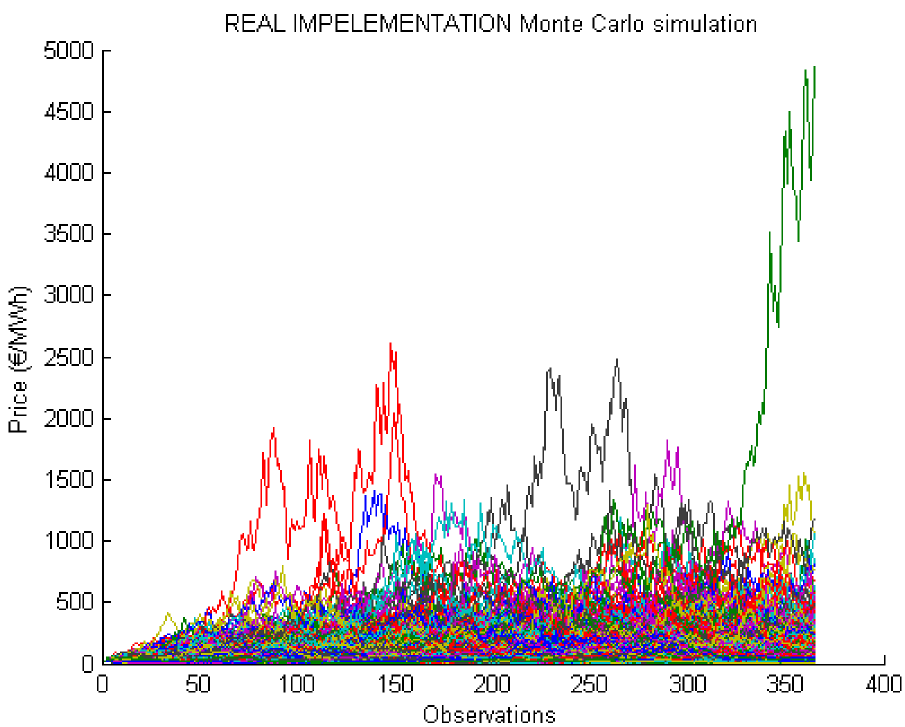

Figure 5.32 - S&S-Medium-term forward testing for French power

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6
CONCLUSIONS

6.1 CONCLUSIONS AND FURTHER RESEARCH

Regarding the results and the analysis made in chapter five, it can be concluded that the performance of the Schwartz-Smith two-factor model, when modeling energy related commodities, is substantially better than the performance of one-factor models like Geometric Brownian motion and Ornstein-Uhlenbeck models.

This conclusion is supported by the log-likelihood scores obtained throughout all commodity analysis, where the Schwartz-Smith two-factor model obtained better log-likelihood scores than one-factor models: Geometric Brownian motion and Ornstein-Uhlenbeck. The errors obtained in the in-sample analysis also support this conclusion, where the Schwartz-Smith two-factor model obtained lower mean absolute error results in almost all future contracts adjusted than the Geometric Brownian motion and Ornstein-Uhlenbeck models.

On the other hand, out-of-sample analysis confirms the generalization capacity of the Schwartz-Smith two-factor model for all commodities, confirming the better performance of two-factor models over one-factor ones.

Comparing results obtained and historic prices, it can also be concluded that Schwartz-Smith two-factor model, along with Monte Carlo simulations, are an appropriate tandem for making medium-term predictions. As it can be observed in the analysis made, most of the projected prices for the different commodities reflect and maintain the main market tendencies observed in the past, supporting the conclusion that both methodologies connected create a useful and unique tool for quantifying prices for the medium-term future.

In order to conclude, it can be stated that the use of the Schwartz-Smith two-factor model for modeling and predicting energy related commodity prices is strongly recommended when applied together with Monte Carlo simulations.

Although for all commodities Schwartz-Smith two-factor model is observed to perform appropriately, electric power commodities present some problems when adjusting and projecting their prices to the future. The complexity of the electricity prices dynamics, in the form of the many variables influencing seasonality as well as the penetration of new generation technologies, make that both Schwartz-Smith factors present difficulties when adjusting electricity prices. This problems are then reflected when projecting prices to the future, obtaining non-expected results that support the necessity of the improvement of the models.

Regarding to what has been previously commented, it can be concluded that the main objective of this master's thesis has been accomplished. The results analyzed along this study prove that the proposed quantitative analysis tool is able to quantify medium-term market risk in electric power utilities, not only being able to quantify electric power market risk, but also being able to quantify market risk in the key energy commodities that heavily impact electric power, having then, a complete and broader view on the market risks undertaken by an electric power utility.

In order to close this master's thesis, for further research, the necessity of improving models to perform better in electric power commodities is recommended. Some studies have tried to tackle this improvement by modifying the structure of the terms included in the models in order to reflect the complex price dynamics. On the other hand, others have tried to introduce new parameters that would improve the model's performance, what indicates that commodity pricing models are in constant development,existing a wide range of opportunities for researching.