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The Study of Different Factors' Effects on the Oil Futures Price by Applying Agent-based Model

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ABSTRACT

An agent-based model is employed for simulating the price of oil futures. The model proceeds as follows: On each time step agents choose their rule for price expectation formation. Next, they bid and ask based on their price and trend expectations. The new price is formed using "the market mechanism". Finally, the time steps forward and the process is repeated in the next day. The agents use 6 different rules to make price and trend expectations. Brent future prices in a 2-year-period (2010-2011) and in 2012 are used for model calibration and validation, respectively. It was shown that market participants weigh U.S. stocks data more than other factors, while OECD stock's data were not that important for the market. It was also inferred that the market does not weigh the technical aspects of the oil price as much as the fundamental aspects.

Keywords: Agent-based Model, Oil Price, Technical/Fundamental Rule
JEL Classifications: C4, C5, Q3, Q4

1. INTRODUCTION

Crude oil price is important for all countries and businesses. Oil has been a main source of energy for many years and despite all the painstaking efforts for reducing its share in the world's primary energy basket, it is still expected to play an important role in coming years. According to many outlook reports oil will still be a main source of primary energy till 2040. (U.S. EIA, 2016a) Hence, oil price will keep to be watched closely by all companies and countries especially the oil importing ones. In addition, crude oil is of utmost importance for the exporting countries. That is because their economies depend on the oil export revenues in terms of trade balance, exchange rate and government budget. Therefore, the oil exporting countries are also sensitive to oil prices.

As a result, simulation of the oil prices has attracted many researchers in order to make it possible for decision makers to understand oil markets better and decide effectively. Knowing the oil price dynamics is also beneficial to businesses related to oil and energy. This is another driver for the vast amount of research done on simulating the oil price.

Simulation models can be categorized according to different criteria. For example oil price models can be bottom-up or top-down. There are models which use behavior of players' data. It is done for OPEC. However, generally oil price simulation models include four different types: Structural models, computational models, reduced form/financial models, and artificial intelligence models. (Huntington et al., 2013) These four different types will be introduced very briefly:

1. Structural models are based on microeconomics and players' interactions. Some examples are (Blitzer et al., 1975), (Gately, 2004), (Dees et al., 2007), (Amano, 1987) & (Kaufmann et al., 2016).
2. Computational models, mostly established by energy study institutes, include many different aspects and factors affecting oil prices. They seek partial or general economic equilibriums. Some examples are (De Santis, 2003), (Huppmann and Holz, 2009), (U.S. EIA, 2016b) & (U.S. EIA, 2016a).
3. Reduced form/financial models consider statistical relationship between oil prices and the factors affecting them. These models were developed because of the financialization of the oil market and introduction of oil futures and other derivatives in the market. Some examples are (Alquist et al.,

2013), (Maslyuk and Smyth, 2008), (Papapetrou, 2009) & (Sadorsky, 2006).

4. Artificial intelligence models try to regenerate the intelligence behind the behavior of living species, especially human mind in order to simulate a complex phenomenon. (Mohaghegh et al., 2011) Artificial neural networks, fuzzy logic and genetic algorithms are among the artificial intelligence paradigms. (Huntington et al., 2013) An example of these models is (Al-fattah, 2013).

Agent-based models[1] should be considered as a bottom-up artificial intelligence type of oil simulation models.

An agent-based model is a simulating model based on autonomous agents who act on the basis of some specific rules. The aggregated action of these agents shapes the environment. Environment here means the parameter which is formed through the aggregate action of the agents. For example, in a market, buyers and sellers are the agents and the price is the environments. (Janssen, 2005), (Scholl, 2001), (Galchynsky et al., 2011), (Farmer, 2011) & (Lee et al., 2014).

Using agent-based modeling for simulating the oil market has the general advantages of bottom-up models. First, it gives insight about the behavior of market and its dynamics instead of regarding the market as a black-box. Second, it enables the modeler to train the model and improve its performance since it has the capability of learning. Finally, if some new events and market structures or prediction methods are to be introduced to the market, an ABM has the capability to adopt. That is because new agent types, new rules and even new market (clearing) mechanisms can be included in an ABM.

In addition, there is an exclusive advantage for using ABMs in the oil market. Due to the fact that the oil price and the behavior of real agents present in this market depend on many mental, political and qualitative factors, purely quantitative models are not able to simulate the oil markets well enough. Instead, ABMs have the capacity to include rules of behavior based on these types of factors. That is why ABMs can simulate some special phenomena like herding behavior or the effects of war or embargos on the oil price.

The literature on bottom-up models especially ABMs for simulating oil prices is not as well established as the literature on other types of models. Yu et al. (Yu et al., 2008) have proposed a compound method which is a combination of intelligent-agent-based predictors and fuzzy group forecasting. They use three methods to predict the oil price and fuzzify these predictions. Then the fuzzy predictions are consolidated and the result is defuzzified.

Ellen et al. (ter Ellen et al., 2010) distinguish three different agents in the oil market: Real actors (i.e., suppliers and buyers), fundamentalists and chartists. While the number of real suppliers and buyers and their rule of behavior are set, the number of agents using fundamental/technical rules is allowed to change during time, based on previous prediction errors of these rules. The total demand and supply is then computed and the price is formed as a function of demand-supply difference.

Vansteenkiste (Vansteenkiste, 2011) distinguishes two main types of agents present in the oil market: Commercial and non-commercial agents. Non-commercial agents are divided into two sections: Fundamentalists and chartists. He, then, writes the pay-off function of these agents and assumes that in every time-step some of them, based on their type and understanding of the market, decide to take part in the market. The model is simulated through a time-varying transition probability Markov-switching model and Brent and WTI[2] historical data is tested.

Because of the financial aspects of the current oil markets, the literature on modeling financial markets (other than the oil market) by using ABMs should also be considered. Lye et al. (Lye et al., 2012) use a model in which N independent traders buy and sell M stocks. The price of a stock increases when a trader buys it and vice versa. They use order parameters to distinguish between three different phases in the market: The dead market, the boom market and the jammed market. Bookstaber (Bookstaber, 2012) argues that ABMs can better explain financial markets since they explore the behavior of individual firms and their effect on the market and its stability as a complex and collective phenomenon. Van den Bergh et al. (Van den Bergh et al., 2001) suggest using intelligent agents for modeling financial markets. They propose some artificial intelligence algorithms for decision-making among agents rather than simple mathematical rules. Outkin (Outkin, 2012) uses ABM to model dealer-mediated markets like NASDAQ and discusses the effect of decimalization in that market. Brian Arthur et al. (Arthur et al., 1997) explore the role of agents' expectations in the complexity and price volatility of an artificial stock market. Yet there are few studies, as mentioned above, which explore the oil future market considering its unique aspects using agent-based models.

2. THE MODEL

The models process is as follows: On each time step (i.e., every day) agents choose their rule for price expectation formation. Next, they bid and ask based on their price and trend expectations. The new price is formed using market mechanism. Finally, the time steps forward and the process is repeated in the next day.

The main aspects of this model include the market mechanism, the rules used for price and trend expectation formation and the way agents choose their rule in every time step. Below, different aspects of the model are discussed.

2.1. Market Mechanism

In this model the price formation mechanism is based on the prices different agents bid and ask. It is assumed that each agent, based on his rule of behavior, makes a price expectation for himself. In

1 ABMs.

2 West Texas Intermediate, the most famous crude oil traded in the United States. WTI is the price index for most of crude oil produced and traded in north America especially the United States.

addition he forms his expectation about the price trend. Hence, if an agent expects the market to go upward, he will bid at a price equal to his price expectation and if he expects a downward trend in the market, asks at a price equal to his expected price.

It will be discussed in the next section that in some steps, some rules may be unable to form price and trend expectations. So, the agents using that rules will not participate in the market, their price expectation is set to be zero and that rule is called "NULL" during that specific time step.

The market clearing house (the modeler), plays the role of a double auctioneer. He works with two numbers: First, the greatest price expectation (the greatest ask) among byers (namely P_b) and the least price expectation (the least bid) among sellers (namely P_s). The market price is then formed based on the following rule:

- If $P_b \geq P_s$, then the market price would be the average of P_b and P_s.
- If $P_b < P_s$, then there would be no deal and the market price will set to be equal to previous market price. That is because the greatest price accepted by buyers is still less than the least price accepted by sellers.
- If either there are some buyers but no sellers or there are some sellers but no byers, then there would be no deal and the market price will set to be equal to previous market price. That is because both the seller and the byer must be present in order for the double auction mechanism to work.

2.2. Price and Trend Expectation Formation Rules

There are three fundamental and three technical rules based on which agents form price and trend expectation. The fundamental rules include

1. Weekly U.S. commercial crude oil stocks: If U.S. energy information administration's (EIA) weekly stocks data shows a build-up/draw-down in the stocks, the agent using this rule will expect the price to decrease/increase by a factor relative to the percentage of the stocks increase/decrease. The stocks are considered to be constant during the week and change on the very specific day the data is released (i.e., Wednesdays). That is because in reality agents are not formally informed about these stocks' data during the week so they cannot form expectations using this rule during the week. That is why this rule is set to be "NULL" within the week.
2. Monthly OECD commercial crude oil stocks: If OECD monthly stocks data shows a build-up/draw-down in the stocks, the agent using this rule will expect the price to decrease/increase by a factor relative to the percentage of the stocks increase/decrease. Here again, the stocks are considered to be constant during the month and change on the very specific day the data is released by International Energy Agency (IEA) oil market report. So, this rule is set to be "NULL" during the month.
3. Daily Dollar-Euro exchange rate: If Dollar-Euro exchange rate increases/decreases (according to daily data released by U.S. Federal Reserve), the agent using this rule will expect the price to increase/decrease by a factor relative to the percentage of the exchange rate increase/decrease.

The technical rules include:

1. Simple moving average (SMA): If SMA crosses above/below the price, the price trend will be expected to be upward/downward by a factor relative to the percentage difference between the moving average and the price. If the SMA does not cross the price or it is equal to the price for two consecutive time steps, the rule will be set to "NULL".
2. Exponential moving average (EMA): If short-term EMA (short EMA) crosses above/below long-term EMA (long EMA), the price trend will be expected to be upward/downward by a factor relative to the percentage difference between the short and long EMA. If the short and long EMA do not cross each other or they are equal for two consecutive time steps, the rule will be set to "NULL".
3. Bollinger bands: If the price reaches near the upper/lower Bollinger band, the agent using this rule will expect the price to decrease/increase by a factor relative to the difference between the price and the upper/lower Bollinger band. If the price is not near the upper nor the lower band, the rule will not say anything about the price and it will be set to "NULL".

2.3. How Agents Choose their Rules of Behavior

Traders, in the real world, must consider the predicting capability and accuracy of the aforementioned rules when they want to choose a rule for price expectation formation. However, it is believed that all of these rules are used at least by a small number of traders. In the model, agents choose the rules randomly and since the number of agents is large enough, there will always be some agents who use a specific rule and all rules will probably be used by at least one agent. That is why choosing the rules on a random basis will not reduce the validity of the model.

As mentioned above, the number of the agents must be large enough to make sure all rules are used on each time step. On the other hand, computation limitations dictates this number to be small. By sensitivity analysis, it is observed that 50 agents fulfill both considerations. Therefore, the number of the agents is set to be 50.

3. RESULTS

Technical rules work only based on the previous price data generated in the model. Therefore, these rules do not need any exogenous data. However, real exogenous data is required for fundamental rules. This data include U.S. weekly commercial crude stocks data, OECD monthly stocks data and Dollar/Euro exchange rate data which are obtained from the EIA, IEA and the Federal Reserve data bank, respectively. The price history data is also required for model calibration and validation. This data is obtained from the EIA data bank of Brent crude futures prices.

A 2-year-period (2010-2011) is considered for model calibration. Model calibration parameters include: The factors forming price expectations in rules and the technical rule factors such as moving average duration and Bollinger band factor. A 1-year-period 2012 is used for model validation. The results of the calibration are shown in Table 1.

Table 1: Calibration parameters; the parameters for price expectation formation rules

Type	Parameter	Value
Agents	Number of agents	50
Technical analysis parameters	SMA time	50 days
	Short-term EMA	8 days
	Long-term EMA	20 days
	Bollinger band factor	2
Price expectation formation rules parameters	U.S. weekly stocks rule factor	9
	OECD monthly stocks rule factor	0.15
	Dollar/Euro exchange rule factor	0.9
	All technical rules' factors	0.5

SMA: Simple moving average, EMA: Exponential moving average

In this table the parameters for price expectation formation rules are shown. These numbers imply that, agents who use for example the U.S. weekly stocks rule expect the prices to decrease nine percent for every one percent increase in U.S. stocks. This setting of calibration parameters is chosen based on minimizing mean absolute percentage error (MAPE), normalized mean square error (NMSE), root mean square deviation (RMSD), normalized root mean square deviation (NRMSD) and maximizing D_{stat}. Figure 1 schematically compares the real and simulated oil price from 2010 to 2011 (years used for model calibration).

Table 2 shows the values of calibration criteria for the setting shown in Table 1.

As discussed above the errors are not sensitive to the number of agents. The parameters for technical analysis is set according to usual values suggested by technical analysts and the model errors do not depend on these parameters significantly.

The model was then tested using the oil prices in 2012. Figure 2 shows the simulated and real prices in 2012.

Figure 2 and Table 3 shows that simulated data comply with real prices. This compliance is both in terms of the absolute value of prices (according to MAPE, NMSE, RMSD and NRMSD) and direction of price changes (according to D_{stat}).

Figure 1: Calibration results (real and simulated prices in U.S. Dollars from 2010 to 2011)

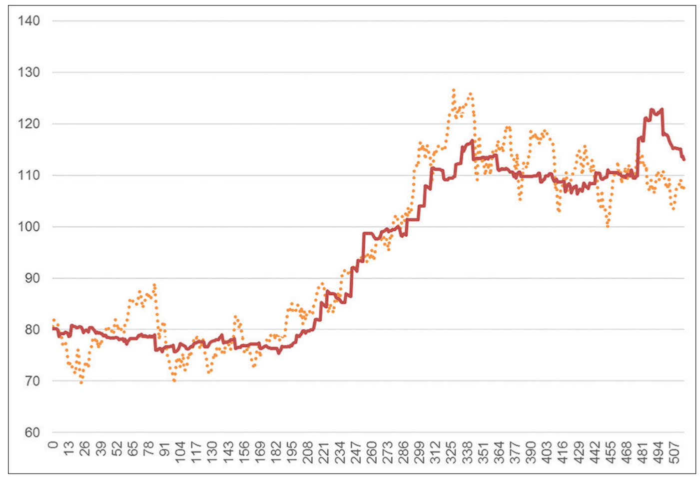
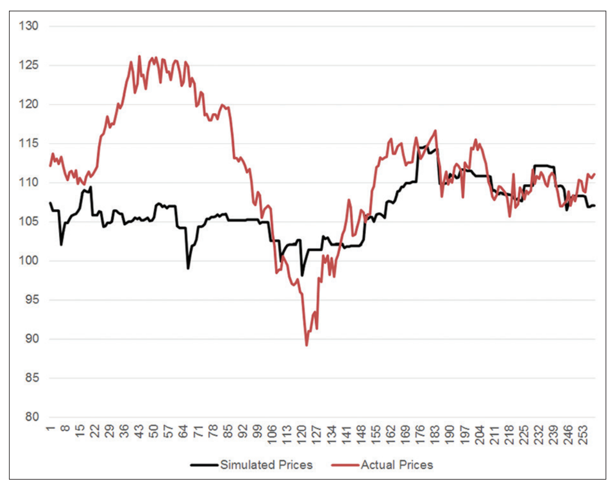


Figure 2: Validation results (real and simulated prices in U.S. Dollars for 2012)



4. DISCUSSION

The calibration parameters determined above (Table 1) form new insights about the oil price dynamics and the factors which have important influence on it. First, the factor of U.S. stock rule is 9. This implies that market participants weigh U.S. stocks data more than other factors and any change in U.S. stocks has a significant effect on price expectations. However, it is inferred from the factor of OECD stocks rule (0.15) that the change in OECD stocks is not considered as an important factor in the market.

Second, the importance of U.S. stocks can be understood considering the amount of these stocks compared to that of OECD. The absolute barrels of oil needed to change U.S. stocks by one percent is less than the amount needed to change OECD stocks by one percent. This means that one barrel change in U.S. stocks is more important for the market than one barrel change in OECD stocks. That's because of the factor used in U.S. stocks rule compared to OCED stocks rule factor as well as the percentage change that a barrel increase/decrease will cause in these two stocks.

Third, the factor of Dollar/Euro exchange rate rule is 0.9 and is relatively high. This means that the relative power of U.S. and Euro economies is a meaningful signal for the market and any change in this relation has an important effect on the oil price. It also implies that the exchange rate change is more important than OECD stocks change.

Table 2: Values of calibration criteria; the values by which it may be concluded that the model is calibrated properly enough

Criterion	Value	Unit
MAPE	5.69	%
NMSE	0.0054	-
D_{stat}	50.19	%
RMSD	6.89	-
NRMSD	7.21	%

Table 3: Validation tests; the values by which it may be concluded that the model is resembling the actual data

Test method	Value	Unit
MAPE	5.55	%
NMSE	0.007	-
D_{stat}	52.73	%
RMSD	9.05	-
NRMSD	8.11	%

Forth, the factor of technical rules is 0.5. It can be inferred that the market does not weigh the technical aspects of the oil price as much as fundamental aspects. It was also seen that among the 359 deals in the calibration period, agents using technical rules were a part of the deal only 17 and 48 times as the seller and buyer, respectively. This implies that either the technical rules have been "NULL" most of the time or the expectations made by these rule have so exaggerated that prevented the agents from being a part of the deal. The calibrated factor of technical rules (0.5) is <1, so the second assumption may not be true because a <1 factor cannot exaggerate the expectation, rather it damps the expectation. (i.e., every one percent change in the technical parameters means a <1% change in price expectation). Thus, it can be concluded that technical rules are "NULL" most of the time which means neither the price cuts the moving average or Bollinger band frequently, nor the short and long term moving averages cross each other.

Finally, the fact that three of the factors are <1 and U.S. stocks rule factor is more than one further confirms the importance of U.S. stocks data for the market and its intensifying effect on the price. A very small change in U.S. stocks means a very large difference between current price and price expectations formed, while large changes in OECD stocks, Dollar/Euro exchange rate and technical parameters is interpreted as small differences between current price and price expectations.

5. CONCLUSION

In this paper, due to the importance of studying the oil prices and the lack of a bottom-up model for oil markets, an agent-based model for the oil market was introduced. There are some agents in the model who randomly choose their rule of behavior (i.e., the rule which forms their price expectation). Price expectations form the new price according to market mechanism. The toolbox of rules include three technical and three fundamental rules.

The results had a fairly good compliance with real data and clarified the importance of U.S. stocks data for the market and show that OECD stocks data are not significant for dealers in the market. This model is a powerful basis for simulating the bottom-up dynamics of the oil market and helps us understand the oil price and the factors affecting it by explaining the price formation mechanism.

Administrative authorities and corporations can use the insight provided by this model to act in the market. Oil importing countries should always pay attention to the U.S. stocks and be informed that the affordability aspect of their energy security is related to how oil stocks in the united states change. Oil exporting countries should also be aware of the stocks and relative strength of the worlds' main economies. This model can be used to predict the future of the oil market by using different scenarios for the future of the worlds' economies and oil stocks.

The agent-based model discussed in this paper can be improved by adding more complex rules for making price expectations. These new rules are suggested to be fundamental and specifically related to political and mental aspects of the market and dealers' trading behavior. The market mechanism can also be improved by using more complex algorithms for clearing the market. The mechanism by which agents choose their rule of behavior is may be upgraded to a mechanism based on the rules' predicting ability record and the agents' tendency to accept risks. However, practically all the rules for making price expectations are use in the market and no rule is put aside. So the upgraded mechanism should not drive a situation in which some rules become useless during time. Price expectation formation mechanism is based on one rule in this model but it can be an average of different expectations formed by different rules.

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