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RESEARCH ARTICLE

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# Nowcasting directional change in high frequency FX markets

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## Summary

Directional change (DC) is an alternative to time series in recording transactions: it only records the transactions at which price changes to the opposite direction of the current trend by a threshold specified by the observer. DC can only be confirmed in hindsight: one does not know that direction has changed until it is confirmed by a later transaction. The transaction in which the price confirms a DC is called a DC confirmation point. DC nowcasting is an attempt to recognize DC before the DC confirmation point. Accurate DC nowcasting will benefit trading. In this paper, we propose a method for DC nowcasting. This method is entirely data driven: it is based on the historical distribution of DC-related indicators. Empirical results suggest that DC nowcasting is possible, even under a naïve rule. This opens the door to a promising research direction on an important topic.

KEYWORDS

directional change, Finance, markets, overshoot, time series

## 1 | INTRODUCTION

Directional change (DC) is an alternative way to time series in recording transactions in a market: instead of recording transactions at the end of each predefined interval as it is done in time series (e.g., recording daily closing prices), DC records transactions at which price changes in the opposite direction of the current trend by a certain threshold, where the threshold is defined by the observer (Bisig et al., 2012). DC approach summarizes the data according to event time (or intrinsic time) and helps in identifying the scale invariant patterns (scaling laws) that are consistent across all granularities of the data (di Matteo, 2007). Scale invariant power law patterns are ubiquitous in commodity and financial markets (Glattfelder et al., 2011; Golub et al., 2017; Li et al., 2015; Tsang & Ma, 2021). For example, existence of power-law correlation between the returns and volume in carbon market is studied by Yan et al. (2020) and scale invariant characteristics of QFII market (Tsang, 2021).

Various models and assumptions from the literature (e.g., Bakhach, Raju Chinthalapati, et al., 2018; Chen & Tsang, 2020; Ma et al., 2017; Tsang et al., 2017) partially explain the scale invariance phenomenon in finance. Scale invariant properties of financial data are studied and applied in risk and volatility modeling (Bouchaud, 2001; Glattfelder & Golub, 2022; He & Chen, 2011; Li et al., 2015; Ma et al., 2017). Several trading strategies are proposed based on the scale laws (di Matteo, 2007) of DC approach. For example, designing trading strategies based on single threshold that are profitable and statistically significant are discussed in Ye et al. (2017); Ao and Tsang (2019); Bakhach et al. (2016); Bakhach, Raju Chinthalapati, et al. (2018); Bakhach, Tsang, et al. (2018); and Zhang, Wang, et al. (2018) and multi-threshold DC-based automated trading algorithm is discussed in Dacorogna et al. (2001). Forecasting DCs (Adegboye et al., 2021; Adegboye & Kampouridis, 2021) attracts substantial research interest due to its direct applications in trading (Adegboye et al., 2022). In this paper, we concentrate on nowcasting DC trends. Ma et al. (2017) proposed a DC trading strategy for invest in the market portfolio in Chinese stock market. Glattfelder and Golub (2022) argued that unlike the underlying rigidity due to the predefined time intervals in traditional time series that hides relevant properties, DC's intrinsic time approach is more versatile in analyzing the complex nature of financial markets.

**TABLE 1** Data used for illustrating how transactions are recorded under DC (Petrov et al., 2020)

| Tick-to-tick data (TD) | | | Directional change (DC) with a 5% threshold | | | | |
|---|---|---|---|---|---|---|---|
| Data point | Time (mm:ss) | Price | Time (mm:ss) | Extreme Point | Last hi/low | Change from last hi/low | DC confirmation |
| 1 | 00:00 | 100 | 00:00 | 100 | 100 | | |
| 2 | 00:10 | 110 | 00:10 | 110 | 110 | | Up |
| 3 | 00:40 | 106 | | | 110 | −3.64% | |
| 4 | 00:50 | 107 | | | 110 | −2.73% | |
| 5 | 01:08 | 98 | 01:08 | 98 | 98 | −10.91% | Down |
| 6 | 01:13 | 105 | 01:13 | 105 | 105 | 7.14% | Up |
| 7 | 01:23 | 90 | | | 105 | −14.29% | Down |
| 8 | 01:28 | 92 | | | 105 | −12.38% | |
| 9 | 01:33 | 83 | 01:33 | 83 | 83 | −20.95% | |
| 10 | 01:38 | 98 | | | 83 | 18.07% | Up |
| 11 | 01:43 | 95 | | | 83 | 14.46% | |
| 12 | 01:48 | 104 | 01:48 | 104 | 104 | 25.30% | |
| 13 | 01:53 | 100 | | | 104 | −3.85% | |
| 14 | 02:08 | 103 | | | 104 | −0.96% | |
| 15 | 02:38 | 101 | | | 104 | −2.88% | |
| 16 | 05:08 | 98 | 05:08 | 98 | 98 | −5.77% | Down |
| 17 | 05:38 | 100 | | | 98 | 2.04% | |
| 18 | 06:08 | 104 | | | 98 | 6.12% | Up |
| 19 | 06:28 | 106 | 06:28 | 106 | 106 | 8.16% | |
| 20 | 06:43 | 102 | | | 106 | −3.77% | |
| 21 | 07:03 | 100 | | | 106 | −5.66% | Down |
| 22 | 07:33 | 95 | | | 106 | −10.38% | |
| 23 | 07:58 | 98 | | | 106 | −7.55% | |
| 24 | 08:28 | 90 | 08:28 | 90 | 90 | −15.09% | |
| 25 | 08:43 | 92 | | | 90 | 2.22% | |
| 26 | 09:08 | 97 | | | 90 | 7.78% | Up |
| 27 | 09:40 | 99 | | | 90 | 10.00% | |
| 28 | 10:00 | 100 | 10:00 | 100 | 90 | 11.11% | |

Table 1 shows how DCs are identified from transactions in a hypothetical market (Petrov et al., 2020). The DC are plotted in Figure 1. The dotted line in Figure 1 shows the price changes; the round labels show the transactions (which take place at irregular times). For an observer who uses a threshold of 5%, the yellow diamond labels indicate the extreme points at which the market changes direction.[1] The first extreme point is at the transaction (00:10, 110). This is recognized as an extreme point when the price dropped to (01:08, 98), as the price drop from 110 to 98 is greater than the threshold of 5%. The price drop from 110 to 106 was ignored because it was less than 5%. Next, the transaction (01:08, 98) is recognized to be an extreme point when the price moved to 105, which is more than 5% above 98. At the transaction (01:23, 90), (01:13, 105) was confirmed to be an extreme point, as the rise from 90 to 105 is more than 5%. (The bounce back from 90 to 92 was ignored because it was less than 5%.) The next DC happened at (01:33, 83), which was recognized when the price reached (01:38, 98).

It is important to point out that extreme points are recognized retrospectively. The transaction (01:48, 104) is only recognized to be an extreme point when one observes the transaction (05:08, 98), which shows a drop of 5.7%. Here, (05:08, 98) is called a DC Confirmation point—it confirms that the market changed its direction at (01:48, 104) if the observer takes 5% as a significant change.

Although the market has changed its direction from (01:48, 104), the observer will not be aware of so before the DC confirmation point is observed. The question is, could the observer recognize that that DC has happened before the DC confirmation point? The problem of recognizing what has already happened is called a nowcasting problem.[2]

## 2 | OBJECTIVE STATEMENT

The objective of this research is to nowcast DCs in the market. This objective is achieved if one could nowcast the DC after the extreme

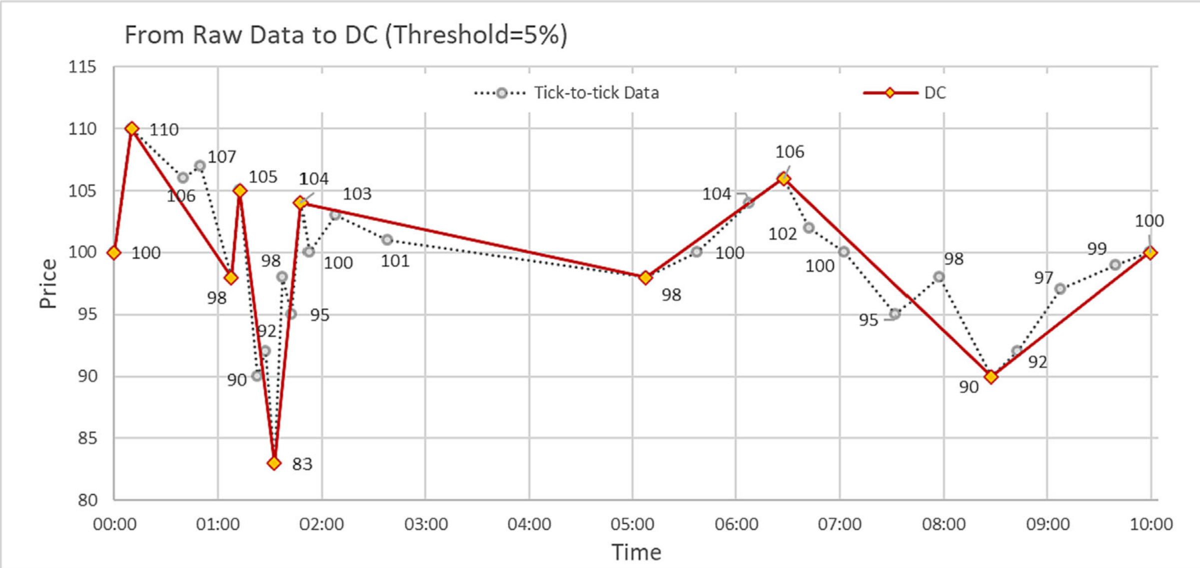


**FIGURE 1** Recording of directional changes from raw transactions, an example

point and before the DC confirmation point. More precisely, the objective of this research is to nowcast DCs in the market, asking at any point in a trend: has a new trend started? The quality of a nowcast can be measured with the following criteria:

1. A nowcast before the extreme point is *incorrect* because the direction has yet to change.
2. A nowcast after the DC confirmation point is *useless* because DC has already been confirmed.
3. We call a nowcast *good* if it is correct and useful. For any good nowcast:

a. Timewise, the earlier it is made, the better.
b. Pricewise, the closer it is to the past extreme point, the more useful it is.

For example, after the transaction (01:48, 104) is observed, if one manages to nowcast at (01:53, 100) that the uptrend has ended and we are now at a downtrend, then this nowcast is good. This nowcast is correct and useful because it is made before the DC confirmation point (05:08, 98). A nowcast at (02:08, 103) or (02:38, 101) is also good. Timewise, the nowcast at (01:53, 100) is better than the nowcast at (02:08, 103), because the former is made 00:05 after the extreme point (01:48, 104) while the latter was made 01:40 after the extreme point. However, pricewise, a nowcast at (02:08, 103) is better than one made at (01:53, 100) because the former is (103−98=) 5 above the DC confirmation price in the new downtrend; the latter only (100−98=) 2 above the DC confirmation price.

Is it possible to nowcast the change of direction? What indicators, if any, could give us clues that DC has already taken place? These are the questions in this research.

## 3 | DC INDICATORS FOR NOWCASTING

Before we can nowcast, we need to identify indicators that may indicate the likelihood of trend reversion. In this section, two indicators are introduced.

We shall adopt the concept of absolute total movement (aTMV) from the literature (Bakhach, Tsang, et al., 2018; Ma, 2022); we shall introduce this indicator here. A trend is made up of two extreme points. Figure 2 shows two trends from the above example: the first trend is from extreme point EP1 (01:33, 83) to EP2 (01:48, 104). The second trend is from EP2 to EP3 (05:08, 98). The trend EP1-EP2 is made up of a DC event (from EP1 to DCC1) and an overshoot event (from DCC1 to EP2). The second trend ends at EP3; no overshoot is observed before the downtrend ends, as EP3 starts the next uptrend.

**Definition 1.** aTMV:

Given a DC observation under the DC threshold θ, in a trend that starts with the extreme point EP, the aTMV of a price P is

$$\mathrm{aTMV}(\mathrm{P}) = (|\mathrm{P} - \mathrm{EP}| \div \mathrm{EP}) \div \theta. \tag{1}$$

We use the absolute value in the definition of aTMV to allow comparison between downtrends and uptrends. The price change is divided by θ to allow observations under different thresholds to be compared. For example, for the trend EP1-EP2 in Figure 2, the prices at EP1 and EP2 are 83 and 104, respectively. The aTMV at EP2 is therefore $(|104-83| \div 83) \div 5\% = 5.06$.

Bakhach et al. (2016) show that the probability of overshoots continuing drops exponentially as aTMV increases. Figure 3 plots the

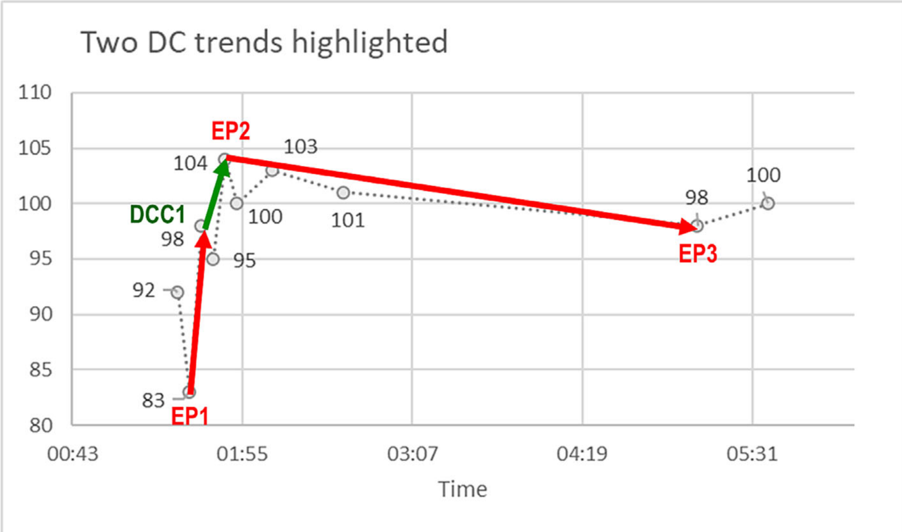


**FIGURE 2** Two trends in Figure 1 highlighted: EP2 (01:48, 104) is (104–83) ÷ 83 = 25.3% above EP1 (01:33, 83). Within the trend EP1-EP2, the absolute TMV of EP2 is 25.3% ÷ 5% = 5.06.

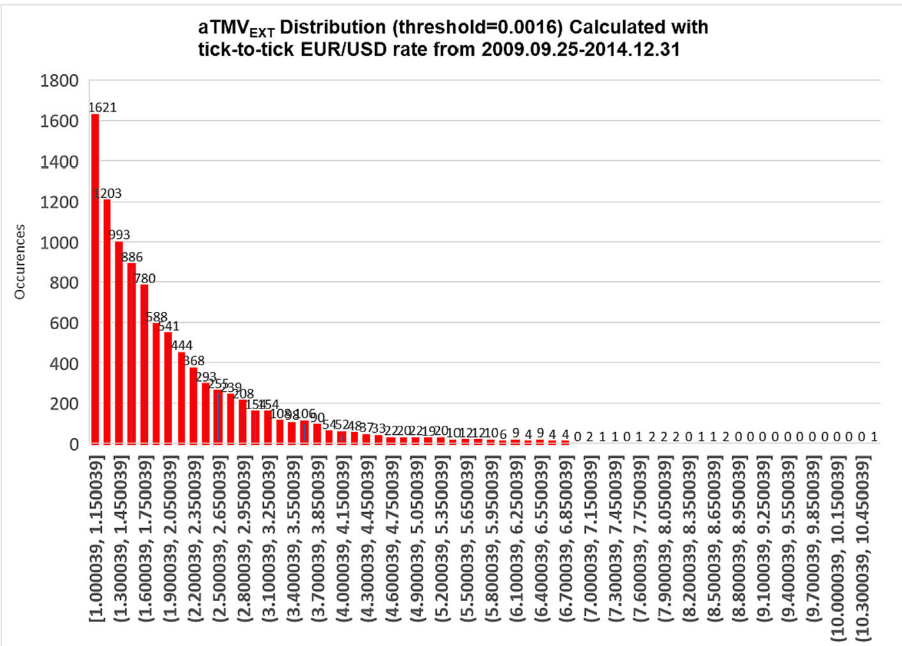


**FIGURE 3** Distribution of aTMV at extreme points in the EUR/USD Forex market between September 25, 2009, and December 31, 2014, observed under the threshold of 0.0016; tick data were used (source: Kantelhardt et al., 2002).

distribution of aTMV at extreme points in the EUR/USD market between September 25, 2009, and December 31, 2014, observed under the threshold 0.0016 (Kantelhardt et al., 2002). In the observed period, 50% of the overshoots end before aTMV reaches 1.614449, and 10% overshoots ends before their aTMV reaches aTMV = 3.128502, 5% before aTMV = 3.766335, and 1% before aTMV = 5.352294. The observed data suggest that as aTMV increases, the probability of an overshoot reaching that aTMV drops exponentially.

The aTMV of the current price in a trend, therefore, gives us some hint on the likelihood of a trend ending. If (a) the aTMV has reached a high value V and (b) the price has reversed substantially from V, then V may have been the extreme point of a new trend. This will be the basis of our nowcasting algorithm in this paper. Following this line, we shall next examine the statistics of rebounds.

**Definition 2.** Below max (BM):

Let Pmax be the price with the maximum aTMV recorded in the current trend. A price P recorded after Pmax has a Below Max (BM) value:

$$\mathrm{BM} = (|\mathrm{Pmax} - \mathrm{P}| \div \mathrm{Pmax}) \div \theta. \tag{2}$$

For example, in the trend EP1-EP2 in Figure 2, when the transaction (01:38, 98) is recorded, Pmax is recorded as 98. The bounce back to (01:43, 95) has a BM value of (|98−95| ÷ 98 ÷ 0.05=) 0.6122449. When the transaction (01:48,104) is encountered, Pmax is updated to104. Although the current uptrend ends with (01:48, 104), it will not be confirmed before the transaction (05:08, 98) is encountered. Without the benefit of hindsight, when the transaction (01:53, 100) is encountered, it is still seen as part of the current uptrend. It has a BM value of (|104−100| ÷ 104 ÷ 0.05=) 0.7692308.

It is useful to remember that 0 ≤ BM < 1. At Pmax, BM is 0. If BM reaches 1 at price P, then P would have confirmed that Pmax was an extreme point (by the definition of DC; Bakhach, Tsang, et al., 2018).

Figure 4 records the maximum BM (MBM) in all completed trends in the EUR/USD forex market between 00:00:10 Sept 25, 2009, and 20:08:53 Dec 31, 2013, observed under the threshold of 0.0016. While the MBM probabilities (the blue line) fluctuate before the value 0.2, the cumulative probability of reaching an MBM value (the red line) decreases exponentially. This suggests that BM may give us some clues about DCs.

## 4 | DESIGN

Figure 3 shows that as aTMV increases, the chance of DC increases exponentially. Figure 4 shows that as BM increases, the chance of it happening after an extreme point (i.e., direction has already changed) increases exponentially. To test the usefulness of aTMV and BM as indicators for DC nowcasting, we shall test the following nowcasting algorithm, which we call NCA:

### 4.1 | Nowcast constant algorithm, NCA ($P_{TMV}$, $P_{BM}$)

Given a current transaction *ct*, in a trend in which the transaction *Max* records the maximum aTMV, we nowcast that *Max* starts a new trend if and only if:

1. aTMV (*Max*) ≥ $P_{TMV}$ and
2. BM (*ct*) ≥ $P_{BM}$.

NCA takes two parameters, $P_{TMV}$ and $P_{BM}$. We use historical data to determine the values of $P_{TMV}$ and $P_{BM}$ in the implementation. For example, from Figure 3, we observe that about half of trends end before aTMV reaches 1.61. We may set $P_{TMV}$ to 1.61 if we want to potentially nowcasting 50% of the trends. If we set $P_{TMV}$ to a bigger value, then condition (1) of NCA will be satisfied in fewer trends. This means NCA will make nowcasts in fewer trends. For example, if we set $P_{TMV}$ to 3.128502, then NCA will make far fewer nowcasts because historically 90% of the trends would have ended before reaching this value. On the other hand, if we set $P_{TMV}$ to 1.0, then condition (1) will always be satisfied (because the aTMV of DCC is ≥1). However, that means NCA completely relies on condition (2). We have decided against doing so, as we would like to test the usefulness of both aTMV and BM, not BM alone. As a proof of concept, we have decided to pick almost arbitrary (though reasonable) values for the parameters; we have not fine-tuned their values.

We have also opted for simplicity and decided against an obvious extension, which is to make $P_{BM}$ a function of $P_{TMV}$.[3] If NCA works, then using machine learning to tune the parameters and find dependency between $P_{BM}$ and $P_{TMV}$ are obvious extensions.

## 5 | EMPIRICAL STUDIES

To test the performance of NCA, we conducted experiments on tick-to-tick data in EURUSD exchange rates. Table 2 shows the periods of the data used. DC profiles of these periods are shown for reference.

The data set was separated into two: one for training and one for nowcasting. The training set is used to find the values of the parameters $P_{TMV}$ and $P_{BM}$.

To test whether NCA is sensitive to the DC threshold value, we have run our experiments on two thresholds: 0.0016 and 0.0032. As

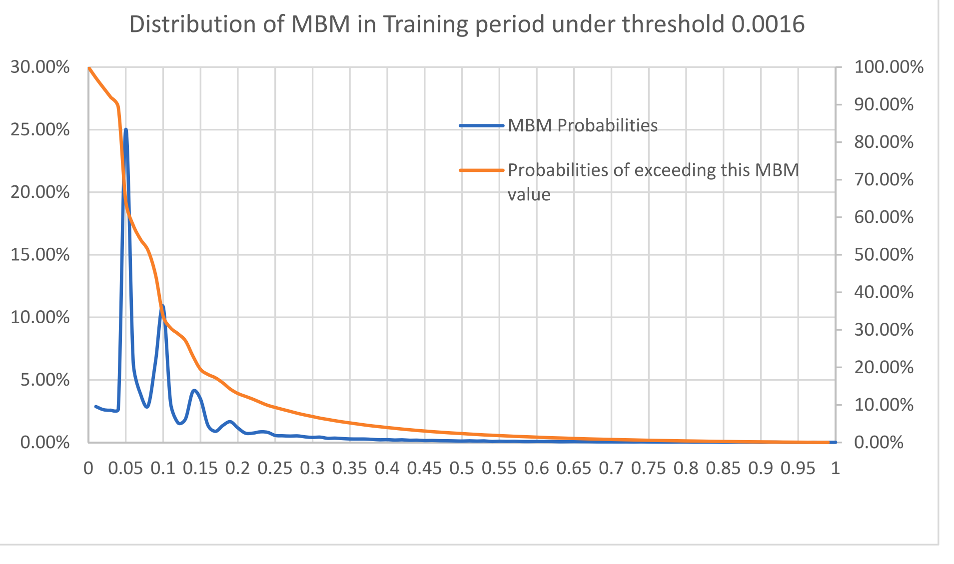


**FIGURE 4** Distribution of MBM in completed trends in the EUR/USD forex market between 00:00:10 Sept 25, 2009, and 20:08:53 Dec 31, 2013, observed under the DC threshold of 0.0016 (source: He & Chen, 2011).

| Threshold | Data in the training period from 00:00:10 Sept 25, 2009, to 20:08:53 Dec 31, 2013, 72,629,464 transactions 0.0016 | 0.0032 | Data in the nowcasting period from 01:30:09 Jan 1, 2014, to 13:02:55 Dec 31, 2015, 33,041,496 transactions 0.0016 | 0.0032 |
|---|---|---|---|---|
| # of DCs | 9,552 | 2,052 | 4,644 | 1,185 |
| Median aTMV | 1.612047 | 1.686975 | 1.596844 | 1.436107 |
| Median T | 2,392 | 12,801 | 1,263 | 4,817 |

**TABLE 2** Tick-to-tick EURUSD exchange rates used, with their DC profiles shown

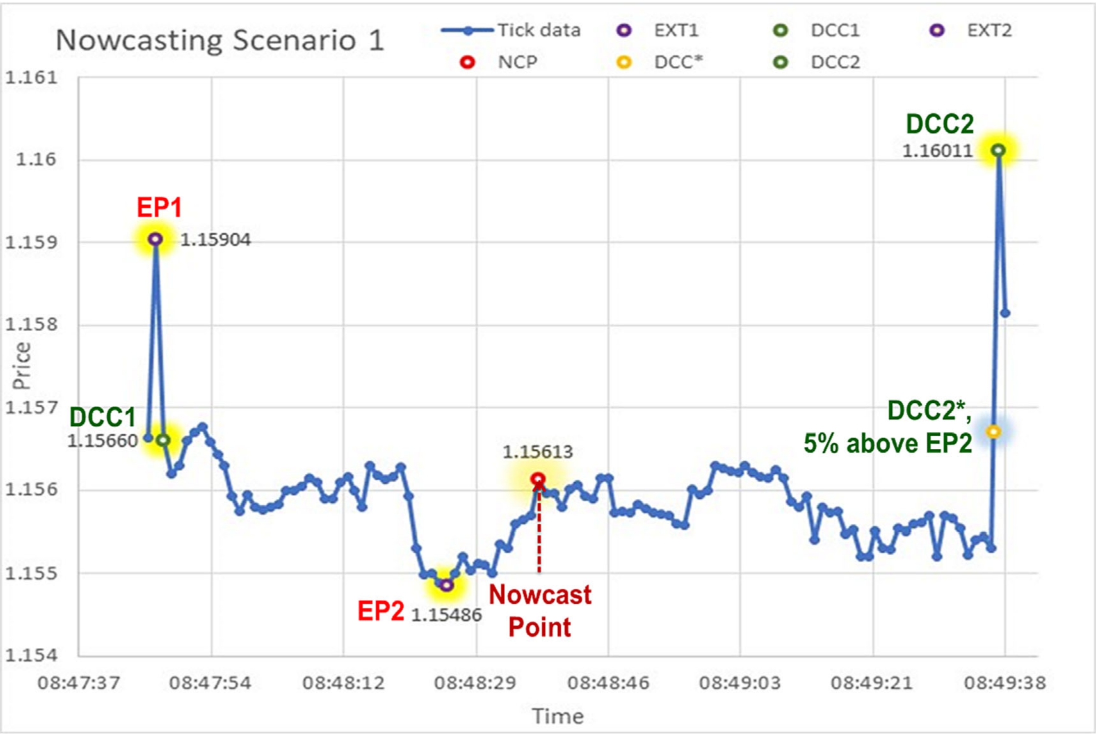


**FIGURE 5** Scenario Nowcast 1 (SNC1), an example of a successful nowcast under the DC threshold 0.0016 (source: He & Chen, 2011)

expected (Bakhach et al., 2016), fewer trends are observed (see the row "# of DCs"), and each trend takes a longer time to finish (see the row "Median T") under the bigger threshold of 0.0032. The Median aTMV values found under the two thresholds are comparable with each other.

Under NCA in the training period, when $\theta = 0.0016$, we set the parameters to $P_{TMV} = 1.68$ and $P_{BM} = 0.68$. There are 46.22% and 0.95% probability that the $P_{TMV}$ and $P_{BM}$ values would exceed 1.68 and 0.68. Under NCA in the training period when $\theta = 0.0032$, we choose $P_{TMV} = 1.60$ and $P_{BM} = 0.61$. There are 54.44% and 0.71% probability that the $P_{TMV}$ and $P_{BM}$ values would exceed 1.60 and 0.61.

## 6 | PERFORMANCE OF NCA

Scenario Nowcast 1 (SNC1) in Figure 5 shows an example of one of the most successful nowcasts by NCA. We shall use this example to explain the performance criteria before we summarize the overall performance of NCA.

In SNC1, the DC confirmation point DCC1 (at the price of 1.15660) confirms that a downtrend has started from the extreme point EP1 (at the price of 1.15904). Without the benefit of hindsight, all the transactions after DCC1 are considered to be part of the downtrend, until DCC2 (the highest point on the right, at 08:49:37, 1.16011) is encountered. At DCC2, one confirms (in hindsight) that EP2 (at 08:48:25, 1.15486) was, in fact, an extreme point. In this scenario, NCA successfully nowcast at the Nowcast Point (NCP, at 08:48:37, 1.15613) that EP1 as an extreme point. NCA nowcasts at NCP that EP2 started a new trend because the two conditions are met:

1. In the current downtrend that started at EP1 (priced at 1.15904), EP2 (priced at 1.15486) records the maximum aTMV ($|1.15486-1.15904|/1.15904/0.0016=$) 2.254, which is bigger than the parameter $P_{TMV}$ set (at 1.68).

2. At NCP, the BM value is (|1.15486−1.15613|/1.15486/0.0016=) 0.6873, which is bigger than the parameter $P_{BM}$ set (at 0.68).

We shall use scenario SNC1 to explain some performance measures.

First, the nowcast in SNC1 is *correct* because NCP is after EP2. Second, the nowcast in SNC1 is *useful* because NCP is before DCC2. For convenience, we call a nowcast *good* if it is correct and useful.

For a good nowcast, we measure its quality by how close they are to EP2, in terms of time and price. We use $TMV_{DCC}$ to denote the TMV measured at the DC confirmation (DCC) point. Following are measures of timeliness, in terms of time and price:

**Definition 3.** $\text{Timeliness}_{\text{Time}}$ of a nowcast:

Let DCC.time be the time at DC confirmation and NCP.time be the time at nowcasting. The $\text{Timeliness}_{\text{Time}}$ of a nowcast measures how early the nowcast is before reaching DCC:

$$\text{Timeliness}_{\text{Time}} = \text{DCC.time} - \text{NCP.time}. \tag{3}$$

**Definition 4.** $\text{Timeliness}_{\text{Price}}$ of a nowcast:

Let aTMV (DCC) be the aTMV of the DC confirmation point and aTMV (NCP) be the aTMV of the nowcasting point. The $\text{Timeliness}_{\text{Price}}$ of a nowcast measures how early the nowcast is in terms of price:

$$\text{Timeliness}_{\text{Price}} = \text{aTMV}(\text{DCC}) - \text{aTMV}(\text{NCP}). \tag{4}$$

In SNC1, the $\text{Timeliness}_{\text{Time}}$ of NCP is (08:49:37−08:48:37=) 60 s, which is a long time for tick data. The aTMV (DCC) is ([|1.16011−1.15486| ÷ 1.15486] ÷ 0.0016=) 2.841253. The aTMV (NCP) is ([|1.15613−1.15486| ÷ 1.15486] ÷ 0.0016=) 0.687313. Therefore, the $\text{Timeliness}_{\text{Price}}$ of NCP is (2.841253−0.687313=) 2.153941.[4]

This scenario shows in a downtrend an extremely valuable nowcast because it recognizes a DC way before the DC confirmation point, both price-wise and time-wise. Careful examination of the tick data reveals that this new trend was confirmed when the transaction price jumped from 1.1557 (which is not yet 0.16% above EP2) to 1.15613 in one transaction. NCA nowcasted the new trend (2.154*0.0016=) 0.3446% in advance. NCA nowcasts just 12 s after EP2, 60 s ahead of DCC2. So this nowcast could have gained a trader a lot of price and time ahead of its competitors.

SNC1 is the most successful nowcast in the experiments in terms of $\text{Timeliness}_{\text{Price}}$ but just a mediocre nowcast in terms of $\text{Timeliness}_{\text{Time}}$. Detailed results of NCA can be found in Ma (2022). Table 3 summarizes the key NCA results in the EUR/USD forex market.

Under the threshold θ = 0.0016, 4,645 trends were captured in the nowcasting period. NCA made 3,452 nowcasts. It is worth noting that multiple nowcasts could have been made within the same trend (some of them may be incorrect nowcasts). Nowcast was not possible for some of the trends. For example, as shown in Figure 3, overshoot in many of the trends are extremely short. For those trends, condition (1) of NCA will never be satisfied. Out of these 3,452 nowcasts, 2,300 (66.63%) were correct (i.e., made after the new trend has started), which means (3,452−2,300=) 1,152 nowcasts were incorrect. Out of the 2,300 correct nowcasts, 2,264 (98.43%) were good (i.e., made before the DC confirmation point). Given such a crude algorithm, where the parameters were untuned, NCA should be seen as being successful given these results. The least that they prove is that aTMV and BM do give us clues for nowcasting.

**TABLE 3** Summary of nowcasting performance

| NCA performance in the nowcasting period shown in Table 2 | | |
|---|---|---|
| **Threshold θ** | **θ = 0.0016** | **θ = 0.0032** |
| TnT: total # of trends | 4,645 | 1,184 |
| Nc: # of nowcasts | 3,452 | 913 |
| GN: # of good nowcasts | 2,264 | 544 |
| CN: # of correct nowcasts | 2,300 | 546 |
| IN: # of incorrect nowcasts | 1,152 | 367 |
| $\text{Precision}_{\text{Correct}}$ = CN ÷ Nc | 66.63% | 59.80% |
| $\text{Precission}_{\text{Good}}$ = GN ÷ CN | 98.43% | 99.63% |
| Average $\text{Timeliness}_{\text{Price}}$ | 0.336 | 0.399 |
| σ $\text{Timeliness}_{\text{Price}}$ | 0.107 | 0.098 |
| Max $\text{Timeliness}_{\text{Price}}$ | 2.154 | 1.961 |
| Average $\text{Timeliness}_{\text{Time}}$ | 1,967 s | 8,789 s |
| σ $\text{Timeliness}_{\text{Time}}$ | 11,745 s | 24,796 s |
| Max $\text{Timeliness}_{\text{Time}}$ | 221,194 s | 229,764 s |

How useful are the nowcasts? Under θ = 0.0016, the average $\text{Timeliness}_{\text{Price}}$ is 0.336 (θ is taken as the unit). Given that the aTMV of the DC confirmation point is around 1, this result means that, on average, good nowcasts were made two thirds of the way from the extreme point to the DCC point. In the best nowcast, $\text{Timeliness}_{\text{Price}}$ is 2.154. This is shown in SNC1 (Figure 5). $\text{Timeliness}_{\text{Price}}$ is greater than 1 in SNC1 because the DC confirmation point was a big jump in the market. The standard deviation of $\text{Timeliness}_{\text{Price}}$ is 0.107 under θ = 0.0016.

Timewise, the average $\text{Timeliness}_{\text{Time}}$ under θ = 0.0016 is 1,967 s (around 30 min). The maximum $\text{Timeliness}_{\text{Time}}$ is 221,194 s (around 2.5 days), which is an astronomical number for tick-to-tick data.

How consistent are results under a different DC threshold? Table 3 shows that results under the two DC thresholds are comparable with each other. By using a bigger threshold, one would find fewer trends under 0.0032, as expected. As each trend takes longer, there is more potential to nowcast with a bigger $\text{Timeliness}_{\text{Time}}$, which is confirmed by the results. As $\text{Timeliness}_{\text{Price}}$ is normalized by the thresholds, the results are comparable under the two different thresholds: the average $\text{Timeliness}_{\text{Price}}$ is 0.336 under θ = 0.0016 and 0.399

under θ = 0.0032. These results suggest that the performance of NCA is not significantly affected by the threshold.

## 7 | FURTHER EMPIRICAL STUDIES

So far, NCA has been tested on EUR/USD. To verify whether the results can be reproduced in other markets, we test NCA on USD/JPY and GBP/USD in this section. In preparation for our nowcasting algorithm, as discussed earlier, we utilize tick-to-tick USD/JPY and GBP/USD rates. Tables 4 and 5 summarize the data used for USD/JPY and GBP/USD, respectively. We separate the data into training and nowcasting periods. Statistics in the former are used to determine the parameters for our nowcasting algorithm, which will be applied during the nowcasting period. For these additional experiments, we set the threshold at 0.0016 for USD/JPY and 0.0032 for GBP/USD.

**TABLE 4** Tick-to-tick USD/JPY exchange rates used, with their DC profiles shown

| Threshold | Data in the training period USD/JPY 0.0016 | Data in the nowcasting period USD/JPY 0.0016 |
|---|---|---|
| Period | From: 00:00:10 Sep 27, 2009<br>To: 23:59:59 Dec 31, 2013 | From 00:00:09 Jan 1, 2014<br>To: 23:50:59 Dec 31, 2015 |
| Number of transactions | 56,820,049 | 28,171,600 |
| Number of DCs | 17,588 | 3,892 |
| Median aTMV | 1.688934 | 1.70645 |
| Median T | 2,882 | 4,350 |

**TABLE 5** Tick-to-tick GBP/USD exchange rates used, with their DC profiles shown

| | Data in the training period GBP/USD | Data in the nowcasting period GBP/USD |
|---|---|---|
| Threshold | 0.0032 | 0.0032 |
| Period | From: 00:00:01 Sep 27, 2009<br>To: 23:59:59 Dec 31, 2013 | From 00:00:01 Jan 1, 2014<br>To: 23:59:59 Dec 31, 2015 |
| Number of transactions | 71,136,369 | 28,026,456 |
| Number of DCs | 3,354 | 747 |
| Median aTMV | 1.702382 | 1.699942 |
| Median T | 15,813 | 25,116 |

The academic literature pertaining to directional forecasting accords significance to the role of volatility. In this discourse, we present a succinct examination of the pertinent literature, exploring the interrelation between empirical analyses in nowcasting and the dynamic nature of market volatility. The academic literature pertaining to directional forecasting accords significance to the role of volatility. In this discourse, we present a succinct examination of the pertinent literature, exploring the interrelation between empirical analyses in nowcasting and the dynamic nature of market volatility. Tsang et al. (2017) introduced the concept that, in DC, various indicators can be employed to measure distinct types of volatility, offering a nuanced approach to tracking market changes. In contrast to time series, where the log return of standard deviation is used, DC utilizes indicators such as number of directional changes (NDC), total price movement (TMV), time (T), time-independent coastline (CDC), and time-adjusted return of DC (RDC) to measure volatility. NDC represents the frequency of DC events within a specified period, making it inversely proportional to T; a higher NDC indicates greater volatility. TMV, another indicator under DC, measures the magnitude of price changes normalized by the DC threshold θ. Both NDC and TMV provide unique perspectives on volatility: NDC reflects the frequency of DCs, while TMV gages the magnitude of price changes in each trend. Consequently, a higher NDC signifies increased frequency of DCs, indicating higher volatility, while a greater TMV suggests more substantial price changes per trend. This comprehensive set of indicators forms a “vocabulary” for understanding and quantifying different facets of market volatility through the lens of DC. By employing the multiple indicators, one can enhance the accuracy and reliability of tracking market volatility. Ma (Shuai Ma's thesis) introduces an innovative approach that combines standard deviation (SD), NDC, and adjusted total price movement (aTMV) to create a novel method for tracking market volatility. This work emphasizes an empirical and data-driven approach, leveraging DC and TS indicators to analyze market data comprehensively. The proposed method integrates DC and time series (TS), enabling effective monitoring of market changes and facilitating a comprehensive summary of market dynamics. The efficacy of DC indicators, NDC, and aTMV, in capturing substantial volatility information is highlighted.

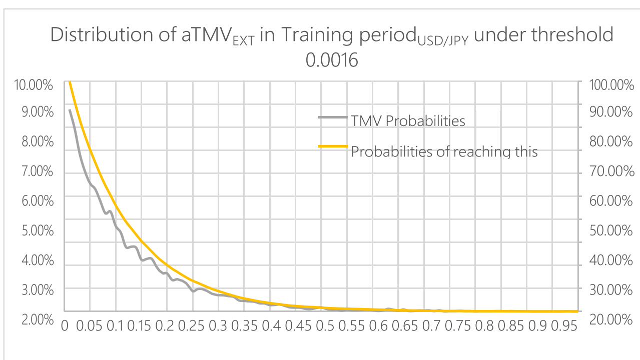


**FIGURE 6** Distribution of $aTMV_{EXT}$ in the training period for USD/JPY under threshold 0.0016

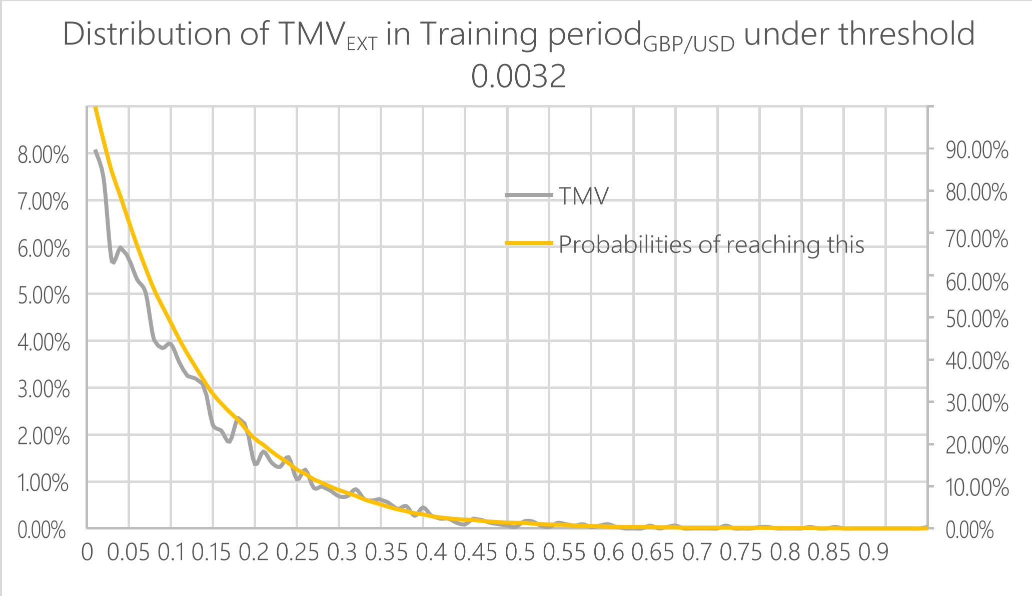


**FIGURE 7** Distribution of $aTMV_{EXT}$ in the training period for GBP/USD under threshold 0.0032

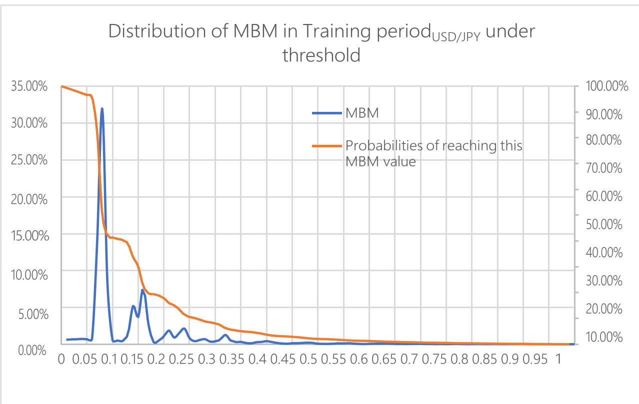


**FIGURE 8** Distribution of MBM in training period for USD/JPY under threshold 0.0016

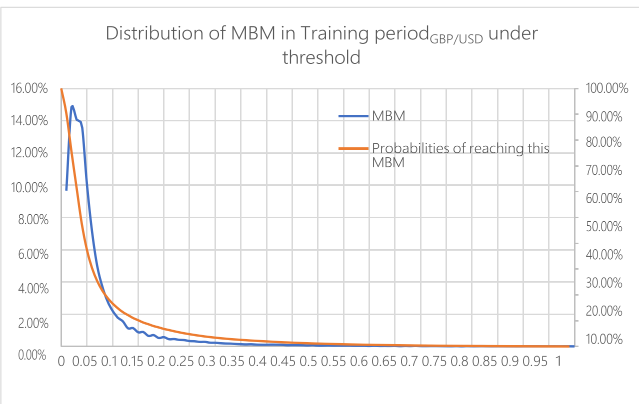


**FIGURE 9** Distribution of MBM in training period for GBP/USD under threshold 0.0032

Both aTMV and T can be considered indicators of volatility in a market period, as the former measures the magnitude of price changes, and the latter measures the frequency of changes. The above comparisons suggest that (1) there is nearly no difference in the volatility of the two periods, as measured by median aTMV and (2) measured by median T; the nowcasting period is much more volatile than the training period; DCs occurred more slowly in the nowcasting period. It is noteworthy that for both USD/JPY and GBP/USD, the two periods exhibit significant differences in their volatility. This difference is observed not in the magnitude of price changes in the trends (measured by aTMV) but in the frequency of DCs (measured

**TABLE 6** Summary of nowcasting performance for USD/JPY

| NCA performance in the nowcasting period for USD/JPY under threshold 0.0016. | |
|---|---|
| **Threshold θ** | **θ = 0.0016** |
| TnT: total # of trends | 3,892 |
| Nc: # of nowcasts | 43 |
| GN: # of good nowcasts | 35 |
| CN: # of correct nowcasts | 35 |
| IN: # of incorrect nowcasts | 8 |
| $\text{Precision}_{\text{Correct}} = \text{CN} \div \text{Nc}$ | 81.39% |
| $\text{Precission}_{\text{Good}} = \text{GN} \div \text{CN}$ | 100% |
| Average $\text{Timeliness}_{\text{Price}}$ | 0.1255 |
| σ $\text{Timeliness}_{\text{Price}}$ | 0.017 |
| Max $\text{Timeliness}_{\text{Price}}$ | 0.1845 |
| Average $\text{Timeliness}_{\text{Time}}$ | 779 s |
| σ $\text{Timeliness}_{\text{Time}}$ | 1,208 s |
| Max $\text{Timeliness}_{\text{Time}}$ | 5,006 s |

**TABLE 7** Summary of nowcasting performance for GBP/USD

| NCA performance in the nowcasting period for GBP/USD under threshold 0.0032. | |
|---|---|
| **Threshold θ** | **θ = 0.0032** |
| TnT: total # of trends | 747 |
| Nc: # of nowcasts | 9 |
| GN: # of good nowcasts | 7 |
| CN: # of correct nowcasts | 7 |
| IN: # of incorrect nowcasts | 2 |
| $\text{Precision}_{\text{Correct}} = \text{CN} \div \text{Nc}$ | 77.78% |
| $\text{Precission}_{\text{Good}} = \text{GN} \div \text{CN}$ | 100% |
| Average $\text{Timeliness}_{\text{Price}}$ | 0.1255 |
| σ $\text{Timeliness}_{\text{Price}}$ | 0.0006 |
| Max $\text{Timeliness}_{\text{Price}}$ | 0.00428 |
| Average $\text{Timeliness}_{\text{Time}}$ | 5,189 s |
| σ $\text{Timeliness}_{\text{Time}}$ | 5,461 s |
| Max $\text{Timeliness}_{\text{Time}}$ | 13,559 s |

by T). Figures 6 and 7 show the graphs of the probability of $\text{aTMV}_{\text{EXT}}$ occurring in each bin and the probability of reaching a certain number of $\text{aTMV}_{\text{EXT}}$ in the training period when the thresholds are equal to 0.0016 and 0.0032, respectively.

Figures 8 and 9 document the MBM in all completed trends in USD/JPY and GBP/USD markets, corresponding to the thresholds 0.0016 and 0.0032, respectively. As mentioned earlier, we arbitrarily chose values for the parameters $P_{\text{TMV}}$ and $P_{\text{BM}}$. During the NCA in the training period for the USD/JPY market, we set the parameters to $P_{\text{TMV}} = 5.58$ and $P_{\text{BM}} = 0.641$. For the GBP/USD market, the parameters were set to $P_{\text{TMV}} = 5.38$ and $P_{\text{BM}} = 0.53$. In both markets, there is a 1% probability that the $P_{\text{TMV}}$ and $P_{\text{BM}}$ values would exceed the specified values. It is important to note that the selection of parameter values determines the number of nowcasting opportunities.

Tables 6 and 7 present the outcomes of the nowcasting algorithm (NCA) during the nowcasting period for the USD/JPY and GBP/USD markets, respectively. In summary, both tables reveal that the mean $\text{Timeliness}_{\text{Price}}$ during nowcast intervals is comparatively low, signifying that, on average, precise nowcasts are generated at approximately 10% of the span from the extreme point to the DCC point. The relatively minor standard deviations of $\text{Timeliness}_{\text{Price}}$ across both tables indicate a consistent trend, with the majority of nowcasts consistently hovering around the 10% mark.

Moreover, Tables 6 and 7 provide empirical support for the notion that NCA yields timely nowcasts in temporal terms. The substantial standard deviations of $\text{Timeliness}_{\text{Time}}$ in comparison to the averages suggest that the implementation of NCA for nowcasting can result in gaining thousands of seconds effectively. $\text{Timeliness}_{\text{Time}}$ gages the extent to which NCA identifies a new trend before the DCC. A greater $\text{Timeliness}_{\text{Time}}$ value implies an earlier recognition of the commencement of a new trend. Nevertheless, during the nowcasting period for GBP/USD under the threshold of 0.0032, the median $\text{Timeliness}_{\text{Time}}$ stands at 2,607, while the average is 5,189. This considerable difference is primarily attributable to extreme values; the maximum $\text{Timeliness}_{\text{Time}}$ reaches 13,559 s, and the minimum is 11. The standard deviation of $\text{Timeliness}_{\text{Time}}$, recorded at 5,461 s, signifies substantial variability. This suggests that within the accurate nowcasts, some occur considerably early before the DCC point, while others do not.

## 8 | CONCLUDING SUMMARY

To summarize, NCA demonstrates that it is possible to nowcast the change of direction in the market. It proves that aTMV and BM could provide us with clues about DC in the market. Being able to nowcast DCs enables traders to act ahead of the market in terms of both time and price.

NCA is only a proof of concept. It opens a valuable yet untapped research direction. For future work, one may attempt to fine-tune the parameters. Besides, NCA uses constant parameter values. A sensible extension would be to make $P_{\text{BM}}$ a function of aTMV: as aTMV increases, the probability of DC happening increases exponentially (Figure 3); therefore, one may nowcast at a lower BM value. Finally, aTMV and BM should not the only indicators for nowcasting. More indicators should help.

### DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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### ENDNOTES

[1] Note that the first and the final transactions, at times 00:00 and 10:00, respectively, are not necessarily extreme points; they are included to show the direction of the price movements.

[2] This is not a forecasting problem, because we are not trying to predict the future.

[3] If we reach a higher aTMV value, then the probability of direction-changing increases. Therefore, we may afford to nowcast DC at a smaller BM. We call the algorithm in this paper the "Nowcast Constant Algorithm" as we anticipate Nowcast Dynamic Algorithm extensions.

[4] In other words, NCP nowcast 2.153941 times the size of the threshold (which is 0.0016 in this case) before DCC. As we did in aTMV, the threshold is used as the unit of measurement here.

### REFERENCES

Adegboye, A., & Kampouridis, M. (2021). Machine learning classification and regression models for predicting directional changes trend reversal in FX markets. *Expert Systems with Applications*, *173*(114), 114645. https://doi.org/10.1016/j.eswa.2021.114645

Adegboye, A., Kampouridis, M., & Otero, F. (2021). Improving trend reversal estimation in forex markets under a directional changes paradigm with classification algorithms. *International Journal of Intelligent Systems*, *36*, 7609–7640. https://doi.org/10.1002/int.22601

Adegboye, A., Kampouridis, M., & Otero, F. (2022). *Algorithmic trading with directional changes*", Artificial Intelligence Review (Vol. 56) (pp. 5619–5644). Springer. https://doi.org/10.1007/s10462-022-10307-0

Ao, H., & Tsang, E. P. K., Trading algorithms built with direction changes, IEEE Conference on Computational Intelligence for Financial Engineering and Economics (CIFEr) 2019 Conference, Shenzhen, China, 2019.

Bakhach, A., Raju Chinthalapati, V. L., Tsang, E. P. K., & el Sayed, A. R. (2018). Intelligent dynamic backlash agent: A trading strategy based on the directional change framework. *Algorithms*, Special Issue on Algorithms in Computational Finance, MDPI Open Access Publishing (ISSN 19994893), *11*(11), 171. https://doi.org/10.3390/a11110171

Bakhach, A., Tsang, E. P. K., & Jalalian, H., Forecasting directional changes in FX markets, IEEE Symposium on Computational Intelligence for Financial Engineering & Economics (IEEE CIFEr'16), Athens, Greece, 2016

Bakhach, A., Tsang, E. P. K., & Raju Chinthalapati, V. L. (2018). TSFDC: A trading strategy based on forecasting directional change. *Intelligent Systems in Accounting Finance and Management*, *25*(3), 105–123. https://doi.org/10.1002/isaf.1425

Bisig, T., Dupuis, A., Impagliazzo, V., & Olsen, R. B. (2012). The scale of market quakes. *Quantitative Finance*, *12*(4), 501–508. https://doi.org/10.1080/14697688.2011.609180

Bouchaud, J. P. (2001). Power laws in economics and finance: Some ideas from physics. *Quantitative Finance*, *1*, 105–112. https://doi.org/10.1080/713665538

Chen, J., & Tsang, E. P. K. (2020). *Detecting regime change in computational finance, data science, machine learning and algorithmic trading*. CRC Press. https://doi.org/10.1201/9781003087595

Dacorogna, M. M., Gencay, R., Muller, U., Olsen, R. B., & Picktet, O. V. (2001). *An introduction to high-frequency finance*. Academic Press. https://doi.org/10.1016/B978-012279671-5.50004-6

di Matteo, T. (2007). Multi-scaling in finance. *Quantitative Finance*, *7*(1), 21–36. https://doi.org/10.1080/14697680600969727

Farmer, J. (2004). Doyne & Fabrizio Lillo, on the origin of power-law tails in price fluctuations. *Quantitative Finance*, *4*(1), 7–11. https://doi.org/10.1088/1469-7688/4/1/C01

Glattfelder, J. B., Dupuis, A., & Olsen, R. B. (2011). Patterns in high-frequency FX data: discovery of 12 empirical scaling laws. *Quantitative Finance*, *11*(4), 599–614. https://doi.org/10.1080/14697688.2010.481632

Glattfelder, J. B., & Golub, A., Bridging the gap: Decoding the intrinsic nature of time in market data, 2022, arXiv:2204.02682

Golub, A., Glattfelder, J., & Olsen, R. B. (2017). The alpha engine: Designing an automated trading algorithm. *High-Performance Computing in Finance, Chapman & Hall/CRC Series in Mathematical Finance*, 49–76. https://doi.org/10.2139/ssrn.2951348

He, L. Y., & Chen, S. P. (2011). Nonlinear bivariate dependency of price–volume relationships in agricultural commodity futures markets: A perspective from multifractal detrended cross-correlation analysis. *Physica A: Statistical Mechanics and its Applications*, *390*(2), 297–308. https://doi.org/10.1016/j.physa.2010.09.018

Kantelhardt, J. W., Zschiegner, S. A., Koscielny-Bunde, E., Havlin, S., Bunde, A., & Stanley, H. E. (2002). Multifractal detrended fluctuation analysis of nonstationary time series. *Physica A: Statistical Mechanics and its Applications*, *316*(1–4), 87–114. https://doi.org/10.1016/S0378-4371(02)01383-3

Li, M., Jiang, Z., Xie, W. J., Xiong, X., Zhang, W., & Zhou, W. (2015). Unveiling correlations between financial variables and topological metrics of trading networks: Evidence from a stock and its warrant. *Physica A: Statistical Mechanics and its Applications*, *419*, 575–584.

Ma, J., Xiong, X., He, F., & Zhang, W. (2017). Volatility measurement with directional change in Chinese stock market: Statistical property and investment strategy. *Physica A: Statistical Mechanics and its Applications*, *471*(C), 169–180. https://doi.org/10.1016/j.physa.2016.11.113

Ma, S. (2022). *Tracking and nowcasting directional changes in the Forex market, PhD thesis, Centre for Computational Finance and Economic Agents (CCFEA)*. University of Essex.

Petrov, V., Golub, A., & Olsen, R. (2020). Agent-based modelling in directional-change intrinsic time. *Quantitative Finance*, *20*(3), 463–482. https://doi.org/10.1080/14697688.2019.1669809

Tsang, E. P. K. (2021). Directional change for handling tick-to-tick data. *Journal of Chinese Economics and Business Studies*, *20*, 171–182. https://doi.org/10.1080/14765284.2021.1989883

Tsang, E. P. K., & Ma, M. (2021). *Distribution of aTMV, an empirical study, Working Paper WP089-21, Centre for Computational Finance and Economic Agents (CCFEA)*. University of Essex. https://www.bracil.net/ccfea/WorkingPapers/2021/TsangMa-TMV_distribution-WP089-2021.pdf

Tsang, E. P. K., Tao, R., Serguieva, A., & Ma, S. (2017). Profiling high-frequency equity price movements in directional changes. *Quantitative Finance*, *17*(2), 217–225. https://doi.org/10.1080/14697688.2016.1164887

Yan, K., Zhang, W., & Shen, D. (2020). Stylized facts of the carbon emission market in China. *Physica A: Statistical Mechanics and its Applications*, *555*, 124739. https://doi.org/10.1016/j.physa.2020.124739

Ye, A., Chinthalapati, V. L. R., Serguieva, A., & Tsang, E., Developing sustainable trading strategies using directional changes with high-frequency data, IEEE International Conference on Big Data, Boston, 11-14 2017

Zhang, W., Li, Y., Zhang, Z., & Shen, D. (2018). The dynamic cross-correlations between foreign news, local news, and stock returns. *Physica A: Statistical Mechanics and its Applications*, *509*, 861–872.

Zhang, W., Wang, P., Li, X., & Shen, D. (2018). Quantifying the cross-correlations between online searches and Bitcoin market. *Physica A: Statistical Mechanics and its Applications*, *509*, 657–672.

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