Detecting Turning Points of Trading Price and Return Volatility for Market Surveillance Agents

Yuming Ou[1], Longbing Cao[1], Ting Yu[2] and Chengqi Zhang[1]
[1] *Faculty of Information Technology, University of Technology, Sydney, NSW 2007, Australia*
[2] *Centre for Integrated Sustainability Analysis, The University of Sydney, NSW 2006, Australia*
[1]*{yuming, lbcao, chengqi}@it.uts.edu.au*
[2]*t.yu@physics.usyd.edu.au*

Abstract

Trading agent concept is very useful for trading strategy design and market mechanism design. In this paper, we introduce the use of trading agent for market surveillance. Market surveillance agents can be developed for market surveillance officers and management teams to present them alerts and indicators of abnormal market movements. In particular, we investigate the strategies for market surveillance agents to detect the impact of company announcements on market movements. This paper examines the performance of segmentation on the time series of trading price and return volatility, respectively. The purpose of segmentation is to detect the turning points of market movements caused by announcements, which are useful to identify the indicators of insider trading. The experimental results indicate that the segmentation on the time series of return volatility outperforms that on the time series of trading price. It is easier to detect the turning points of return volatility than the turning points of trading price. The results will be used to code market surveillance agents for them to monitor abnormal market movements before the disclosure of market sensitive announcements. In this way, the market surveillance agents can assist market surveillance officers with indicators and alerts.

1. Introduction

Trading agent concept [1] is very useful for trading strategy design and market mechanism design [2]. Besides that, we are also particularly interested in the use of trading agents for market surveillance. Market surveillance agents can be developed for market surveillance officers and management teams to present them alerts and indicators of abnormal market movements. In particular, we investigate the strategies for market surveillance agents to detect the impact of company announcements on market movements. This is useful for detecting abnormal market movements associated with pre-disclosure of market sensitive announcements. The identified indicators or alerts can be delivered to market surveillance officers through market surveillance agents. Market surveillance officers can then further digest and investigate the alerts and indicators for necessary and effective treatments of abnormal trading behavior.

The detection of insider trading is of importance to market integrity. Insider trading is defined as the trading of a security by one who has access to material, nonpublic information about the security. Insider trading often occurs just before the release of market sensitive announcements, because the informed traders can profit from their exclusive information before it is made public.

One of approaches to detect insider trading is to spot the market movement that is earlier than capturing the release time of announcement. As shown in Figure 1, if any insider trading occurs, there will be a market movement reacting to the coming announcement within the pre-release session. Any abnormal market movement within the pre-release session would be a signal of the potential insider trading. In our previous work [3], segmentation is used to detect the turning point of trading price. As shown in Figure 2, the trading price time series is divided into pieces through segmentation to analyze its moving trends. The turning points of trading price relating to announcements are the points that separate two trends around the release time of announcements. If the turning points is significantly earlier than the release time of company announcement and large volumes of trading also occur, it is highly likely that the inside information has been disclosed before the release time. However, the task of detecting turning point of trading price tends to be difficult because there is often a large amount of noises or other effectors around the turning points, especially in the case of high frequency intraday data.

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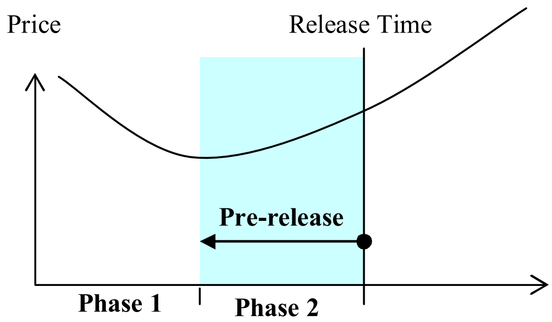

Figure 1. Pre-release period

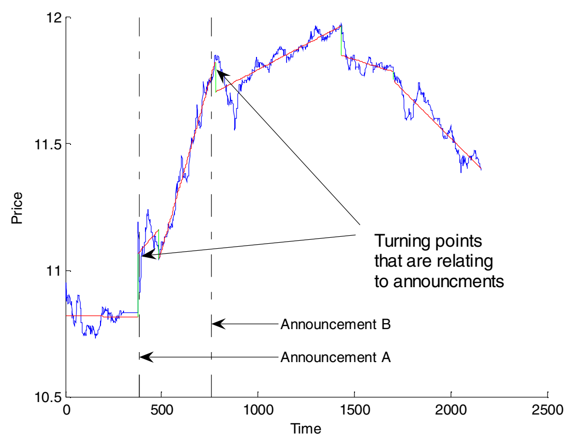

Figure 2. Detecting turning points relating to announcements

Much literature has documented that the news arrival and the resolution of its informational impact are directly related to the dynamics of the return volatility process [4,5]. This inspires us to spot the turning points of return volatility rather than the turning points of trading price. From Figure 3, it can be seen that the volatility can capture the market movement better than the trading price. The trend of price dose not change but the volatility does. In this case, the task of spotting the turning points of trading price is harder that that of spotting the turning points of return volatility. Therefore, in this paper an investigation is conducted on comparing the performance of detecting turning points based on trading price and return volatility.

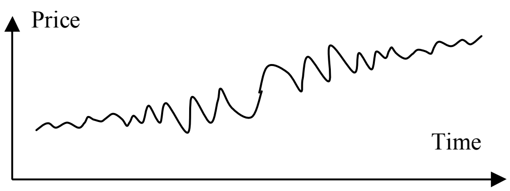

Figure 3. The trend of volatility changes but the trend of price does not change over the period

2. Return Volatility

The formulas for calculating return volatility are as follows.

$$V = \frac{std(r_t)}{\sqrt{T}} \quad (1)$$

$$r_t = \ln \frac{P_t}{p_{t-1}} \quad (2)$$

$$P = \frac{\sum volume * price}{\sum volume} \quad (3)$$

where V is the return volatility for a time range of T, r_t is the logarithmic return and P is the Volume Weighted Average Price (VWAP) over a time interval p_i. Using VWAP can remove some noises in high frequency intraday data. A sliding window with size T is used to calculate the return volatility. All VWAPs falling into the sliding window are used to calculate the return volatility through the above formulas. With the sliding of the window over the time series of VWAP, a time series of return volatility is generated.

3. Segmentation Model

Segmentation is a helpful tool to analyze the change of market trend. As in our previous work [3], segmentation works well to detect the turning point of trading price. This paper still employs segmentation to detect the turning point of return volatility. Thinking of that the basic idea of *piecewise linear fitting* is straightforward and it works well under the condition of high frequency data that contains much noise, we use *piecewise segmented model* in this paper. The piecewise segmented model is described in [6] as follows.

$$Y = \begin{cases} f_1(t, w_1) + e_1(t), (1 < t < \theta_1) \\ f_2(t, w_2) + e_2(t), (\theta_1 < t < \theta_2) \\ \vdots \\ f_k(t, w_k) + e_k(t), (\theta_{k-1} < t < \theta_k) \end{cases}$$

where the $f_i(t,w_i)$ is the linear function that fits in segment i, and $e_i(t)$ is the error. This model segments the time series into pieces that have minimal total error:

$$\sum_{i=1}^{k} e_i(t).$$

The user needs to specify the number of segments that are expected.

4. Experiments

This experiment is carried on five datasets to compare the performance of detecting turning points based on return volatility with that based on trading price. The five datasets are the intraday trading price for security code AMP (AMP Limited Australia) in Australian Stock Exchange (ASX). Table 1 shows the features of the five datasets such as *trading date*, *number of announcements* released during normal trading hours (from 10am to 4pm) of that day and *release time of announcements*.

Table 1. The features of the five datasets

No.	Trading date	Number of announcements	Release time	Release time
1	20/11/2001	2	11:12:32	13:25:36
2	27/02/2003	2	12:31:44	13:53:55
3	13/03/2003	2	12:33:11	14:41:55
4	31/03/2003	1	11:16:23	
5	07/05/2003	1	12:01:45	

To avoid bias, the two time series for price and volatility are generated under same circumstances and segmented by the same model. The time series of prices is generated through formula (3), while the time series of volatility is generated through formula (1). Both of them are based on VWAP. The interval p_i for calculating VWAP is one minute. The size of the sliding window to calculate volatility is 30 minutes. After the time series are generated, they are divided into pieces by piecewise segmented model described in Section 3 to spot the turning points. The *turning points* are defined as the points that separate two adjacent trends and have the shortest distance from the release time of announcements.

As mentioned above, in the piecewise segmented model, a user needs to specify the number of segments that will be generated. The result generated from the model is sensitive to this parameter. To make sense of the specified number of segments, it is important to involve the supervision of domain experts. Intuitively, they may have a rough idea of how the trends are and how many segments should be by reviewing the time series curve before the segmentation. This rough idea is helpful to set a parameter to obtain better result of segmentation. In this experiment, we test different values of the parameter to find out the optimal segmentation.

The best segmentation satisfies the following conditions: (1) the distance between a turning point and the release time of announcement is shortest, and (2) the number of segments generated is as less as possible but the turning points that are related to the announcements can still be detected. The reason for introducing the second condition is to avoid overfitting. If too many segments are generated, either the turning points will be overwhelmed by the noise surrounding them or the fitting curve will resemble the actual one. The software for segmentation is the bottom up segmentation [6] in the Matlab.

Table 2. Experimental results

Dataset 1			
release time	11:12:32	13:25:36	number of segments
real index	73	206	
turning point of price	71	235	14
turning point of volatility	79	225	7
Dataset 2			
release time	12:31:44	13:53:55	number of segments
real index	152	234	
turning point of price	147	241	18
turning point of volatility	159	243	15
Dataset 3			
release time	12:33:11	14:41:55	number of segments
real index	154	282	
turning point of price	155	279	13
turning point of volatility	159	277	4
Dataset 4			
release time	11:16:23		number of segments
real index	77		
turning point of price	71		6
turning point of volatility	77		3
Dataset 5			
release time	12:01:45		number of segments
real index	122		
turning point of price	119		10
turning point of volatility	125		4

The results are given in Table 2. The “real index” rows indicate the points that correspond to the release time of announcements. The “number of segments” columns stand for the minimal number of segments that are needed to be generated to detect the turning points.

As shown in Table 2, with the similar segmentation effect, the number of segments needed for detecting the turning points of return volatility is less than that for detecting the turning point of trading price. This means that the return volatility can capture the announcement arrival better than trading price. The turning points of return volatility are distinguished from the noise around them, and the trends before and after them are quite different. Therefore, they are easy to be spotted by less number of segments. Whereas the turning points of trading price tend to be overwhelmed by the noise surrounding them so that they need more number of segments to be detected.

To make it more clear, the time series of trading price and return volatility for dataset 4 are plotted in Figure 4. The vertical lines indicate the release time of announcement. The turning points of trading price around the vertical lines are hard to be spotted. On the contrary, the turning point of return volatility is easy to be detected. Therefore, the overall performance of detecting turning points based on return volatility is superior to that based on trading price.

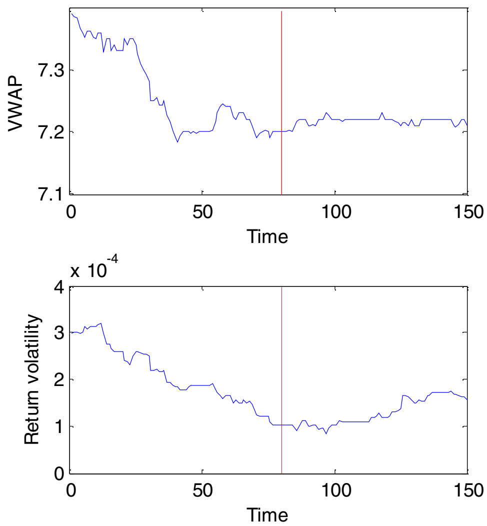

Figure 4. The time series of trading price and return volatility for dataset 4

5. Conclusions

Trading agents can also be used for market surveillance. A particular use is to develop market surveillance agents. When powered with proper detection algorithms for abnormal trading behavior, market surveillance agents can monitor and detect abnormal market sensitive movements, and generate alerts and indicators associated with abnormal market announcements. The delivery of such alerts and indicators to market surveillance officers can greatly help them distinguish and investigate pre-disclosure of price sensitive announcements.

To design effective strategies for trading agents, this paper has investigated the performance difference of segmenting the time series of trading price and return volatility associated with price sensitive announcements, respectively. The purpose of segmentation is to detect the turning points of market movements caused by announcements, which is useful to spot the insider trading. The experimental results show that the minimal number of segments that are needed to be generated to detect the turning points of return volatility is less than that of trading price. This indicates that the return volatility can capture the market movement caused by the release of announcements better than trading price. The turning points of return volatility are easier to be detected than the turning point of trading price.

Our further work is on developing algorithms for trading agents to detect abnormal movements of market dynamics. The detected alerting indicators will be reported to market surveillance officers through personal assistant agents for them to further check and manage the case.

6. Acknowledgements

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7. References

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