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Persistency of Price Patterns in the International Oil Industry, 2001-2016

Ana Lorena Jiménez-Preciado[1], Salvador Cruz-Aké[2], Francisco Venegas-Martínez[3]*

[1]Instituto Politécnico Nacional, Mexico, [2]Instituto Politécnico Nacional, Mexico, [3]Instituto Politécnico Nacional, Mexico.
*Email: fvenegas1111@yahoo.com.mx

ABSTRACT

This paper is aimed at studying price patterns and their persistency in selected international oil companies (Exxon Mobil, British Petroleum, Royal Dutch Shell, and China Petroleum Sinopec). The proposal uses a one-step counting of price patterns and a two-step counting derived from transition probabilities of price patterns both procedures based on Japanese candlesticks. An extension of Kolmogorov–Smirnov test for discrete variables, provided by Taylor and Emerson (2011), is used to measure the statistical significance of the obtained results. Furthermore, the persistence of patterns is examined via the correlation in two-step conditional probabilities by using Blomqvist's beta test. This method is useful to identify patterns even under market booms and busts, and in high and low volatility environments.

Keywords: Oil Industry, Transition Probabilities, Persistent Price Patterns
JEL Classifications: G14, C81, G11

1. INTRODUCTION

Currently, the global oil market stands for a complex system that involves a gathering of participants that is affected by political and idiosyncratic aspects, as well as endogenous, and exogenous economic and financial variables (production, technology, investment, preserves, prices, transaction costs, financial cost, exchange rates, etc.). This complexity has led to a great quantity of literature devoted to the better understanding of the price behavior of this market. It has also been a topic of discussion as to whether this market allocates resources efficiently.

This research deals with technical analysis of oscillators and moving averages of historical prices represented by Japanese candlesticks. To do this, conditional probabilities of market movements as a function of their immediate past are analyzed. It is important to point out that returns obtained by using technical analysis could be illusory because the transactions costs could reduce or exhaust the expected return. For plenty of practitioners and traders, the technical analysis represents a methodology that delivers a superior return because it shows the "market sentiment" (Bajgrowicz and Scaillet, 2012). In this investigation, we argue that if there was a "market sentiment," it would produce stable patterns in the price behavior, and the patterns can have certain conditional probability given the recent history (in this case, the previous period). To do this, we develop an algorithm that uses the relations among opening, closing, maximum, and minimum prices of selected oil companies to identify patterns of Japanese candlestick. Subsequently, we analyze the resulting probabilities of such patterns in one step and the conditional probabilities in two steps according to a transition matrix. Finally, we use Blomqvist's beta to capture the dependence structure that arises from the patterns.

The firms in the oil industry are intensive in capital and heavily dependent on economic conditions. We argue that the "market sentiment" will produce a high concentration among the firms. We use data from Exxon Mobil, British Petroleum, Royal Dutch Shell and China Petroleum Sinopec from January 20, 2001 to January 20, 2016. This provides 3772 daily observations. The empirical findings suggest that five patterns determine the 60% of the behavior of prices in the oil companies and that those patterns are persistent through time along the sample. Moreover, memory effects are observed in the two-step transition matrix where conditional probabilities of the repetitive patterns represent 77% of the sample. Finally, empirical evidence of a positive relationship of dependency of two-step conditional probabilities is found.

This research is organized in four sections. The next section analyzes the price behavior in the oil industry. Section 3 provides some methodological aspects from combining Dow Theory and Japanese candlesticks. Section 4 carries out an empirical analysis on persistency of oil price patterns. Finally, Section 4 concludes and acknowledges limitations of the research.

2. PRICE BEHAVIOR OF OIL COMPANIES

There is a vast literature on oligopolistic practices in the oil sector; see, for instance, Roncaglia (2015), Yanyan (2013), and Verleger (2015). This paper attempts to investigate whether prices from the oil sector have a similar behavior (related to the industry conditions), and if each price dynamic shows a common trade pattern depending on the company's fundamentals and news.

It is worth pointing out that the behavior of prices has been previously analyzed using other techniques such as, for example, wavelets in Jammazi (2012), fractals in Ibarra-Valdez et al. (2016), and fractional Brownian motion in Jiang et al. (2014). However, the behavior has not been compared among companies to examine whether they show a common behavior. We will focus our attention in finding persistent patterns in the prices of oil companies. Thus, an oil company located in China may show a similar behavior to other located in the United States, showing similar memory effects. In other words, regardless their location, the past information may affect the subsequent behavior of the whole industry.

The first oil company studied in this research is Exxon Mobil (XOM). This is an American oil corporation which according to Forbes 2015 ranking[1], in 2014, registered 4.7 millions of equivalent barrels of oil and natural gas (BOEPD). Additionally, its share's price is included in the DJ Composite Index, standard and poor (S and P) 100 and S and P 500. The second oil company is British Petroleum[2] (BP PLC). This firm registered 3.7 BOEPD in 2014. Its share's price is considered in the following indexes: NYSE TOP International 100 and NYSE Composite. Similarly, Royal Dutch Shell (RDS-B) produced approximately the same amount of BOEPD in 2014 according to Forbes. The NYSE TOP International 100 and NYSE Composite indexes also include BP stock prices. Finally, PetroChina (PTR) is indexed in NYSE TOP International 100 and NYSE Composite, and produced 4 million BOEPD in 2014. Figure 1 shows the behavior of the closing prices during 2001-2016.

Figure 1 shows that the PTR price has the most volatile behavior previous to the 2007-2009 financial crisis. In the rest of the cases, the companies showed similar behavior in their price dynamics with comparable peaks and bottoms. Extending this visual analysis, Figure 2 shows the oil companies returns with outstanding volatility clusters observed in 2008. The price fall is due to the temporary contraction of demand for oil mainly caused by the 2007-2009 financial crisis raised in the US (Varella and Abebe, 2013).

In the next section, we will be using technical analysis with Japanese candlesticks to identify whether exist similar patterns in prices of oil companies by using a one-step counting procedure of price patterns.

3. METHODOLOGICAL ASPECTS FROM COMBINING DOW THEORY AND JAPANESE CANDLESTICKS

In Dow theory the stock market can be analyzed based on three kinds of trends: Primary trend, secondary trend, and daily fluctuations. Once the primary trend is identified, although its duration and length are unpredictable, the secondary trend corrects tendencies. If the previous trend is bearish (downtrend), the secondary trend is called rallies. When the previous trend is bullish (uptrend), the secondary trend is named corrections. Finally, daily fluctuations focus on closing averages, and they are useful for determining long or short positions for traders (Rhea, 1994; Murphy, 1999; Bulkowski, 2011). It is important to mention that technical analysis is a short-term analysis and candlestick represents the synthesis of opening, high, low, and closing prices. Figure 3 shows a general classification of Japanese candlesticks that arose from the combination of those prices.

The first candle has a big white body with small tails and it stands for a confirmation signal of a bullish trend. The second candle has the same meaning although for a downtrend. The third candle (short tails and bodies) suggest a hold position where neither buyers and sellers pressure the market. Candles 4 and 5 (long tails and short bodies) represent a trend reversal signal. Finally, Candle 6 (long tails and short bodies) indicate domain by buyers or sellers during the day, but at the end, the opening and closing prices are relatively close[3]. Figure 4 shows the results from combining elements of Dow theory and Japanese candlestick information for all selected companies[4].

4. EMPIRICAL ANALYSIS ON PERSISTENCY OF OIL PRICE PATTERNS

Previously, it was mentioned how to construct the candlesticks and their taxonomy depending on the relations between the selected prices. Therefore, candlesticks could be classified based on the size of their bodies and tails and their relations, therefore an algorithm that distinguishes among each pattern will be provided in Table 1.

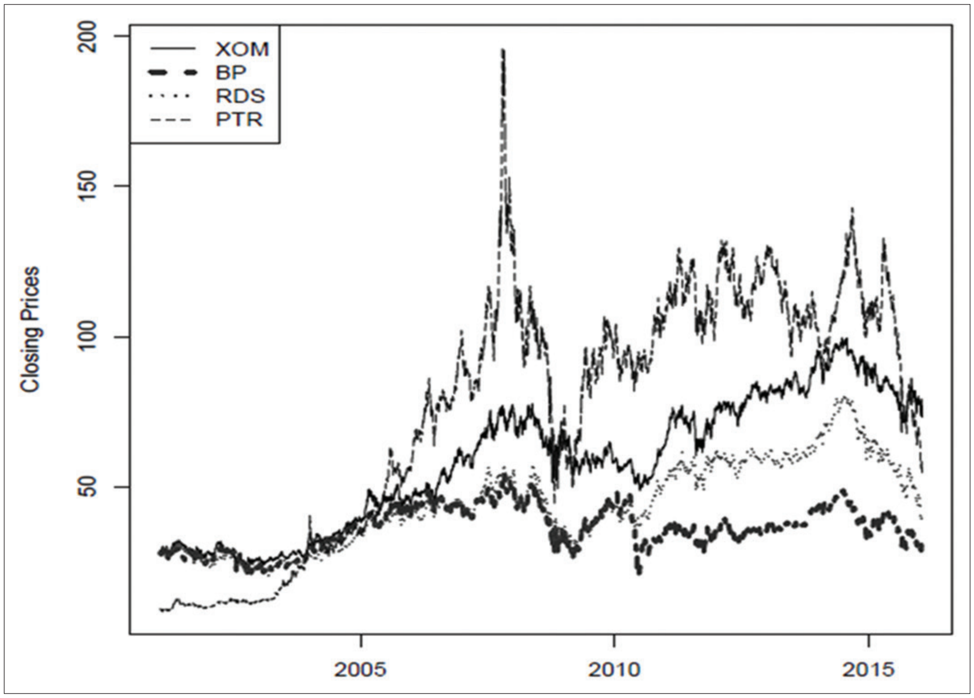
1 Available from: http://www.forbes.com/pictures/eedh45fjlkk/the-worlds-biggest-oil/.

2 Established in the United Kingdom in 1909.

3 It is important to point out that the information reveled by the candlesticks is not always accurate; for example, it is not possible to detect the oscillation of the prices in the candle, that is why most of the times it is necessary to considerate the previous candle in order to detect if the trend still going up, down or remaining neutral.

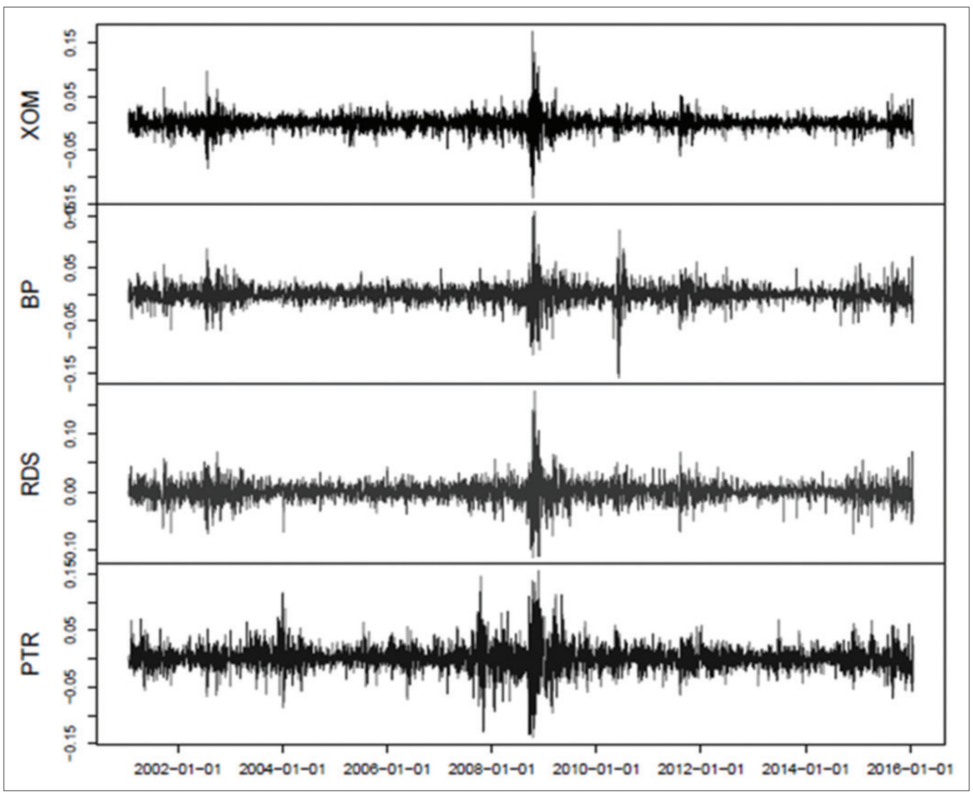
4 Under this framework, Dow theory represents the foundations of the technical analysis as expressed in Edwards et al. (2013).

Figure 1: Oil companies closing prices, January 20, 2001 to January 20, 2016



Source: Own elaboration based on Jeffrey (2015) in R programming language

Figure 2: Oil companies returns, January 20, 2001 to January 20, 2016

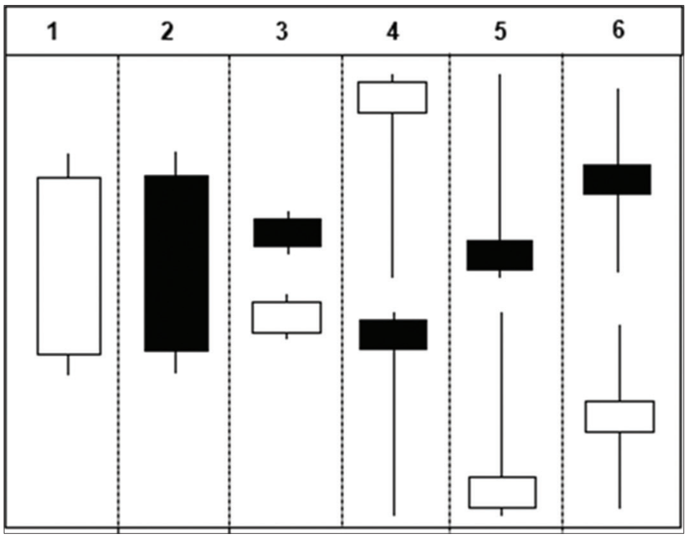


Source: Own elaboration based on Jeffrey (2015) in R programming language

Once the types of bodies and tails that arise from the candlestick analysis have been defined, we build the characterization of the patterns, obtaining a total of 54 after combining all the possible types of bodies and tails. After analyzing those results, only 25 are feasible; this means that there are no contradictions between the information given by the combination of bodies and tails. As a final result, we got 12 bullish candlesticks and 12 bearish candlesticks plus an additional pattern provided by a point meaning no movement on the market during that period. For practical purposes, the following nomenclature will be used: (1) White body candle (Bullish) - WB; (2) white upper tail (Bullish) - UWT; (3) white lower tail (Bullish) - UWT; (4) body black candle (Bearish) - BB; (5) upper black tail (Bearish) - UBT; and (6) lower black tail (Bearish) - UWT.

Table 2 shows the behavioral patterns identified in Exxon Mobil (XOM), British Petroleum (BP-PLC), Royal Dutch Shell (RDSB), and PetroChina (PTR). First, we test the uppers tails *vs*. lowers tails (white and black), and then we matched the bodies between both

Figure 3: Patterns from candlestick analysis



Source: Adaptation from McDonald (2002)

Table 1: Bodies and tails construction

Bullish candlestick	First condition	Second condition
Body of the candlestick	[Close - Open] >0	-
Upper tail	[High - Close] >0	[Close - Open] >0
Lower tail	[Open - Low] >0	[Close - Open] >0
Bearish candlestick	**First condition**	**Second condition**
Body of the candlestick	[Open - Close] >0	-
Upper tail	[High - Open] >0	[Open - Close] >0
Lower tail	[Close - Low] >0	[Open - Close] >0

Source: Author's own elaboration

tails. After applying such procedure, we establish a sequence of conditions for every feasible combination and assigned a number for that pattern.

We emphasize that patterns from 1 to 12 are symmetric to those from 13 to 24. The first set can be labeled as bullish while the second is bearish. In Table 3, we group the patterns from Table 2 as a function of the information that they provide. That is, patterns that confirm the trend, patterns that reverse trends and patterns of uncertainty. Furthermore, each pattern is associated with a type of candle. Thus, instead of studying the behavior of the oil companies through prices, a series of patterns will be studied through a discrete transformation.

Table 3 shows eight confirmation patterns that include four strong confirmation patterns: 9, 11, 21 and 23. These patterns confirm and accent the active path. On the other hand, we have ten reversion patterns with two strong reversion patterns, 4 and 15. Their interpretation is analogous to strong confirmations patterns. Finally, patterns related to situations of uncertainty are 3, 12, 15 and 24.

After grouping the patterns, we count them to know which of them have a higher sample recurrence (one-step counting). The procedure for the one-step counting considers the number of repetitions of each pattern in the sample (3772 observations for each oil company). A Pareto graph provides the results. We selected this chart style because it highlights how each of the elements in a group (patterns in this case) contributes to the distribution of the sample (i.e., the trajectory of the prices). The Pareto principle suggests that given a set of elements or factors that contribute to the same effect, just a few factors cause the most of it. The following section shows these results achieved.

4.1. One-Step Counting

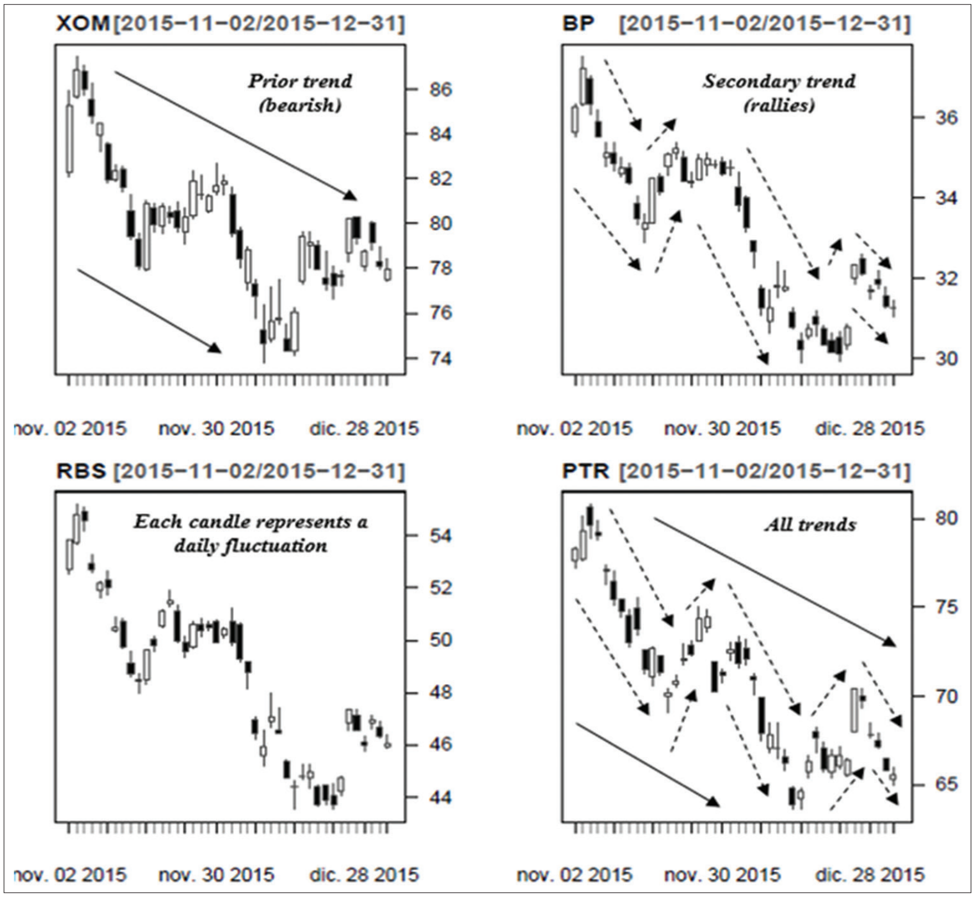
To identify patterns in oil companies, we transform the Japanese candlesticks into trend patterns (more specifically, into a discrete variable). Table 4 shows the number of repetitions of those patterns for each of the selected oil companies.

Table 2: Pattern formations

Bullish candlesticks (withes)				Bearish candlesticks (blacks)			
UWT versus LWT	WB versus UWT	WB versus LWT	Pattern	UBT versus LBT	BB versus UBT	BB versus LBT	Pattern
Condition 1	Condition 2	Condition 3		Condition 1	Condition 2	Condition 3	
UWT>LWT	WB>UWT	WB>LWT	1	UBT>LBT	BB>UBT	BB>LBT	13
UWT>LWT	WB<UWT	WB>LWT	2	UBT>LBT	BB<UBT	BB>LBT	14
UWT>LWT	WB<UWT	WB<LWT	3	UBT>LBT	BB<UBT	BB<LBT	15
UWT>LWT	WB<UWT	WB=LWT	4	UBT>LBT	BB<UBT	BB=LBT	16
UWT>LWT	WB=UWT	WB>LWT	5	UBT>LBT	BB=UBT	BB>LBT	17
UWT<LWT	WB<UWT	WB<LWT	6	UBT<LBT	BB<UBT	BB<LBT	18
UWT<LWT	WB>UWT	WB>LWT	7	UBT<LBT	BB>UBT	BB>LBT	19
UWT<LWT	WB>UWT	WB<LWT	8	UBT<LBT	BB>UBT	BB<LBT	20
UWT<LWT	WB>UWT	WB=LWT	9	UBT<LBT	BB>UBT	BB=LBT	21
UWT<LWT	WB=UWT	WB<LWT	10	UBT<LBT	BB=UBT	BB<LBT	22
UWT=LWT	WB>UWT	WB>LWT	11	UBT=LBT	BB>UBT	BB>LBT	23
UWT=LWT	WB<UWT	WB<LWT	12	UBT=LBT	BB<UBT	BB<LBT	24
UWT=LWT	WB=UWT	WB=LWT	25	UBT=LBT	BB=UBT	BB=LBT	25

Pattern 25 arises when all conditions have the same value; notably these combinations represent a single point since all prices (open, high, low, close) are equal, so we cannot determine if is bullish or bearish. Source: Author's own elaboration

Figure 4: Applications of Dow theory's trends for the selected oil companies from November 02, 2015 to December 31, 2015



Source: Own elaboration in R programming language based on Jeffrey (2013)

Table 4 shows the five most repeated patterns for each oil company along the sample (3772 daily observations for each firm). We emphasize that the same five patterns represent near to 60% of each sample. It is remarkable the fact that the patterns with more repetitions for XOM and RDS-B are 1 and 7 which accounts for a bullish trend confirmation. Those patterns seem to be a long-run trend for the companies, although they also present a high number of repetitions of bearish patterns.

For BP and PetroChina, patterns 19 and 1 are the most common. Pattern 19 represents a bearish trend confirmation, and pattern 1 is a bullish confirmation. Note that all of them have the pattern 20 (a bearish trend reversion) and it is the fifth with more repetitions. We also remark that all quotes have the same common patterns with little differences in the frequency and position. These results suggest that all these oil companies have similar patterns, and exhibit a common behavior.

A question that may arise after our analysis is whether patterns are the same and whether market is volatile or not. To answer this question, we analyzed the similarity between patterns when they are in a period of high and low volatility. The selection criteria of such episodes considered "volatile" is taken from a generalized autoregressive conditional heteroskedasticity (GARCH) model, specifically a GARCH (1,1). Next figure shows the volatility of returns calculated from the closing price versus its conditional standard deviations.

Observe in Figure 5 that all oil companies show greater volatility at the end of 2008, except for BP. There is also a volatility cluster at the end of 2010. Similarly, PTR presents high volatility in 2008 and 2009. Table 5 shows the five most recurrent patterns when oil firms are in high and low volatility environments[5].

For the case of XOM, it is observed a slight change in its patterns; although pattern 1,7, 12, 19 and 20 still are the more repetitive (for all oil companies). In 2008, pattern 15 is the fifth most repeated and represents uncertainty or a Doji candlestick. Likewise, in 2010 pattern 6 arises as the fourth most repeated suggesting a reversal bull (hammer). In Table 4 we show the pattern repetition conditioned on its volatility. We observe that XOM represents a cumulative percentage of 62.8% in 2008, 58.8% in 2009, and 61.2% in 2010.

Regarding BP, pattern 8 is the fifth most repeated suggesting a reversion bull trend. Also, in 2009 and 2010 pattern 6 indicate the same behavior; the last to hammers correspond to recoveries in the share price of BP after thundering falls. Jointly, the cumulative percentage for BP is 63.2% in 2008, 60.4% in 2009, and, finally, 62.4% in 2010.

With respect to the RDS patterns in a high volatility environment, they are stable in the sense that they are displayed in the general

5 For the data set of 3772 elements, it is considered a partition of 250 in order to analyze pattern formation each year.

Table 3: Pattern classification

Pattern	Kind of pattern	Kindred candlestick
1	Confirmation	Candlesticks with big bodies
2	Reversion	Shooting star
3	Uncertainty	*Doji*
4	Reversion (strong)	Inverted hammer
5	Reversion	Inverted hammer
6	Reversion	Hammer
7	Confirmation	Candlesticks with ig bodies
8	Reversion	Hammer
9	Trend confirmation (strong)	Candlesticks with big bodies and long lower tails
10	Reversion	Hammer
11	Trend confirmation (strong)	*Marubozu*
12	Uncertainty	Spinning top
13	Confirmation	Candlesticks with big bodies
14	Reversion	Inverted hammer
15	Uncertainty	*Doji*
16	Reversion (strong)	Shooting star
17	Reversion	Shooting star
18	Reversion	Hanging man
19	Confirmation	Candlesticks with big bodies
20	Reversion	Hanging man
21	Confirmation (strong)	Candlesticks with big bodies and long lower tails
22	Reversion	Hanging man
23	Confirmation (strong)	*Marubozu*
24	Uncertainty	Spinning top
25	Pattern 25 is a point; it cannot associate with any candlestick	

Source: Author's own elaboration

Table 4: One-step count of patterns

Oil company	Pattern	Frequency	Cumulative percentage
XOM	1	550	14.58
	7	514	28.21
	19	463	40.48
	13	442	52.20
	20	265	59.23
BP	19	553	14.66
	1	542	29.03
	7	513	42.63
	13	472	55.14
	20	263	62.12
RDS-B	7	553	14.66
	1	542	29.03
	19	538	43.29
	13	396	53.79
	20	289	61.45
PTR	19	615	16.30
	1	573	31.50
	7	469	43.93
	13	346	53.10
	20	275	60.39

Pattern 1 and 7 is a bullish trend confirmation, Pattern 13 and 19 is a bearish trend confirmation, Pattern 20 is a bearish trend reversion. Source: Author's own elaboration. XOM: Exxon Mobil, BP: British Petroleum, RDS-B: Royal Dutch Shell, PTR: PetroChina

sample, except in 2010 when a reversal bull pattern 8 appeared (associated to an uptrend recuperation for the share). The cumulative percentage for the five most repeated patterns are 63.6% in 2008, 61.6% in 2009, and 66% in 2010.

Finally, it is important to point out that the case of PTR is similar to that of RDS with patterns observed in the overall sample for all companies. The difference lies in 2010 when the fifth most repetitive pattern is number 3 and this implies uncertainty or a Doji form. With respect to its cumulative percentage for the five patterns with higher frequency is 63.6% in 2008, 61.6% in 2009, and 64.4% in 2010.

For all the oil companies, on average, the five patterns with more frequency exhibit slightly more than 60% cumulative percentage in high volatility environments. Patterns 1, 7, 12, 19 and 20 remain as the most observed, but hammers (patterns 6 and 7), and Doji's (patterns 3 and 15) appear more regularly. To corroborate that the previous result is not spurious, we analyze the stability of the pattern distribution. Subsequently, we calculate the empiric cumulative distribution function (CDF) for each oil company and perform a test by using Kolmogorov–Smirnov (KS) adapted for discrete variables[6]. For each oil companies we have a group of CDF, and the notation for Exxon Mobil is C_1, for BP is C_2, for Shell is C_3, and PetroChina is C_4. To evaluate the distance among CDF's, we take Exxon Mobil as a benchmark of comparison with the other companies. The selection of Exxon is arbitrary and it has the purpose of observing the difference between each CDF.

Figure 6 shows graphical results of the KS tests. We observe a similar behavior in the distribution of patterns, corroborating the similarity in price behavior and trends of the selected companies.

4.2. Two-Step Conditional Probabilities Counting

We now carry out the two stages counting procedure based on a transition matrix. This allows us to model the probability of occurrence of each of the patterns; since it is already known the frequency for one step counting. In this case, the Markov chain has to two possible states denoted by s1 and s2 and the conditional probability is p_{ij} $(i, j = 1, 2,\ldots 25)$. In consequence, the transition matrix is a 25×25 matrix.

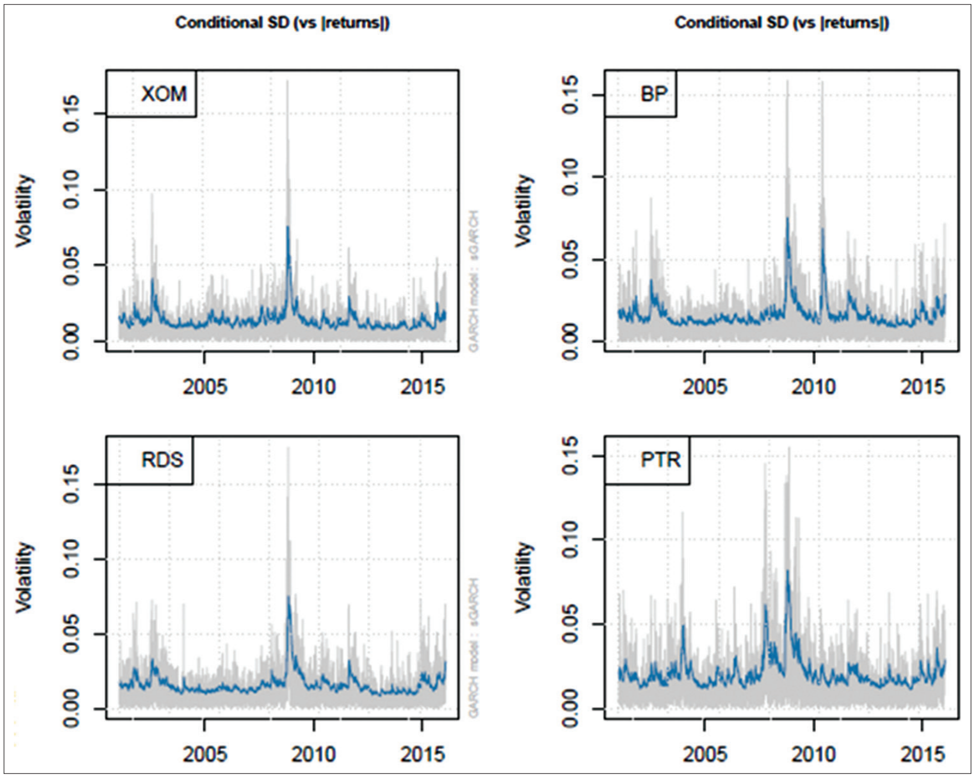
With the two-step counting procedure, the most repeated patterns are presented in Table 6. The whole period is divided into high and low volatile periods (the same periods of Table 5). The results show the probability of occurrence of a pattern *m* given a pattern *n*. Also, Table 6 shows that the most common pair of patterns is 1 given a pattern 13 for XOM for the sample.

Table 6 shows that there is a possibility that a pattern influences another despite its low probability of occurrence. This means that oil prices have "memory." The concept of memory implies persistence in the autocorrelations samples indicating that innovations of such series have temporary effects enduring for long (otherwise all probabilities would be equal zero).

It is remarkable that, besides the memory effect, the two most repeated patterns are consistent with the most frequent one step counting patterns, suggesting that the process can be partially replicated even in high volatility periods since the most

6 For details on this test, Young (1977), Razali and Wah (2011), and Darling (1957).

Figure 5: Conditional standard deviations versus returns for each oil company



Source: Own elaboration based on Ghalanos (2015): Univariate generalized autoregressive conditional heteroskedasticity models (1.3-6) in R programming language

Table 5: More frequently patterns in high volatility periods

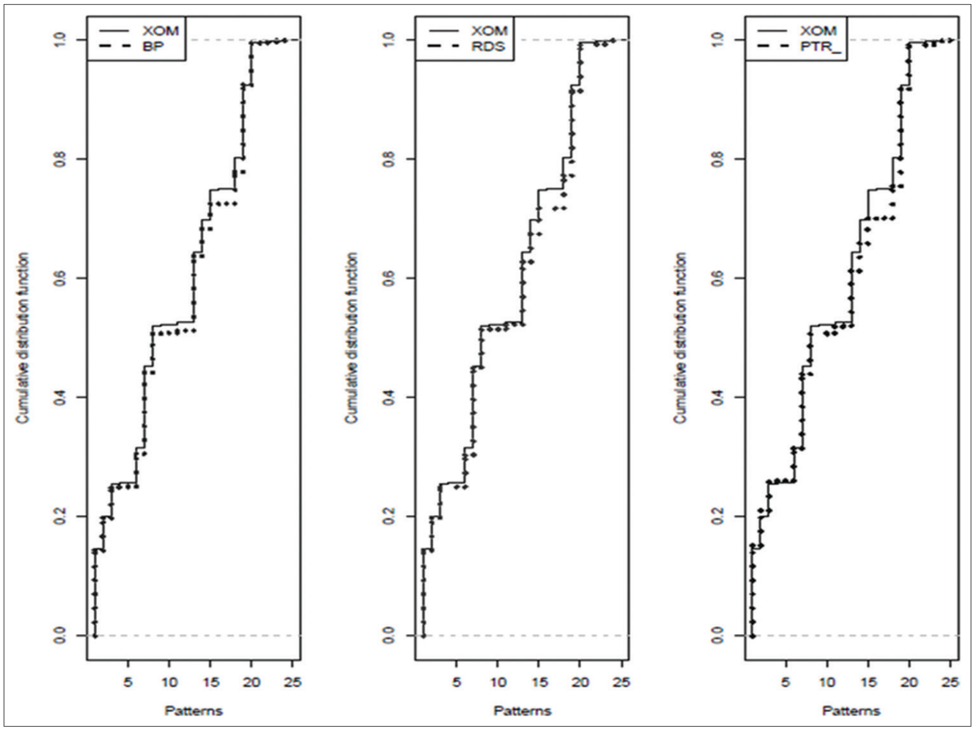
Oil Companies	January 09, 2008 to January 05, 2009			January 06, 2009 to January 04, 2010			January 04, 2010 to January 29, 2010		
	Pattern	Frequency	%	Pattern	Frequency	%	Pattern	Frequency	%
XOM	7	42	17	1	35	14	7	40	16
	1	38	15	13	34	14	1	37	15
	13	35	14	7	31	12	19	31	12
	19	23	9	19	29	12	6	25	10
	15	19	8	20	22	9	13	20	8
BP	19	42	17	1	37	15	1	40	16
	1	32	13	19	36	14	7	37	15
	7	32	13	7	35	14	13	31	12
	13	27	11	6	20	8	19	31	12
	8	25	10	13	20	8	6	17	7
RDS	19	43	17	1	40	16	7	54	22
	1	35	14	7	38	15	1	40	16
	7	33	13	19	34	14	19	35	14
	13	29	12	13	21	8	8	18	7
	20	19	8	20	21	8	20	18	7
PTR	19	43	17	1	40	16	1	50	20
	1	35	14	7	38	15	7	47	19
	7	33	13	19	34	14	19	26	10
	13	29	12	13	21	8	20	20	8
	20	19	8	20	21	8	3	18	7

Source: Own elaboration. XOM: Exxon Mobil, BP: British Petroleum, RDS-B: Royal Dutch Shell, PTR: PetroChina

predominating patterns are still observed (although with a slightly lower accuracy due to uncertainty and reversal patterns that stand out in these environments).

Another interesting fact is that memory is greater in periods of high volatility compared to the whole sample. For example, the sum of the five conditional probabilities for two-step counting more repetitive to XOM in 2008 is 14.46%, in 2009 is 12.45%, in 2010 is 10.84%, whereas for the entire sample is 10.58%, i.e. at high volatility periods there is greater dependence on data. BP has 12.85% in 2008 and 10.04% in 2009, while for the entire sample the sum of probabilities is 9.41%. RDS also presents higher

Figure 6: Kolmogorov–Smirnov test for empiric cumulative distribution function



Source: Own elaboration based on R Core Team (2013) and R Statistical Package (3.3.0)

Table 6: Two steps pattern transition probabilities matrix in high volatility periods

Oil companies	2008-2009		2009-2010		2010-2010		Full sample	
	P	Pr %	P	Pr %	P	Pr %	P	Pr %
XOM	7, 13	3.61	1, 13	2.81	7, 13	2.81	1, 13	2.36
	1, 7	2.81	7, 13	2.41	1, 19	2.01	19, 1	2.31
	1, 13	2.81	7, 19	2.41	6, 20	2.01	1, 1	2.04
	7, 1	2.81	13, 18	2.41	7, 6	2.01	7, 19	1.96
	13, 13	2.41	13, 19	2.41	7, 7	2.01	7, 1	1.91
BP	1, 7	2.41	1, 7	2.81	1, 7	1.61	1, 7	1.78
	1, 19	2.41	1, 19	2.41	1, 19	1.61	1, 19	2.15
	7, 1	2.41	7, 1	1.61	7, 1	2.41	7, 1	1.91
	7, 19	2.41	7, 19	2.41	7, 19	1.20	7, 19	1.91
	13, 7	3.21	13, 7	0.80	13, 7	0.40	13, 7	1.67
RDS	1, 1	4.02	1, 1	2.81	1, 1	3.61	1, 1	2.60
	1, 19	2.01	1, 19	3.21	1, 19	4.42	1, 19	2.07
	6, 13	2.01	6, 13	0.80	6, 13	0.40	6, 13	0.66
	13, 7	2.01	13, 7	0.40	13, 7	0.00	13, 7	1.51
	13, 19	4.02	13, 19	2.01	13, 19	1.61	13, 19	1.62
PTR	1, 7	2.81	1, 7	2.81	1, 7	3.21	1, 7	1.99
	1, 19	3.21	1, 19	2.01	1, 19	0.80	1, 19	2.33
	7, 1	3.21	7, 1	2.41	7, 1	1.61	7, 1	1.75
	7, 7	2.81	7, 7	0.40	7, 7	0.80	7, 7	1.27
	7, 19	2.81	7, 19	2.81	7, 19	3.21	7, 19	2.52

Source: Own elaboration. P: Pattern *m* conditional to pattern *n*, Pr: Probability, XOM: Exxon Mobil, BP: British Petroleum, RDS-B: Royal Dutch Shell, PTR: PetroChina

probabilities in 2008, 2009 and 2010 with 14.06%, 9.24%, and 10.04% respectively. Also, RDS has more memory in 2008 since the sum of probabilities is 14.86% for the first five conditional patterns, 10.44% in 2009 and 9.64% in 2010, whereas for the whole sample the sum of probabilities is 9.86%.

To examine if there is a dependence structure among the two-step transition matrix, we use a nonparametric medial correlation coefficient, also known as Blomqvist's beta. According to Blomqvist's (1950), beta is calculated by means of:

$$\beta_{X,Y} = \Pr\left[\left(X-\tilde{x}\right)\left(Y-\tilde{y}\right)>0\right]-\Pr\left[\left(X-\tilde{x}\right)\left(Y-\tilde{y}\right)<0\right]$$

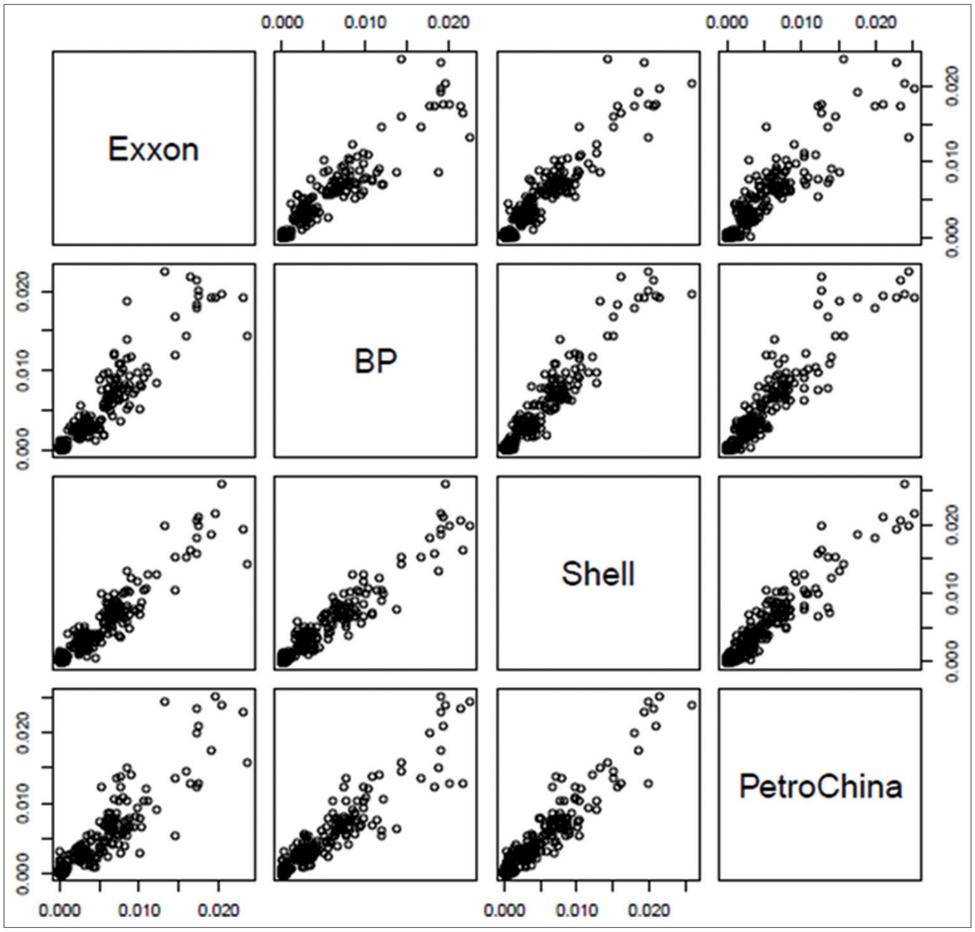
Where, X and Y stand for continuous random variables with medians $\tilde{x}$ and $\tilde{y}$. For a multivariate version of Blomqvist's beta, following Úbeda (2005) notation, suppose H as continuous n-variate distribution and let X have distribution H. If, $\beta_{n,H} = 1$, then there exists perfect positive dependence. Table 7 shows the Blomqvist's beta associated to each two steps pattern based on a transition matrix.

It is noteworthy mentioning that the positive medial correlation among prices of the analyzed oil companies. Finally, to corroborate this result, we use a scatter plot for the probabilities transition matrix in Figure 7.

5. CONCLUSIONS

The main purpose of this study has been to identify patterns and their persistency in selected oil companies, Exxon Mobil, British Petroleum, Royal Dutch Shell and China Petroleum Sinopec, in the period from January 20, 2001 to January 20, 2016, with a total of 3772 daily observations. To achieve this, we transform the daily market prices into a set of discrete variables that represents Japanese candlesticks. After that, we proved that the selected stock prices exhibit a common behavior along the sample, we also demonstrate in the one-step analysis that there are common patterns even when there is a volatile environment. In such analysis, we showed that there are five common patterns

Figure 7: Scatterplot for the two-steps transition matrix probabilities



Source: Own elaboration based on R Core Team (2013): The R Stats Package. R package version 3.3.0

Table 7: Blomqvist's beta for two-steps patterns probabilities

Blomqvist β	XOM	BP	RDS	PTR
XOM	1	1	1	1
BP	1	1	1	1
RDS	1	1	1	1
PTR	1	1	1	1

Source: Own elaboration. XOM: Exxon Mobil, BP: British Petroleum, RDS-B: Royal Dutch Shell, PTR: PetroChina

(1, 7, 19, 13 and 20) that represent near of the 61% of the sample for all the selected companies.

We use a set of KS test to show that all the oil companies share common patterns even when there is a volatile environment. To make this comparison easier, we used the distribution of Exxon Mobil (XOM) as a reference to compare all the rest of the selected companies. Under this procedure, we showed that there is not a statistically significative difference between the pattern distribution of all the companies.

With the purpose of corraborating the dependence and common trend for all the selected companies, we also include a Blomqvist beta analysis to check the medial correlation between their patterns. This analysis showed that there are significant medial correlation dependence and common trends among them. We want to emphasize that dependence measurement is free of distributional assumptions and does not depend on the selected threshold to measure the dependence.

The previous results are important because they give significative empirical evidence of the common behavior of all the companies, suggesting that a big part of their stock price behavior are industry related and that this characteristic remains untouched even in the presence of high volatility. The causes of the departures from this behavior seem related to idiosyncratic reasons.

To make a deeper analysis of the dependence structure, we include the probabilities of a two-steps process for each selected oil company. To simplify the analysis and make it comparable to the previous section, we transform the outcomes of a two-step transition matrix of 25 possible outcomes on each step into an artificial one-step process with 25^2 possible outcomes. In this case, there is a probability that a pattern influences another, this means that oil companies prices have "memory." In addition to this, it is important to highlight how conditional patterns or two-step patterns are similar to the most repeated at one-step counting. These results provide more empirical evidence of non-independent distributions.

Finally, we performed the Blomkvist's beta analysis for the transformed two-step patterns and obtained similar results of strong dependence than those obtained in the one-step analysis. This is a piece of empirical evidence of the joint structure of the stock prices in the oil industry. All the analysis performed allows us to prove our hypothesis of industry-driven and non-independent prices in the main companies of the oil industry around the world.

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