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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.

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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:

- 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.
- 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

$$aTMV(P) = (|P - EP| \div EP) \div \theta.$$
(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 $25.3\% \div 5\% = 5.06$.



FIGURE 3 Distribution of aTMV at extreme points in the EUR/USD Forex market between September 25, 2009, 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 aTMVincreases, 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 TSANG ET AL.

and December 31, 2014, observed under

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:

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

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 ($|98-95| \div 98 \div 0.05=$) 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 ($|104-100| \div 104 \div 0.05=$) 0.7692308.

It is useful to remember that $0 \le BM < 1$. 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*) \ge P_{TMV} and

2. BM (ct) \ge 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 $\mathsf{P}_{\mathsf{TMV}}$ 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 tickto-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).

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Threshold	Data in the training from 00:00:10 Sept to 20:08:53 Dec 31, 72,629,464 transact 0.0016	period 25, 2009, 2013, ions 0.0032	Data in the nowcas from 01:30:09 Jan to 13:02:55 Dec 31 33,041,496 transac 0.0016	ting period 1, 2014, ., 2015, tions 0.0032	exchange rates profiles shown
# 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 2Tick-to-tick EURUSDexchange rates used, with their DCprofiles 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. Timeliness_{Time} of a nowcast:

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

 $Timeliness_{Time} = DCC.time - NCP.time.$ (3)

Definition 4. Timeliness_{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 Timeliness_{Price} of a nowcast measures how early the nowcast is in terms of price:

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

In SNC1, the Timeliness_{Time} of NCP is (08:49:37–08:48:37=) 60 s, which is a long time for tick data. The aTMV (DCC) is ([$|1.16011-1.15486| \div 1.15486] \div 0.0016=$) 2.841253. The aTMV (NCP) is ([$|1.15613-1.15486| \div 1.15486] \div 0.0016=$) 0.687313. Therefore, the Timeliness_{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 Timeliness_{Price} but just a mediocre nowcast in terms of Timelines- s_{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

TABLE 3 Summary of nowcasting performance

NCA performance in the nowcasting period shown in Table ${\bf 2}$			
Threshold θ	$\boldsymbol{\theta}=\textbf{0.0016}$	$\boldsymbol{\theta}=\boldsymbol{0.0032}$	
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	
$Precision_{Correct} = CN \div Nc$	66.63%	59.80%	
$Precission_{Good} = GN \div CN$	98.43%	99.63%	
Average Timeliness _{Price}	0.336	0.399	
$\sigma \text{ Timeliness}_{\text{Price}}$	0.107	0.098	
Max Timeliness _{Price}	2.154	1.961	
Average Timeliness _{Time}	1,967 s	8,789 s	
$\sigma \text{ Timeliness}_{\text{Time}}$	11,745 s	24,796 s	
Max Timeliness _{Time}	221,194 s	229,764 s	

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.

How useful are the nowcasts? Under $\theta = 0.0016$, the average Timeliness_{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, Timeliness_{Price} is 2.154. This is shown in SNC1 (Figure 5). Timeliness_{Price} is greater than 1 in SNC1 because the DC confirmation point was a big jump in the market. The standard deviation of Timeliness_{Price} is 0.107 under $\theta = 0.0016$.

Timewise, the average Timeliness_{Time} under $\theta=0.0016$ is 1,967 s (around 30 min). The maximum Timeliness_{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 Timeliness_{Time}, which is confirmed by the results. As Timeliness_{Price} is normalized by the thresholds, the results are comparable under the two different thresholds: the average Timeliness_{Price} is 0.336 under $\theta = 0.0016$ and 0.399

under $\theta=0.0032.$ 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	hown

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 To: 23:59:59 Dec 31, 2013	From 00:00:09 Jan 1, 2014 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 s	hown

	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 To: 23:59:59 Dec 31, 2013	From 00:00:01 Jan 1, 2014 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	$\theta = 0.0016$		
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		
$Precision_{Correct} = CN \div Nc$	81.39%		
$\text{Precission}_{\text{Good}} = \text{GN} \div \text{CN}$	100%		
Average Timeliness _{Price}	0.1255		
σ Timeliness _{Price}	0.017		
Max Timeliness _{Price}	0.1845		
Average Timeliness _{Time}	779 s		
σ Timeliness _{Time}	1,208 s		
Max Timeliness _{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 $\boldsymbol{\theta}=0.0032$ TnT: total # of trends 747 9 Nc: # of nowcasts GN: # of good nowcasts 7 CN: # of correct nowcasts 7 IN: # of incorrect nowcasts 2 77.78% $Precision_{Correct} = CN \div Nc$ $\text{Precission}_{\text{Good}} = \text{GN} \div \text{CN}$ 100% Average Timeliness_{Price} 0.1255 0.0006 σ Timeliness_{Price} Max Timeliness_{Price} 0.00428 Average Timeliness_{Time} 5,189 s $\sigma \text{ Timeliness}_{\text{Time}}$ 5,461 s Max Timeliness_{Time} 13,559 s

by T). Figures 6 and 7 show the graphs of the probability of $aTMV_{EXT}$ occurring in each bin and the probability of reaching a certain number of $aTMV_{EXT}$ 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_{TMV} and P_{BM} . During the NCA in the training period for the USD/JPY market, we set the parameters to $P_{TMV}=5.58$ and $P_{BM}=0.641$. For the GBP/USD market, the parameters were set to $P_{TMV}=5.38$ and $P_{BM}=0.53$. In both markets, there is a 1% probability that the P_{TMV} and P_{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 Timeliness_{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 Timeliness_{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 Timeliness_{Time} in comparison to the averages suggest that the implementation of NCA for nowcasting can result in gaining thousands of seconds effectively. Timeliness_{Time} gages the extent to which NCA identifies a new trend before the DCC. A greater Timeliness_{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 Timeliness_{Time} stands at 2,607, while the average is 5,189. This considerable difference is primarily attributable to extreme values; the maximum Timeliness_{Time} reaches 13,559 s, and the minimum is 11. The standard deviation of Timeliness_{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_{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.
- $^{\rm 2}$ 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 directionchanging 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.

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