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Intra-day Price Bubbles

In recent years, the topic of price or economic bubbles has received significant attention. As we wrote this article, Nobel Prize winner Robert Shiller discussed how bitcoins resembled past market bubbles[1]. Several methods specifically for real-time detection of bubbles have been proposed such as the recursive unit root tests (Phillips, Wu and Yu, 2011) and Generalized sup-ADF test (Philips, Shi and Yu, 2015). Determination of bubble periods is useful as they are phases of extreme exuberance or pessimism (as in case of negative bubbles).

While the general notion is that bubbles are usually "bad" several studies suggest that investors may want to ride bubbles for a period of time before exiting. For instance, Brunnermeier and Nagel (2004) examined holdings of hedge funds during the technology bubble of 1998–2000 and found that hedge funds managed to capture the tech-bubble by skewing their portfolio heavily in favor of tech-stocks. Interestingly, many of these hedge funds were also able to exit several months prior to the tech-crash.

In our research, we modify the conventional bubble detection algorithms and apply to intra-day data for determination of a trend signal. Most of the literature so far use lower frequency data for detection of bubbles but to our knowledge this is the first time that anyone has utilized such techniques on high frequency or intra-day data. We define intra-day bubbles as periods of brief regime changes when price tends to be in an explosive phase. These intra-day bubbles are typically directional and can last from a few seconds to several minutes. Our research pertains to taking advantage of this unsustainable growth in prices in a manner that we could cautiously tread in the direction of the bubble till it explodes. We also find that intra-day price bubbles can occur during all possible time horizons, and so we apply our algorithm at various intraday time-intervals. To this effect, we are in agreement with the term of "riding the bubble" as coined in the literature because our signal is essentially a ***well-timed momentum signal***.

We compute intraday bubble periods by using the recursive right tailed test as in Phillips et al. (2011,2015b) with some modifications to suit fat tailed distribution as observed in high-frequency data. The test itself is based on the following prototypical model, where y_t indicates price series and p is the lag order of the auto-regressive process.

$$y_t = \rho\left(y_{t-1} - \bar{y}\right) + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \qquad (1)$$

It is intuitive to see that in the above equation when $\rho > 1$ then the price series would explode away from its long run average of $\bar{y}$. The empirical regression version of this model is essentially an augmented Dickey–Fuller (ADF) test for a unit root against the alternative of an explosive root based on the estimated $\hat{\rho}$; that is, the modified null hypothesis is tested as $H_0 : \hat{\rho} <= 1$ against the right-tailed alternative hypothesis $H_1 : \hat{\rho} > 1$. The model in equation (1) would not be the true model at all times, especially when applied to the entire time series. However, over a short time window, the price series could be in a "bubble-phase". The idea is to run the above regression on time windows of various durations and look for instances when t-stat of $\hat{\rho}$ computed as $\text{DF}_t = \hat{\rho}/\text{Std.Error}\left(\hat{\rho}\right)$ would exceed the corresponding critical value. Since high frequency data tends to be much more fat tailed, we adjust our critical values accordingly for the actual distribution rather than using the standard values for a normal distribution. We also find that adding additional criteria for filtering the bubbles aids us in improving the overall prediction power of the technique.

We ran the above mentioned technique over an out-of-sample history (from January 2016 till Sep 2017) to generate our signals and found the average forecast performance to be significant. Furthermore, the average performance in backtesting was found to be equally strong for buy vs. sell signals. We presented some examples from S&P 500 e-mini futures'

[1] CNBC interview, Wednesday, Sep 6 2017

intra-day price series on the next page. In the graphs shown, the black line shows the price time series, the down/up arrows are generated by our model and indicate a sell/buy signal at the labelelled time, the red dot at the end of all the down arrows shows the time when the model score drops below the critical value. In other words, at this point (indicated by red circle), we would expect the price to either revert or stop trending.

In the figure 1, there was a mild momentum from 12:45 pm CDT on Apr 26, 2017 that intensified at around 12:48 pm. The model was able to catch the further drop of around 3 points before it reversed and generated an exit signal. Similarly in figure 2, we can see that the model predicted the small window of price spike correctly around 2:40 A.M CDT on Apr 7, 2017 for approximately 5 minutes. However there was already a reasonable upward momentum before the model triggered the entry point. As shown in these examples, the model would slightly lag the price momentum for entry and would need a slight reversal thereafter to exit.

The richness of the high frequency data and speed of computing goes a long way in helping us identify the explosive phase of prices within few milli-seconds. Furthermore, the nature of the model is generic enough to be applied to other futures instruments as well. The utilization of such a high-frequency intraday bubble detector would potentially improve the execution slippage.

References

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Example: Sell Signal

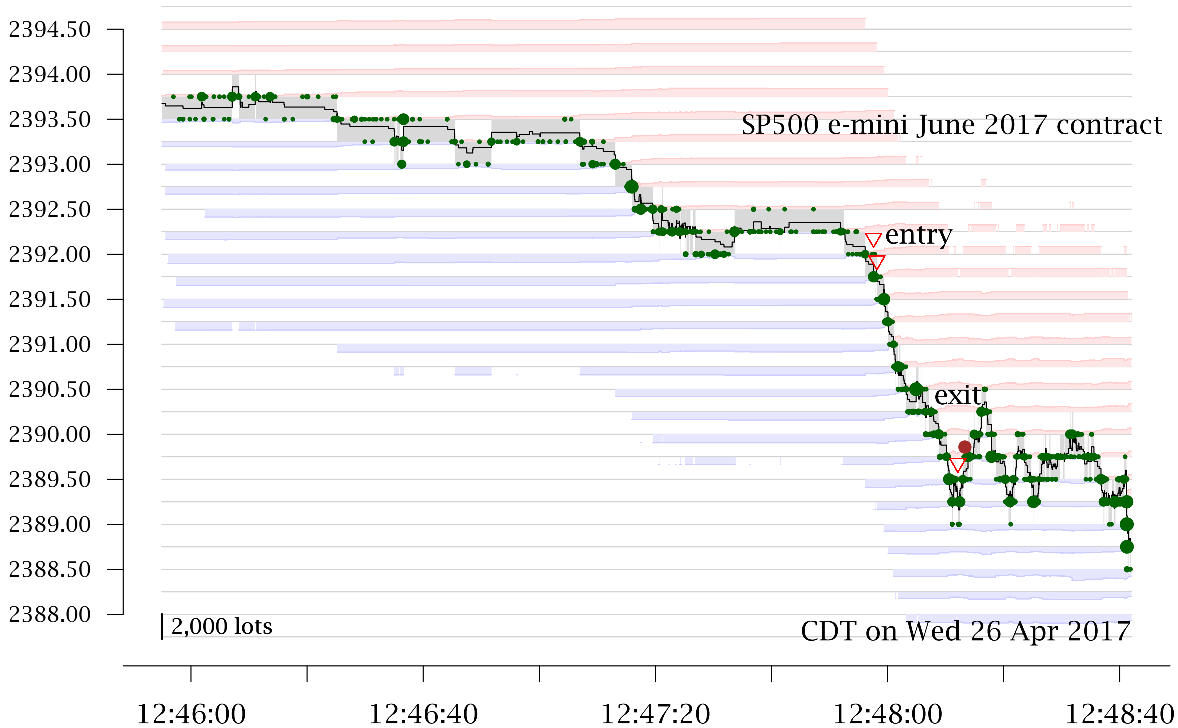

Figure 1: Price was already dropping from 12:45 pm. Model picked the further drop in price correctly

Example: Buy Signal

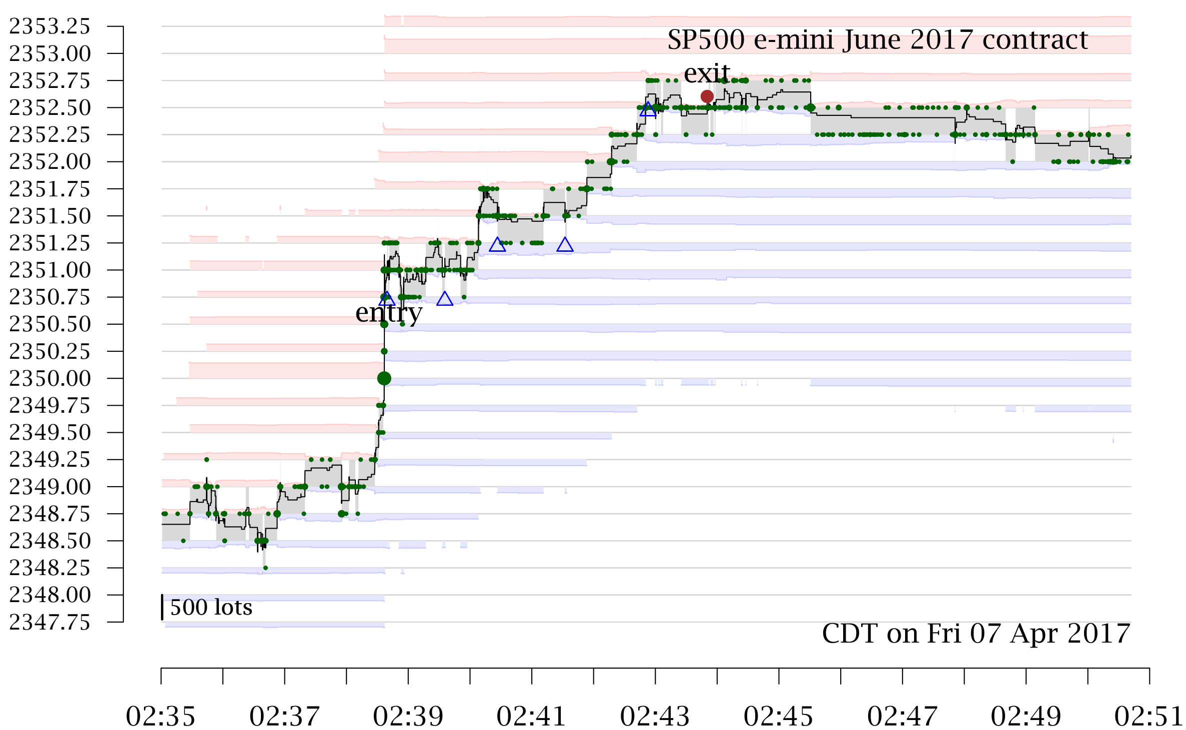

Figure 2: Model picked the upward momentum and exited after the price flattened around 2:43 am