

Do Japanese Candlesticks help solving the trader's dilemma?

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Abstract

In this paper we investigate whether Japanese candlesticks influence the transaction costs of sequences of orders and whether they can help traders with their decision of timing or not. Based on fixed-effect panel regressions on a sample of 81 European stocks, we show that market timing costs are not lower when Hammer-like and Doji configurations occur, indicating that they fail to predict future short-term return. However, market impact costs are much more lower when and after a Doji structure has occurred, suggesting that market members may benefit from candlesticks to solve the trader's dilemma. We further check the potential gains through order submission simulations and find that a submission strategy based on the occurrence of Dojis significantly results in much lower market impact cost than a random submission strategy.

JEL Classification: G14, G10

Key Words: Candlesticks, Transaction costs, Market timing, Market impact

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1 Introduction

Transaction costs management has always been a major concern for the implementation of trading decisions. There are different components in what we consider as transaction costs which are usually divided into two categories, i.e. explicit and implicit costs. Explicit costs, which can be determined before the execution of the trade, refer to brokerage commissions, market fees, clearing costs, settlement costs and taxes. Implicit costs, which represent the invisible part of transaction costs that cannot be measured ex ante, consist of bid-ask spread, market impact and opportunity costs.¹ Bid-ask spread is a compensation for the supply of liquidity. Market impact is the cost incurred for consuming more than the liquidity available at the best opposite quote (BOQ hereafter). Opportunity costs are due to the price movement that takes place between the trade decision and the trade itself.

The main challenge when implementing trade decisions resides in the impossibility to reduce all costs components simultaneously. The most tricky issue is linked to the so-called trader's dilemma. When they place market orders, traders have always to decide whether they should split their orders, to reduce market impact, or submit them in full and probably incur the cost of drying out quantities outstanding at the BOQ. When they split an order, market members are however exposed to a potential adverse price evolution that may hinder their performance, i.e. market timing opportunity cost. For instance, if a trader wants to buy a big quantity, and therefore decide to split the order, and the price rises the next day, the price appreciation will significantly affect the execution of the order.

¹Opportunity costs are made of three different components: operational opportunity costs, market timing opportunity costs and missed trade opportunity costs. Operational opportunity costs arise when the delay required to trade is operational, the second component is due to the market timing under the control of the broker and the missed trade opportunity costs occur when the trader is not able to fully fill his order.

One can wonder whether it is possible to solve the transaction costs' dilemma. In this
1 paper, we investigate whether Japanese candlesticks may help to answer the question:
2 should the order be split or not. Japanese candlesticks are an Eastern charting technique
3 that is in essence very similar to bar charts. Candlestick charts give market participants
4 a quick snapshot of buying and selling pressures, as well as turning points. There are
5 many reasons that may indicate that candlesticks are related to transaction costs. First,
6 as outlined by Kavajecz and Odders-White (2004), price dynamics, easily characterized
7 by candlesticks, are expected to be related to modifications in the state of the limit or-
8 der book and to the supply of liquidity. Transactions costs evolution is directly opposed
9 to liquidity evolution: market impact rises (drops) rapidly for liquidity is low (high).
10 Wang et al. (2012) also outline that order submission behaviors were related to tech-
11 nical analysis in the Taiwan Stock Exchange. They also argue on causality indicating
12 that technical analysis drives changes in order submission behaviors. Second, Mazza
13 (2012) finds that liquidity is higher when some particular candlestick structures occur,
14 indicating that a relationship does exist between limit order book variables and price
15 movements. Third, according to the literature on Japanese candlestick, some structures
16 may help to forecast future prices, which determines market timing cost. This argument
17 stands directly against the efficient market hypothesis of Fama (1970) and should not be
18 verified. In this paper, we restrict our analysis to Doji and Hammer-like configurations
19 which are described in the following sections.

Using market data on a sample of European stocks of three national indexes, we study
20 sequences of orders and estimate fixed-effects panel regression models including market
21 impact or market timing opportunity costs of these sequences as dependant variable and
22 dummies variables for the occurrence of candlestick structures as well as a set of control
23 variables. We establish different types of relationships with contemporaneous and lagged

1 signals in order to check whether it is possible to benefit from a potential signal after its
2 apparition. In a second step, in order to further assess whether candlesticks are useful or
3 not in this regard, we compare the market impact cost of an average quantity submitted
4 after the apparition of a signal to the market impact cost of the same quantity submitted
5 randomly along the day.

Our results suggest that market impact is lower at the time and after a Doji has
6 appeared. There are no impacts for Hammer-like configurations. Market timing cost is
7 not lower when these structures occur. The latter cost being determined by the price
8 movement, this finding questions the usefulness of candlesticks in predicting future stock
9 prices and contributes to previous literature on the efficient market hypothesis and the
10 performance of trading rules based on Japanese candlesticks. The order processing
11 simulation also shows that transaction costs are lower when the order is fully submitted
12 at the time of a signal. It seems that candlesticks partly help market members in their
13 attempts to solve the transaction costs' dilemma by identifying the right moment for
14 submitting aggressive orders.

The remainder of the paper is organized as follows. Section 2 provides a descrip-
15 tion of Japanese candlesticks. Section 3 describes the dataset. Section 4 presents the
16 methodology that we apply and section 5 reports the results. The final section concludes.

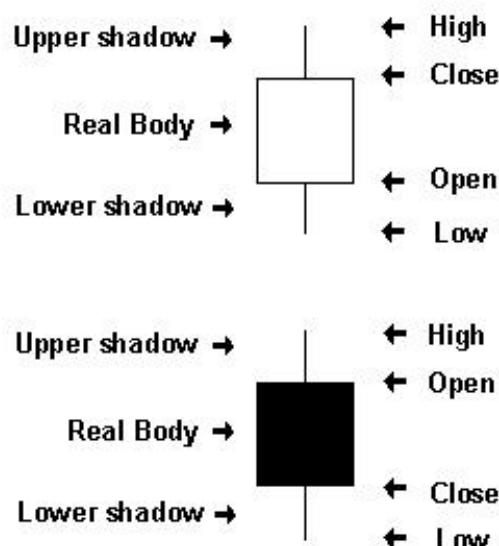
17 **2 Japanese Candlesticks**

18 Japanese candlesticks are a technical analysis charting technique based on High-Low-
19 Open-Close prices.² They are similar to bar charts but they are easier to interpret.

²Even if Japanese candlesticks have been used for centuries in eastern countries, Steve Nison was the first to bring this method to the west in the nineties. Japanese candlesticks have been first used by Munehisa Homma who traded in the rice market during the seventeenth century. The original names

1 The body is indeed black for negative days (yin day) and white for positive days (yang
 2 day). Bar charts do not contain this information. The formation process of candlesticks
 3 appears in figure 1. There exist plenty of structures, formed by one to five candles,
 4 depending on the length of the shadows and the size and color of the bodies. These
 5 candlesticks emphasize what happened in the market at that particular moment. Each
 6 configuration can be translated into traders' behaviors through price dynamics implied
 7 by buying and selling pressures.

Figure 1: Candlestick formation process



Japanese candlesticks are interesting because they summarize a lot of information in
 8 one single chart: the closing price, the opening price as well as the lowest and highest
 9 prices. With the raising interest in high frequency trading and the narrowing of trading
 10 intervals, they have been increasingly used by practitioners to capture short term price
 of the candlestick structures come from the war atmosphere reigning in Japan at that time. At the
 beginning, there were only basic structures from one to three candles but more complex configurations
 have been identified since then. The predictive power of these configurations is still discussed. Nison
 (1991), Nison (1994), Morris (1995) and Bigalow (2001) are the best known and used handbooks of
 candlestick charting.

1 dynamics. Papers addressing candlesticks enter in the "stock return predictability"
2 category. For example, Marshall et al. (2006) and Marshall et al. (2008) find no evidence
3 that candlesticks have predictive value for the Dow Jones Industrial Average stocks and
4 for the Japanese equity market, respectively. They replicate daily data with a bootstrap
5 methodology similar to the one used in Brock et al. (1992). However, intraday data
6 is more relevant as traders do not typically wait for the closing of the day to place an
7 order. Nevertheless, using intraday candlesticks charts on two future contracts (the DAX
8 stock index contract and the Bund interest rate future), Fock et al. (2005) still find no
9 evidence which suggests that candlesticks, alone or in combination with other methods,
10 have a predictive ability. However, none of these papers looks at the relationships
11 between candlestick configurations and the transaction costs of trade sequences. To
12 our knowledge, this paper is the first research study that investigates the information
13 content of HLOC price movements for execution purposes.

In this paper, we investigate two categories of candlesticks structures. The first
14 one is the Doji category. The Doji is one of the core structures of the literature on
15 Japanese candlesticks. A Doji appears when the closing price is (almost) equal to the
16 opening price. Candlestick books³ refer to it as *the magic Doji*. We observe different
17 types of Dojis.⁴ The most frequent Doji is a "plus", i.e. no real body and almost equal
18 shadows. If both closing and opening prices are also the highest price of the interval, the
19 Doji becomes a Dragonfly Doji. By contrast, it becomes a Gravestone Doji when both
20 closing and opening prices are equal to the lowest price of the interval. In essence, the
21 Doji is not an indicator of price reversal: it only helps to detect the end of the current
22 trend. Our signals are based on these three Doji structures, i.e. traditional, Dragonfly
23 and Gravestone, and are disentangled in bullish and bearish signals: the Doji is bullish

³Nison (1991), Nison (1994) and Morris (1995).

⁴A description of the presented structures is available in appendix.

1 (bearish) when the previous candle is black (white) and the next candle is white (black).
2 If these structures are able to forecast future short-term return, bullish (bearish) signals
3 should result in higher (lower) market timing cost when the trader buys. The opposite
4 should also be verified for sales.

The second category contains Hammer-like configurations. Among Hammer-like
5 structures, there are four structures that are characterized by a long shadow and a
6 small real body.⁵ The Hammer appears at the end of a downtrend and is made of a
7 very small real body with (almost) no upper shadow and a very long lower shadow. The
8 same structure may appear at the end of an uptrend but, in that case, it is called a
9 Hanging Man. Inverting the shadows, i.e. the upper shadow becomes the lower shadow
10 and vice-versa, we obtain an Inverted Hammer at the end of a downtrend or a Shooting
11 Star at the end of an uptrend. As these figures are said to be strong reversal structures
12 in the Japanese Candlesticks literature, they should have an influence on market timing
13 cost, if EMH does not hold: for purchases (sales), Hammer and Inverted Hammer should
14 lead to higher (lower) market timing cost, while Hanging Man and Shooting star should
15 lead to lower (higher) market timing cost.

As outlined by Duvinage et al. (2012) and Marshall et al. (2006), candlestick-based
16 strategies fail to beat a Buy-and-Hold strategy and therefore are not able to help predict-
17 ing future short-term returns, confirming EMH. As a result, we do not expect market
18 timing to be improved around the occurrence of these structures. However, as out-
19 lined by Mazza (2012) and Kavajecz and Odders-White (2004), technical analysis and
20 Japanese Candlesticks in particular are related to higher liquidity in the limit order
21 book and therefore should be related to lower transaction costs, among which market
22 impact costs.

⁵A description of the presented structures is available in appendix.

1 **3 Data**

2 **3.1 Sample**

3 We use Euronext market data on 81 stocks belonging to three national indexes: BEL20,
4 AEX or CAC40. We have tick-by-tick data for 61 trading days from February 1, 2006
5 to April 30, 2006, including information on hidden orders and market members' ID.

We have rebuilt High-Low-Open-Close prices from this database for the 81 stocks
6 over the whole sample period. As tick data are not adapted for candlestick analysis, we
7 build 15-minute-intervals which leads to 34 intervals a day. This interval length is the
8 best trade-off which allows to include intraday trends and to avoid noisy candlesticks
9 patterns resulting from non-trading intervals. We use the HLOC prices calculated above
10 in order to identify candlestick configurations based on TA-Lib.⁶ We obtain a total of
11 167068 records (81 firms, 61 days, 34 intervals/day). From this dataset, we remove 'Four
12 Prices Dojis' because they are associated with non-trading patterns.⁷

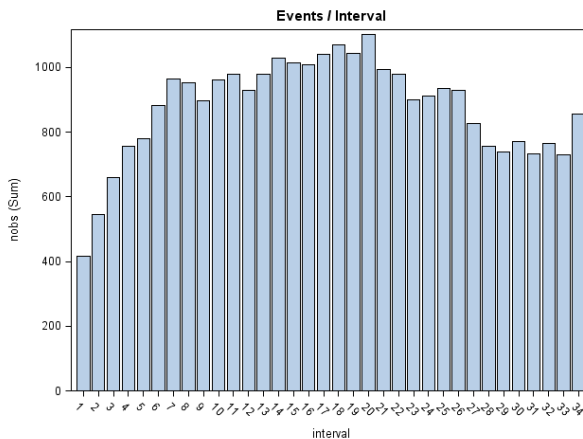
We look at the occurrences of the identified structures and check whether Dojis
13 appear at a particular moment during the day. Figure 2 shows that the distribution of
14 Dojis is roughly uniform with the most significant peaks occurring during lunch time
15 and maybe resulting from non-trading. Dojis also seem to not occur frequently during
16 the first two intervals of the day. This may be explained by the strong unidirectional

⁶The TA-lib library is compatible with the MATLAB Software. For each type of configuration and for each record, it returns "1" if the bullish part of the structure is identified, "-1" for the bearish part and "0" otherwise. As the structures are bullish, bearish or both, for each event type, the values that may appear are [0 ; 1], [-1 ; 0] or [-1 ; 0 ; 1]. The TA-lib allows some flexibility in the recognition of the configurations. As it is an open source library, we have been able to check the parametrization of the structures. The structures are recognized according to the standard flexibility rules presented in Nison (1991) and Morris (1995). The TA-lib contains 61 pre-programmed structures.

⁷A Four Prices Doji occurs when all the prices are equal. When they occur in daily, weekly or monthly charts, they are a strong clue of a potential reversal. However, in intraday price charts, they represent non-trading intervals.

1 movement that appears at that moment, as trends are at their very beginning. This
 2 should not influence our results. Table 3.1 presents the number of each structure which
 3 is identified in our dataset through the TA-lib.

Figure 2: Dojis by Interval



1 3.2 Sequences of trades

2 Building on Chan and Lakonishok (1995), we treat entire sequences of orders that we
3 define ex post as the basic units of analysis. However, our purposes and our methodology
4 differ. While Chan and Lakonishok (1995) try to capture ex post the trading intention
5 of institutional funds⁸, we try to capture ex post the market timing intention of traders,
6 that is their strategy of breaking up large orders into smaller ones in order to avoid large
7 market impact costs and/or to avoid revealing too much information to the market.

We make the following assumptions when building our sequences: firstly, we only
8 consider principal orders so that, in a given sequence, every order is submitted by the
9 same market member for his own account. Secondly, we do not consider orders that
10 provide liquidity because they do not generate transaction costs. Lastly, the maximum
11 duration of a sequence is one day.

Then, we use the market member identity code⁹ to construct the sequences of orders
12 for each stock. For a given market member, a sequence is initiated with a first mar-
13 ketable order and cumulates the following marketable orders in the same direction. The
14 sequence stops when the market member submits a passive order,¹⁰ when he changes
15 order direction, or simply at the end of the continuous session.

Finally, In order to match our sequences with candlestick's intervals, we divide our
16 sequences into 15 minutes intervals and allocate them among the existing 15 minutes
17 intervals of the day. Cross-sectional descriptive statistics on sequences are provided in
18 Table 2

⁸See Chan and Lakonishok (1995) for more details.

⁹Actually, these ID codes are numerical in order to ensure market members' anonymity but allow us to isolate the whole set of orders or trades associated with a given member from the other orders and trades in the sample.

¹⁰By passive order we mean an order that is neither a market order nor a marketable limit order.

Table 2: Sequences - Descriptive Statistics

CAC40	Mean	Median	Maximum	Minimum	Standard Deviation
Duration	00:04:23	00:02:49	00:15:00	00:00:01	00:04:20
Volume	203191	96391	14234329	23	362943
N	3.45	3.00	428.00	2.00	3.25
AEX					
Duration	00:04:26	00:02:51	00:15:00	00:00:01	00:04:23
Volume	192262	95249	30830446	31	337990
N	3.30	2.00	121.00	2.00	2.47
BEL20					
Duration	00:06:19	00:05:19	00:15:00	00:00:01	00:04:59
Volume	88801	52762	6460514	41	140701
N	3.44	2.00	100.00	2.00	4.64

Cross-sectional statistics on the sequences are reported for the whole sample regarding their exchange. N refers to the sequence's number of orders. Volume is the sequence's volume expressed in currency units. Duration refers to the execution period of time of the sequences.

1 3.3 Transaction costs measures

2 The market impact of an order i is computed as the signed difference between the
3 average execution price (AEP_i) and the BOQ prevailing at the order i submission's
4 time (BOQ_i), expressed in percentage of the BOQ:

$$MI_i^{buy} = \frac{(AEP_i - BOQ_i)}{BOQ_i} * 100 \quad (3.1)$$

5

$$MI_i^{sell} = \frac{(BOQ_i - AEP_i)}{BOQ_i} * 100 \quad (3.2)$$

6 The market impact of a sequence j of n orders is expressed in percentage of the total
7 amount that the investor would pay without any transaction costs, i.e. the amount if
8 the entire volume of the sequence executes at the BOQ prevailing at the beginning of
9 the sequence (BOQ_1). Practically, for a sequence j of n orders, we compute the sum of
10 the market impact of the n orders in EUR that we divide by the total quantity executed

1 in the sequence j multiplied by the BOQ prevailing at the submission of the first order
 2 (BOQ_1).

$$MI_j^{buy/sell} = \frac{\sum_{i=1}^n Q_i * BOQ_i * MI_i}{\sum_{i=1}^n Q_i * BOQ_1} * 100 \quad (3.3)$$

Let's assume a sequence that is made of two buy orders of 100 units respectively.
 3 The BOQ at the submission time of the first order is equal to 84.5 and its AEP is equal
 4 to 84.75. The BOQ at the submission time of the second order is equal to 85 and its
 5 AEP paid is equal to 85.25. The market impact of the first order and the second order
 6 are equal to 0.295% and 0.294% respectively. The market impact of the entire sequence
 7 is equal to:

$$MI = \frac{(100 * 0.295\% * 84.5) + (100 * 0.294\% * 85)}{(200 * 84.5)} = 0.2954\% \quad (3.4)$$

The market timing of an order i is computed as the difference between the BOQ_i
 8 prevailing just before the submission of the order and the BOQ_1 prevailing at the sub-
 9 mission of the first order of the sequence. It is expressed as a percentage of the BOQ_1 .

$$MT_i^{buy} = \frac{(BOQ_i - BOQ_1)}{BOQ_1} * 100 \quad (3.5)$$

10

$$MT_i^{sell} = \frac{(BOQ_1 - BOQ_i)}{BOQ_1} * 100 \quad (3.6)$$

The market timing of a sequence j of n orders is then expressed in percentage of
 11 the total amount the investor pays if the entire volume of the sequence executes at the
 12 BOQ_1 prevailing at the beginning of the sequence. Practically, for a sequence j of n
 13 orders, we compute the sum of the market timing cost of the n orders in EUR and

1 we divide it by the total quantity executed in the sequence j multiplied by the BOQ_1
 2 prevailing at the submission of the first order.

$$MT_j^{buy/sell} = \frac{\sum_{i=2}^n MT_i * Q_i * BOQ_1}{\sum_{i=1}^n Q_i * BOQ_1} * 100 = \frac{\sum_{i=2}^n MT_i * Q_i}{\sum_{i=1}^n Q_i} * 100 \quad (3.7)$$

In the example mentioned above, the market timing cost of the second order is equal
 3 to 85 minus 84.5 divided by 84.5 (0.5917%). And the market timing cost of the entire
 4 sequence is equal to:

$$MT = \frac{0.5917\% * 100}{200} = 0.2958\% \quad (3.8)$$

5 **4 Methodology**

6 **4.1 Panel regressions**

7 We test the impact of candlestick structures on both market timing and market impact
 8 transaction costs components through different fixed-effects panel regression models in
 9 order to control for stock's effect. The robustness of standard errors is a major concern
 10 in panel regressions. Based on Petersen (2009), we apply the clustering approach that
 11 makes standard errors heteroscedasticity-consistent. As outlined by Petersen (2009),
 12 this method produces unbiased standard errors when a firm effect does exist, as opposed
 13 to White, Newey-West, and Fama-MacBeth correction methods. Clusters are used to
 14 control for common factors in the fixed effects. For instance, macroeconomic news may
 15 evenly affect all the stocks that are present in an index. Omitting to control for common
 16 factors may lead to potential biases.

In our fixed-effect panel regression model, transaction costs are the dependent vari-

1 able. We establish different regressions for the two components that we investigate, i.e.
2 market timing and market impact. We include dummy variables for each of the four
3 candlestick structures, i.e. Hammer (H), Inverted Hammer (IH), Hanging Man (HM)
4 and Shooting Star (SS). These dummies are equal to 1 when the structure has been
5 detected and 0 otherwise. We also include some control variables. We first include the
6 number of orders ($Orders$) of the sequence, its duration ($Duration$) as well as its vol-
7 ume (V). We then control for the state of liquidity at the beginning of the sequence by
8 including the depth ($Depth$), and the relative spread, (RS). The ($Depth$) proxy sums
9 the quantities outstanding at the five best opposite quotes, i.e. $Depth = \sum_{i=1}^5 QB_i$, in
10 case of sell orders and $Depth = \sum_{i=1}^5 QA_i$, in case of buy orders, where QB_i and QA_i
11 are respectively the bid and ask quantities outstanding at the limit i .

12 The model that we estimate is specified as follows:

$$M_{i,s,t}^{buy} = \alpha_0 + \alpha_1 Orders_s + \alpha_2 Duration_s + \alpha_3 V_s + \alpha_4 Depth_s \\ + \alpha_5 RS_s + \alpha_6 H_{i,t} + \alpha_7 IH_{i,t} + \alpha_8 HM_{i,t} + \alpha_9 SS_{i,t} + \nu_s,$$

13 where $M_{i,s,t}^{buy}$ is the transaction cost component, measured for the buying sequence s
14 that begins during interval t for stock i , that can be either market impact or market
15 timing.

The effect estimated in this regression is contemporaneous. We also conduct a similar
15 regression with lagged signals, i.e. the dummy identification variables H , IH , HM and
16 SS are lagged once:

$$M_{i,s,t}^{buy} = \alpha_0 + \alpha_1 Orders_s + \alpha_2 Duration_s + \alpha_3 V_s + \alpha_4 Depth_s \\ + \alpha_5 RS_s + \alpha_6 H_{i,t-1} + \alpha_7 IH_{i,t-1} + \alpha_8 HM_{i,t-1} + \alpha_9 SS_{i,t-1} + \nu_s,$$

We conduct this regression in order to assess whether we can effectively base a
 1 strategy on the apparition of the signal once it has fully appeared.

We apply the same methodology to Doji configurations, separately for all types Dojis
 2 (D) and Dragonfly (DF) and Gravestone (GR) Dojis. However, for market timing
 3 cost, we need to know which evolution of future prices the signal should lead to. We
 4 disentangle bullish and bearish Dojis by investigating the previous trend, i.e. if the
 5 previous trend is negative (positive), the Doji is a bullish (bearish) signal. This process
 6 is only applicable to market timing costs as market impact is not affected by future
 7 price movements. The models are specified as follows:

$$MI_{i,s,t}^{buy} = \alpha_0 + \alpha_1 Orders_s + \alpha_2 Duration_s + \alpha_3 V_s + \alpha_4 Depth_s \\ + \alpha_5 RS_s + \alpha_7 D_{i,t} + \nu_s,$$

$$MI_{i,s,t}^{buy} = \alpha_0 + \alpha_1 Orders_s + \alpha_2 Duration_s + \alpha_3 V_s + \alpha_4 Depth_s \\ + \alpha_5 RS_s + \alpha_6 DF_{i,t} + \alpha_7 GR_{i,t} + \nu_s,$$

for contemporaneous effects on market impact. We apply a similar process for lagged
 8 signals and:

$$MT_{i,s,t}^{buy} = \alpha_0 + \alpha_1 Orders_s + \alpha_2 Duration_s + \alpha_3 V_s + \alpha_4 Depth_s \\ + \alpha_5 RS_s + \alpha_6 Dbull_{i,t} + \alpha_7 Dbear_{i,t} + \nu_s,$$

$$MT_{i,s,t}^{buy} = \alpha_0 + \alpha_1 Orders_s + \alpha_2 Duration_s + \alpha_3 V_s + \alpha_4 Depth_s \\ + \alpha_5 RS_s + \alpha_6 DFbull_{i,t} + \alpha_7 DFbear_{i,t} + \alpha_8 GRbull_{i,t} + \alpha_9 GRbear_{i,t} + \nu_s,$$

where $Dbull_{i,t}$ is a dummy variable indicating the presence of a bullish Doji and
1 $Dbear_{i,t}$, the presence of a bearish Doji. A similar process is applied to Dragonfly Dojis
2 ($DFbull_{i,t}$ and $DFbear_{i,t}$) and Gravestone Dojis ($GRbull_{i,t}$ and $GRbear_{i,t}$). The same
3 regression specification is also implemented for lagged signals.

We expect market impact to be lower when one of these structures occur, implying
4 a negative sign for the dummy variables. This comes from a higher liquidity supply in
5 the order book around technical signals, as outlined by Mazza (2012) or Kavajecz and
6 Odders-White (2004). If the signal is also an indicator of future price movements, which
7 is directly struggling EMH, dummy variables associated with future prices drops decrease
8 (increase) market timing costs of buy (sell) sequences. An opposite process should
9 apply for signals of positive future prices evolution, if EMH stands. As the performance
10 of candlesticks in predicting returns has been seriously tackled in the literature, e.g.
11 Duvinage et al. (2012) and Marshall et al. (2006), we do not expect any significance for
12 market timing regressions.

Orders and *Duration* should be negatively correlated with market impact and posi-
13 tively correlated with market timing. Splitting orders over a long time logically reduces
14 market impact while increasing market timing. The volume of the sequence, V , should
15 be positively correlated with all the costs. Liquidity as measured by *depth* and *RS*
16 should be negatively related to transaction costs. Therefore, we expect *depth* to be
17 negatively related to market impact and *RS* positively related to this cost. The effect
18 should be less significant for market timing as, because of the order splitting, liquidity
19 is less important.

1 4.2 Order processing simulation

2 In order to verify whether a trader may benefit from the potential changes in transaction
3 costs for existing sequences, we simulate order processing and compare a strategy based
4 on candlesticks to a random strategy.

The candlestick-based strategy consists in placing a quantity Q , equal to the mean
5 of the sizes of the sequences for this security over the whole sample, each time a signal
6 occurs. The philosophy behind this strategy is that candlesticks have an informational
7 content towards liquidity and therefore should result in a lower market impact. Then,
8 the market impact is computed by averaging all days for each stock separately. If there
9 are $n_{d,i}$ signals occurring on the same day d for security i , $n_{d,i}$ orders are submitted just
10 after total apparition of the structures. This enables us to check the profitability of a
11 trader who waits for the end of the signal.

The random strategy consists in randomly submitting $n_{d,i}$ orders separately for each
12 day and stock. The strategy is based on a random submission of the same number of
13 orders with an equal quantity. The only thing that differs between the two strategies is
14 the time of the order submission. The market impact is then computed for each trade
15 and averaged in the same way as for the candlesticks-based strategy.

In order to have results robust to chance, we replicate the sample selection in the
16 random strategy 500 times, i.e. for each day d and each stock i , we create 500 random
17 samples of size $n_{d,i}$. We calculate the market impact for each replication and compare
18 this cost to the original strategy. We then count the number of times the replications
19 beat the strategy and compute a p-value. If more than 95% of the replicated samples
20 fail to have a lower cost than the original strategy, then the strategy yields significantly
21 better results than random simulations.

1 5 Results

2 5.1 Panel regressions

3 Table 3 to 7 present the results of the fixed-effects panel regression models by cluster of
4 firms. First of all, the control variables behavior is consistent with our intuitions for all
5 models, for both lagged and contemporaneous effects. The market impact cost is lower
6 when *Orders* and *duration* increase with a less significant effect for the latter as the main
7 evolution is captured through the *Orders* variable. Market timing presents opposite
8 results, as expected. *V* exhibits strongly significant positive parameters indicating an
9 evolution in the same direction as transactions costs. *Depth*'s negative effect is strongly
10 significant, even for market timing costs. A possible explanation is that traders execute
11 more volume against the depth available at the start of the sequence and are therefore
12 less exposed to the market timing cost. The *RS* variable is strongly significant for market
13 impact and show different results for market timing for both purchases and sales models.
14 It seems that the spread negatively affects market timing cost only for sales. The result
15 is very significant. A wide spread, as outlined by Glosten and Milgrom (1985), through
16 a large adverse selection component, could reveal the presence of informed trading from
17 buyers and explain the occurrence of price movements in favor of the market timing
18 cost.

As expected, Table 3 shows that EMH holds and that market timing costs (Panel
19 C and D) may not be better managed by looking at Hammer-like structures, whatever
20 for contemporaneous or lagged signals. Some parameters are significant but exhibit
21 the opposite sign. To refute the hypothesis that candlesticks may help predict returns,
22 Hammer and Inverted Hammer should exhibit positive (negative) signs for purchases
23 (sales) while Hanging Man and Shooting Star should exhibit positive (negative) signs for

1 sales (purchases). The strong differences between the parameters and their significance
2 indicate that we may not base a market timing strategy on these signals. Panel A
3 and B also show that market impact results are consistent with Mazza (2012) who
4 outlines a relationship between liquidity and the occurrence of Hammer and Hanging
5 Man configurations. We however observe that this relationship is only valid for purchases
6 as parameters for sales models do not present any significance. The effect seem to be
7 very short-lived as lagged models display less significant results.

Table 3: Market Impact and Market Timing - Hammer-like configurations

<i>Model</i>	<i>Orders</i>	<i>Duration</i>	<i>V</i>	<i>Depth</i>	<i>RS</i>	<i>H</i>	<i>IH</i>	<i>HM</i>	<i>SH</i>
Panel A : Market Impact - Purchases									
<i>t</i>	-0.006***	-0.001*	0.007***	-0.001***	1.176***	-0.038***	-0.019	-0.049***	0.037
<i>t - 1</i>	-0.006***	-0.001**	0.007***	-0.001***	1.175***	-0.040**	0.005	-0.009	0.017
Panel B : Market Impact - Sales									
<i>t</i>	-0.004***	-0.001**	0.005***	-0.001***	0.796***	-0.006	-0.032**	-0.006	-0.005
<i>t - 1</i>	-0.004***	-0.001**	0.005***	-0.001***	0.797***	-0.008	0.006	-0.025	0.126*
Panel C : Market Timing - Purchases									
<i>t</i>	0.057***	0.072***	0.037***	-0.004***	-1.902	0.034	-1.843***	-0.111	0.173
<i>t - 1</i>	0.057***	0.072***	0.038***	-0.004***	-1.910	-0.077	-0.578***	-0.148	0.990**
Panel D : Market Timing - Sales									
<i>t</i>	0.043**	0.072***	0.040***	-0.005***	-4.641***	-0.445***	0.429**	-1.125***	-0.159
<i>t - 1</i>	0.043**	0.072***	0.040***	-0.005***	-4.595***	0.010	0.017	-0.308*	-0.446

This table presents the results of different panel regression models. Panel A and B present the results for the market impact cost for purchases and sales respectively. Panel C and D display parameter estimates for market timing models respectively for purchases and sales. *t* and *t - 1* stand for contemporaneous and lagged signals respectively. *Orders* indicate the number of order of a sequence *s*, *Duration* its duration and *V* its volume. *Depth* and *RS* are liquidity proxies respectively for depth and relative spread. *H*, *IH*, *HM* and *SH* are candlesticks identification dummies, respectively for Hammer, Inverted Hammer, Hanging Man and Shooting Star, that equal 1 when the structure occurs for contemporaneous models (*t*) and when the structure has occurred during previous interval for lagged models (*t - 1*). These dummies equal 0 otherwise.

Tables 4 and 5 also show that Doji configurations do not help to reduce market timing
8 costs as the parameters show inconsistent signs and only for contemporaneous signals.

- 1 For lagged signals, the parameters are not significant anymore. This is consistent with
2 EMH and the incapacity of candlesticks to predict future short term price evolution.

Table 4: Market Timing - Dragonfly and Gravestone Dojis

<i>Model</i>	<i>Orders</i>	<i>Duration</i>	<i>V</i>	<i>Depth</i>	<i>RS</i>	<i>DFbull</i>	<i>DFbear</i>	<i>GRbull</i>	<i>GRbear</i>
Panel A : Purchases									
<i>t</i>	0.057***	0.074***	0.037***	-0.004***	-1.937	-0.329*	-0.669***	-1.191***	-0.830***
<i>t - 1</i>	0.057***	0.072***	0.038***	-0.004***	-1.897	-0.451**	-0.374**	-0.171	0.003
Panel B : Sales									
<i>t</i>	0.043**	0.074***	0.040***	-0.005***	-4.582***	-1.254***	-0.755***	-0.373**	-0.362***
<i>t - 1</i>	0.043**	0.072***	0.040***	-0.005***	-4.577***	-0.040	-0.176	-0.151	-0.207

This table presents the results of different panel regression models. Panel A and B present the results for the market timing cost for purchases and sales respectively. t and $t - 1$ stand for contemporaneous and lagged signals respectively. *Orders* indicate the number of order of a sequence s , *Duration* its duration and V its volume. *Depth* and *RS* are liquidity proxies respectively for depth and relative spread. *DFbull*, *DFbear*, *GRbull* and *GRbear* are candlesticks identification dummies, respectively for Bullish Dragonfly Doji, Bearish Dragonfly Doji, Bullish Gravestone Doji and Bearish Gravestone Doji, that equal 1 when the structure occurs for contemporaneous models (t) and when the structure has occurred during previous interval for lagged models ($t - 1$). These dummies equal 0 otherwise.

Table 5: Market Timing - Doji

<i>Model</i>	<i>Orders</i>	<i>Duration</i>	<i>V</i>	<i>Depth</i>	<i>RS</i>	<i>DBear</i>	<i>DBull</i>
Panel A : Purchases							
<i>t</i>	0.057***	0.075***	0.037***	-0.004***	-1.962	-0.714***	-0.671***
<i>t - 1</i>	0.057***	0.072***	0.038***	-0.004***	-1.926	-0.070	-0.240***
Panel B : Sales							
<i>t</i>	0.043**	0.074***	0.039***	-0.005***	-4.594***	-0.652***	-0.539***
<i>t - 1</i>	0.043**	0.072***	0.040***	-0.005***	-4.579***	-0.186**	0.141

This table presents the results of different panel regression models. Panel A and B present the results for the market timing cost for purchases and sales respectively. t and $t - 1$ stand for contemporaneous and lagged signals respectively. *Orders* indicate the number of order of a sequence s , *Duration* its duration and V its volume. *Depth* and *RS* are liquidity proxies respectively for depth and relative spread. *DBull* and *DBear* are candlesticks identification dummies, respectively for Bullish Doji and Bearish Doji, that equal 1 when the structure occurs for contemporaneous models (t) and when the structure has occurred during previous interval for lagged models ($t - 1$). These dummies equal 0 otherwise.

- Tables 6 and 7 however show very interesting results which are consistent with pre-
3 vious findings, as in Mazza (2012). Doji structures are likely to help in reducing market

1 impact costs. Market impact is much lower for sequences beginning during the inter-
2 val that contains a Doji and for sequences beginning during the next interval. These
3 findings indicate that we may benefit from a transaction cost strategy based on these
4 costs.

Table 6: Market Impact - Dragonfly and Gravestone Dojis

<i>Model</i>	<i>Orders</i>	<i>Duration</i>	<i>V</i>	<i>Depth</i>	<i>RS</i>	<i>DF</i>	<i>GR</i>
Panel A : Purchases							
<i>t</i>	-0.006***	-0.001*	0.007***	-0.001***	1.175***	-0.062***	-0.042***
<i>t - 1</i>	-0.006***	-0.001*	0.007***	-0.001***	1.179***	-0.030**	-0.035**
Panel B : Sales							
<i>t</i>	-0.004***	-0.001*	0.005***	-0.001***	0.797***	-0.033***	-0.041***
<i>t - 1</i>	-0.004***	-0.001**	0.005***	-0.001***	0.799***	-0.024*	-0.016

This table presents the results of different panel regression models. Panel A and B present the results for the market impact cost for purchases and sales respectively. *t* and *t - 1* stand for contemporaneous and lagged signals respectively. *Orders* indicate the number of order of a sequence *s*, *Duration* its duration and *V* its volume. *Depth* and *RS* are liquidity proxies respectively for depth and relative spread. *DF* and *GR* are candlesticks identification dummies, respectively for Dragonfly Doji and Gravestone Doji, that equal 1 when the structure occurs for contemporaneous models (*t*) and when the structure has occurred during previous interval for lagged models (*t - 1*). These dummies equal 0 otherwise.

Table 7: Market Impact - Doji

<i>Model</i>	<i>Orders</i>	<i>Duration</i>	<i>V</i>	<i>Depth</i>	<i>RS</i>	<i>D</i>
Panel A : Purchases						
<i>t</i>	-0.006***	-0.001*	0.007***	-0.001***	1.173***	-0.049***
<i>t - 1</i>	-0.006***	-0.001*	0.007***	-0.001***	1.177***	-0.022**
Panel B : Sales						
<i>t</i>	-0.004***	-0.001*	0.005***	-0.001***	0.796***	-0.023***
<i>t - 1</i>	-0.004***	-0.001**	0.005***	-0.001***	0.799***	-0.022***

This table presents the results of different panel regression models. Panel A and B present the results for the market timing cost for purchases and sales respectively. *t* and *t - 1* stand for contemporaneous and lagged signals respectively. *Orders* indicate the number of order of a sequence *s*, *Duration* its duration and *V* its volume. *Depth* and *RS* are liquidity proxies respectively for depth and relative spread. *D* is a Doji identification dummy that equals 1 when a Doji occurs for contemporaneous models (*t*) and when a Doji has occurred during previous interval for lagged models (*t - 1*). This dummy equals 0 otherwise.

In a nutshell, the results show that market timing is not affected by the reversal
1 potential that candlesticks contain. The results are somehow significant but the sign
2 of the estimates are opposite to what should be expected according to the literature
3 on Japanese candlesticks. This is consistent with our hypothesis that EMH holds and
4 that Japanese candlesticks are not able to predict future price returns, as outlined in
5 Duvinage et al. (2012) and Marshall et al. (2008).

The other main result of these panel regressions is the relationship between market
6 impact cost and the occurrence of these structures. We find that market impact is much
7 lower when a Doji occurs, whatever its type. This is consistent with Mazza (2012)
8 which outlines that liquidity is higher when a Doji appears on a price chart. The effect
9 is also lasting long enough as sequences beginning after the occurrence of these Dojis still
10 exhibit lower market impact costs. The results are also valid for Hammer and Hanging
11 Man for purchases only and with much less significance as well as short-lived effects.

12 **5.2 Simulation**

13 Table 8 shows the results of the order processing simulation. The average market impact
14 of the Doji-based strategy is equal to 0.02806 basis points for buy orders and to 0.02883
15 basis points for sell orders. These results are significantly lower than the market impact
16 paid by the random submission for both buy and sell orders, suggesting that investors
17 may benefit from candlesticks to reduce their transaction costs.

Table 8: Simulation

	<i>MeanRandomMI</i>	<i>MeanStrategyMI</i>	<i>p - value</i>
Panel Buy	0,032154	0,02806	0,00
Panel Sell	0,031626	0,02883	0,00

This table presents the results for the simulation and the original sample. Panel A and B present the results for purchases and sales respectively. Mean Random Mi refers to the average of the market impact for the 500 replications and the 81 securities. Mean Strategy is the average of the market impact for the 81 securities. The p-value is computed as the number of time the market impact of the random replication for the 81 securities beats the original sample divided by 500.

1 6 Conclusion

2 Transaction costs management has always been a tricky issue, as it is not possible to
3 improve all of them simultaneously. Market members are always confronted to the so-
4 called trader’s dilemma which is based on the choice of an execution strategy, namely
5 splitting orders or not. This dilemma may be summarized by two transaction costs
6 components: market impact, that arises when a large order is submitted, and market
7 timing that arises when a big order is split into smaller ones that executes at different
8 prices through time.

In this paper, we investigate the information content of Japanese Candlesticks in this
9 regard, i.e. the possibility that they may bring an answer to the trader’s dilemma. There
10 are different elements in the literature that may encourage such a relationship. First, as
11 outlined by Kavajecz and Odders-White (2004), it seems that liquidity, which is inversely
12 correlated to transactions costs, is higher for a given set of technical analysis indicators.
13 Wang et al. (2012) also indicate that order submissions are related to technical analysis
14 in the Taiwan Stock Exchange. Second, Mazza (2012) finds that liquidity measured in

1 the limit order book is higher when particular candlesticks structures occur. Finally,
2 as candlesticks are said to help forecasting future price evolution, which is directly
3 struggling with EMH, their impact on order splitting should be assessed.

Based on a sample of 81 European stocks from three Euronext indexes, we investigate
4 whether the two components of transaction costs of sequences of orders are impacted
5 by the occurrence of particular candlesticks structures. We focus on two categories
6 of structures, Hammer-like and Doji configurations, as they are the best known single
7 lines of the Japanese Candlesticks literature. We estimate fixed-effects panel regression
8 analyzes including market impact or market timing cost as dependant variable and
9 candlestick identification dummies as well as a set of control variables, including the
10 number of orders, duration, volume of the sequences, and liquidity proxies, as exogenous
11 variables. In order to further assess whether a market member may benefit from the
12 occurrence of a given signal, we also conduct order processing simulations in which we
13 compare the market impact cost of a candlestick-based execution strategy to a random
14 execution of an average quantity throughout the day.

Our results are consistent with the existing literature and present interesting findings.
15 First, candlesticks fail to predict future price evolution as market timing costs are not
16 lower when or after that one of these configurations has occurred. This is coherent
17 with the EMH and previous findings as outlined in Duvinage et al. (2012) and Marshall
18 et al. (2006). Second, consistent with Mazza (2012), we find that market impact cost
19 is significantly lower when and after that a Doji structure has occurred. The effect is
20 lasting long enough to allow sequences of orders that begin in the next interval to exhibit
21 lower cost. This is also true for Hammer and Hanging Man but only for purchases. It
22 seems that trading after these structures help to reduce transaction costs. This result
23 is further investigated in order processing simulations which show similar outcomes, i.e.

1 Doji-based strategy exhibits significantly lower market impact cost than the random
2 one.

As a conclusion, this paper outlines an interesting feature of candlesticks by examin-
3 ing whether a market member could benefit from them for execution purposes. We find
4 that they provide a partial response to the trader's dilemma as they help detect time
5 windows where transaction costs are lower and therefore are suitable for the submission
6 of very aggressive orders.

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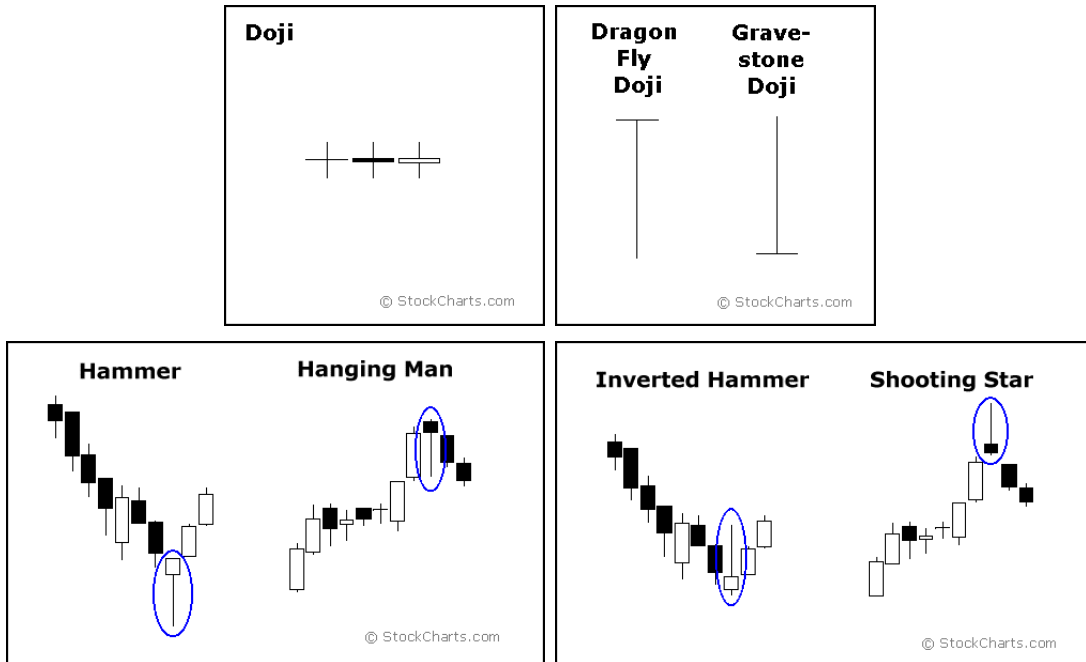
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1 7 Appendix

Figure 3: Dojis and Hammer-like structures



The Doji presents a closing price (almost) equal to the opening price. It occurs when there is an agreement on the fair value of the asset and where markets are 'on a rest'. The Doji indicates the end of the previous trend. The most traditional Doji is a 'plus' sign but Dragonfly and Gravestone Dojis are also frequent. A Dragonfly Doji appears when a strong selling pressure directly follows a strong buying pressure implying an upper shadow almost equal to zero. The Gravestone Doji occurs when the buyers have dominated the first part of the session and the sellers, the second one. The Hammer and the Hanging Man appear when sellers dominate the first part of the session and buyers, the second part. By construction, they present a long lower shadow and almost no upper shadow. The Hammer occurs at the end of a downtrend while the Hanging Man puts an end to an uptrend. The Inverted Hammer and the Shooting Star are made with a small real body, a very long upper shadow and almost no lower shadow. The Inverted Hammer appears at the end of a downtrend and the Shooting Star occurs at the end of an uptrend. These structures are said to be strong reversal ones.