Distribution of aTMV, an empirical study

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Abstract

aTMV is a metric in Directional Change (DC) which measures the magnitude of price changes in each trend. In this paper, we study the historical distribution of aTMVs (in absolute values) at the end of the trends, denoted by $|aTMV_{EXT}|$, in the EUR/USD exchange market. We show that the aTMVs under two different DC thresholds form a power-law distribution: the chance of a DC event happening increases exponentially as aTMV increases. While this is no surprise to DC researchers, information such as "only 5% of the trend will reach an |aTMV| of 1.7" may be useful for future research.

I. Introduction

Olsen et al [7][9] introduced the concept of Directional Change (DC) as an alternative way to sample transactions: the idea is to let data determines when a transaction should be sampled. A transaction is recorded when a significant price change in the opposite direction of the current trend has taken place, where "significance" is observer-dependent. Every observer defines its threshold for calling a price reversal a DC Event. The trend continues until the next DC Event takes place. Thus, the market is partitioned into uptrends and downtrends, delimited by peaks and troughs, which are extreme points. The formal definition of DC can be found in Appendix A in [14]. DC has been applied to forecasting [2], market analysis [13][11], monitoring [6][10] and trading [8][3][4][16][1][6]. Tsang [15] argues that DC is particularly suitable for handling high frequency data.

With data sampled in irregular times, new measures are needed for measuring risk under DC. Tsang et al [13] introduced several orthogonal measures to risk in DC. Following are two of these measures:

1. The number of DC Events in a given period of time, NDC, measures the frequency of directional changes in that period. Everything being equal, the higher the frequency of changes, the more volatile the market is.
2. A DC Event is confirmed when price has reversed by the DC threshold. The magnitude of price change in each trend measures the market's volatility within that trend.

Definition 1. Absolute Total Movement (**aTMV**) in DC:

$$aTMV = (|P_c - P_{EP}| \div P_{EP}) \div Threshold \quad (1)$$

Where P_c is the current price, P_{EP} is the preceding extreme price, Threshold is the threshold used to determine significance in the DC summary. By normalisation with the Threshold, the aTMV values obtained in different DC summaries can be compared, even if they were derived from different thresholds.

This paper studies on the historical distribution of aTMV values.

II. Emperical studies on $|aTMV_{EXT}|$ distributions

We denote the aTMV at an extreme points that ends a trend $aTMV_{EXT}$. Glattfelder et al [9] discovered the power law in historical DC trends; in aTMV terms, they found that historically the mean of $|aTMV_{EXT}|$ is 2. In this paper, we study the distribution of $aTMV_{EXT}$.

In this paper, we study the historical distributions of aTMV in EUR/USD. We use the tick-to-tick EUR/USD exchange rate from 00:00:10 25th September 2009 to 20:14 31st December 2014. We will calculate $|aTMV_{EXT}|$ under threshold 0.0016 and 0.0032. For each of these thresholds, we found the DC trends as explained in [6].

The data used are summarized in Table 1. With threshold 0.0016, we found 9,552 trends. With threshold 0.0032, we found 2,052 trends.

Table 1. Summary of data used

Tick-by-tick EUR/USD exchange rate was used		
	Threshold 0.0016	**Threshold 0.0032**
Period	From: 00:00:10 25th September 2009 To: 20:08:53 31st December 2013	
Number of transactions	72,629,464	
Number of trends	9,552	2,052

III. Historical distribution of $|aTMV_{EXT}|$

For each trend, we calculate the $|aTMV_{EXT}|$ as defined in Definition 1. Results are summarized in Table 2.

Table 2. Analysis of $|aTMV_{EXT}|$ distributions

	Threshold = 0.0016	Threshold = 0.0032
Number of trends	9,552	2,052
Min	1.000039	1.001114
Max	10.575712	8.790733
Mean	1.904441	2.011402
Median	1.614331	1.682255
Standard Deviation	0.939099	1.014672
aTMV occurrence percentage:		
<50%	1.614449	1.682692
<10%	3.128502	3.340872
<5%	3.766335	4.062711
<1%	5.352294	5.615179
<0.5%	6.042095	6.195014
Power law function fitting:	y=c1*e^-(c2/TMV)+c3	
C1	10.981249	11.122123
C2	5.100878	5.166847
C3	1.075028	1.085923
Error	0.004906	0.004619

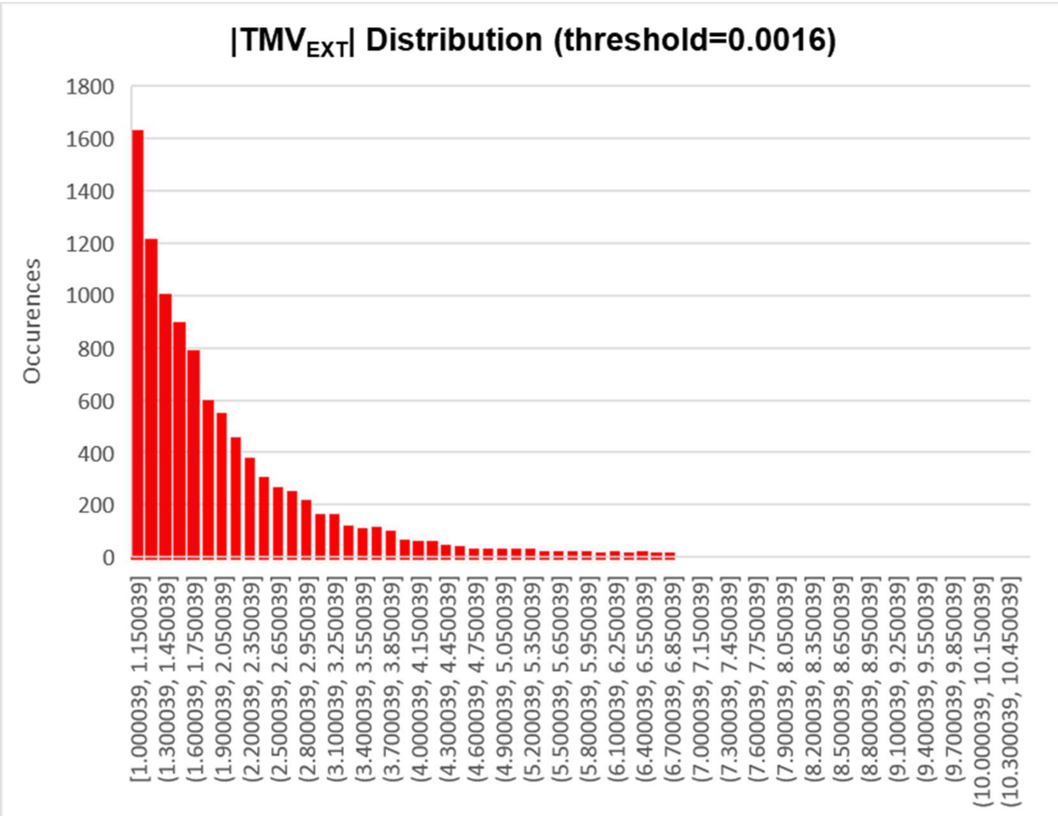

Figure 1. Number of occurrences in $|aTMV_{EXT}|$ values under threshold 0.0016

The number of $|aTMV_{EXT}|$ found in each window under 0.0016 are shown in Figure 1. The historical probability of the $|aTMV_{EXT}|$ reaching a certain value is shown in Figure 2. Under threshold 0.0016, 50% of the |aTMV|s were below 1.614449, as shown in Table 2. This means after reaching the DC Confirmation point (which minimum $|aTMV_{EXT}|$ is 1.0), half of the trends ended before they reached 61.4449% of the threshold (calculating from the preceding extreme point). 95% of the trends ended before their |aTMV| reached 3.766335, 99% ended before their |aTMV|s reached 5.352294. These $|aTMV_{EXT}|$s may be useful references for designing algorithmic trading, which is beyond the scope of this paper.

We attempted to fit the results to the following equation:

$$y = c1 \times e^{-\left(\frac{c2}{x}\right)} + c3 \qquad (2)$$

where y is the probability of the |aTMV| reaching x. The parameters c1, c2 and c3 are shown in Table 2. Equation (2) is a good fit to the empirical data; under threshold 0.0016, the error was 0.004906.

Similar results were found under threshold 0.0032. The $|aTMV_{EXT}|$ distribution for 0.0032 is shown in Figure 3. The distribution is similar to those found under 0.0016, as seen in Table 2. The main difference between the results is that fewer extreme $|aTMV_{EXT}|$ are found under the larger threshold. The parameters (c1, c2 and c3) in Equation (2) under the two thresholds are slightly different, but the overall distribution are very similar, as seen in Table 2.

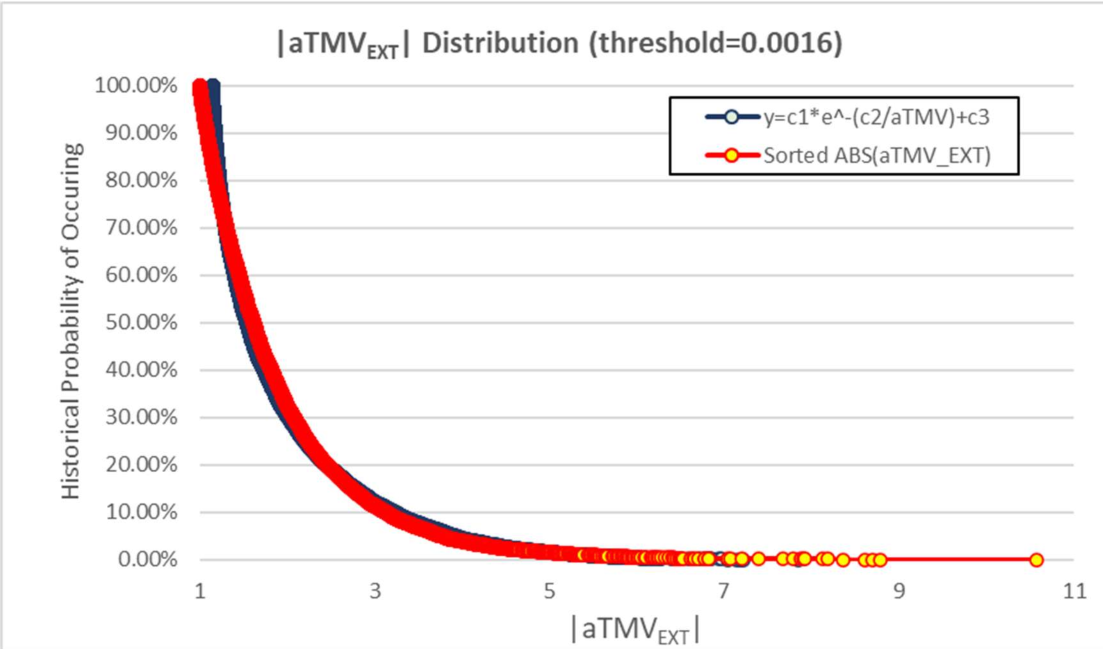

Figure 2. Historical distrubition of |$aTMV_{EXT}$| values under threshold 0.0016

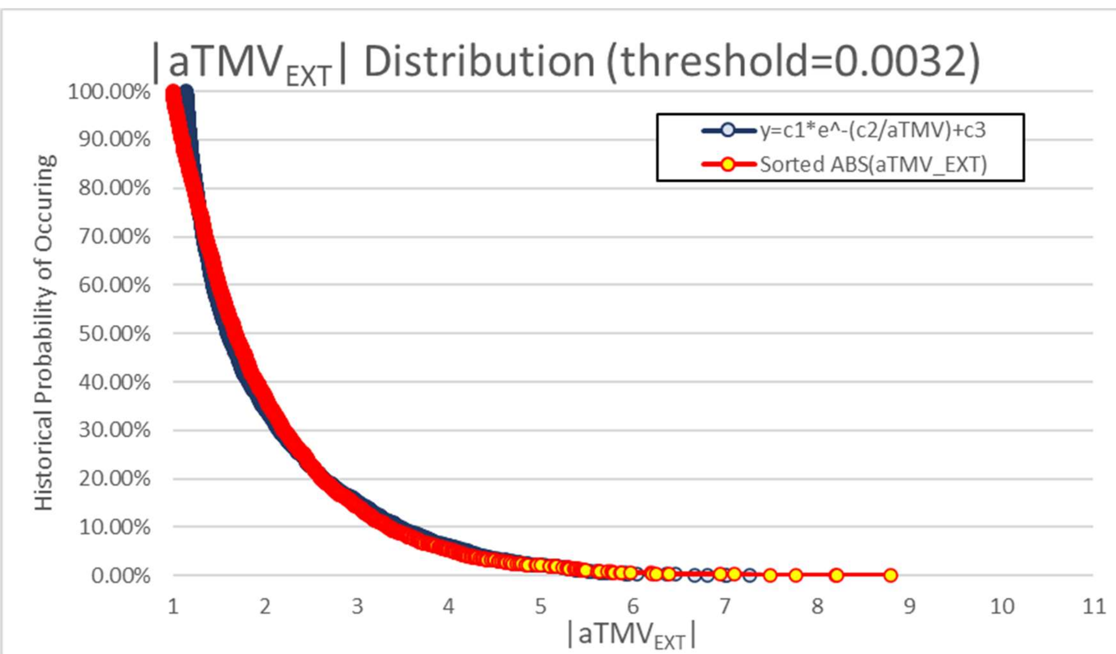

Figure 3. Historical distrubition of |$aTMV_{EXT}$| values under threshold 0.0032

IV. Concluding Summary

By observing different foreign exchange pairs under multiple thresholds, Glattfelder et al [9] showed that overshoot increases exponentially as the threshold increases. They also showed that on average overshoot is approximately equal to the threshold used in a DC summary. In the context of this paper, this mean aTMV is approximately equal to 2.[1]

This paper shows that, for a given threshold, the distribution of aTMV values also follow a power law distribution. While this is common knowledge to most DC researchers, it is worth putting it on record. Besides, it is worth associating aTMV values to historical probabilities. These values may be useful for market monitoring, which will be left for future work [10].

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[1] Readers are reminded that aTMV is equal to the threshold plus the overshoot, normalized by threshold (Definition 1).

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