Pandemic Forecasting via Stock Market Indicators

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Importance

People around the world have been struggling with CoVID-19

239,437,517
confirmed cases

4,879,235
deaths
People around the world have been struggling with CoVID-19.

We turned to stock markets in order to find new forecasting tools.
Technical indicators can predict trend continuation and reversals.
Tools for identifying trend reversals which we explore:

- Candlesticks
- Candlestick patterns
- MACD analysis
- RSI analysis
Candlesticks

The first tool we adapt from finance to pandemics are candlesticks. This collects the time series into larger units and presents the information as follows:

\[
\text{Candlestick}_t = (O_t, C_t, H_t, L_t).
\]
Example

Line plot for Apple’s share price can be translated into candlesticks:
Application to the Pandemic

Organize daily new cases into weekly candlesticks.
Candlestick Patterns

Candlestick patterns – combinations of specific consecutive candlesticks – used as stock market forecasters.

Prominent examples that we shall study for COVID are:

- Bullish Engulfing
- Bearish Engulfing
- Hammer
- Hanging Man
- Dark Cloud Cover

Bullish (Bearish) pattern predicts reversal to Uptrend (Downtrend).
Candlestick Patterns

Example: Bullish Engulfing

- Pattern shown in the centre of chart (right).
- Preceding trend is downtrend.
- Predicts reversal of trend.
MACD: Moving Average Convergence Divergence

MACD indicator claims predictive power in stock markets.

MACD is based on observations on moving averages.

Example from S&P 500 Index.
RSI: Relative Strength Index

RSI is another indicator claiming predictive power in stock markets.

RSI identifies asset prices that have move “too quickly”.

Example from S&P 500 Index.
Application to the Pandemic

We explore the application of these indicators to COVID data.

Our R code scans WHO COVID data of 237 countries and identifies different signals and patterns.

<table>
<thead>
<tr>
<th>Signal Name</th>
<th>Number of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bullish Engulfing</td>
<td>99</td>
</tr>
<tr>
<td>Bearish Engulfing</td>
<td>123</td>
</tr>
<tr>
<td>Hammer</td>
<td>127</td>
</tr>
<tr>
<td>Hanging Man</td>
<td>156</td>
</tr>
<tr>
<td>Dark Cloud Cover</td>
<td>30</td>
</tr>
<tr>
<td>Bullish MACD</td>
<td>217</td>
</tr>
<tr>
<td>Bearish MACD</td>
<td>245</td>
</tr>
<tr>
<td>Bullish RSI</td>
<td>46</td>
</tr>
<tr>
<td>Bearish RSI</td>
<td>1057</td>
</tr>
</tbody>
</table>
Application to the Pandemic

Our R code identified 99 occurrences of Bullish Engulfing Pattern.

We then perform statistical test: \( p \)-value (\( y \)-axis) is calculated \( n \) days after the pattern (\( x \)-axis).

Circles below blue (red) line imply \( p \)-value of 0.1(0.05).

Bullish Engulfing is a significant forecaster for COVID data.
Pandemic Forecasting via Stock Market Indicators

Results

Repeat for other indicators, here we show selection.

Many are statistically significant forecasters of future COVID cases.
We have repurposed technical indicators of stock market for use in pandemics.

Intuition due to fact pandemic and stock market both can be modeled as random walks.

We showed that technical indicators do have statistically significant forecasters of near term COVID cases.

Forecasting can aid in allocating medical resources.
I would like to thank Prof. James Unwin for his guidance along the way and MIT PRIMES-USA for making this collaboration possible.

Thank You!
Exponentially Moving Average

Consider a dataset of length \( n \), normally the closing prices, \( \{ C_i \} \)

\[
V_i[C_i] = \begin{cases} 
  C_1 & i = 1 \\
  \alpha C_i + (1 - \alpha) V_{i-1} & i > 1 
\end{cases}
\]

where \( \alpha \) is the smoothing factor. \( V_n \) is the Exponentially Moving Average (EMA) of \( \{ C_i \} \). In particular,

\[
V_n = \alpha [C_n + (1 - \alpha) C_{n-1} \cdots (1 - \alpha)^{n-1} C_1] .
\]

- Places greater weight on \( C_n \)
Moving Average Convergence Divergence

The signals are from two intertwining lines. Common values for \((n_1, n_2, n_3) = (12, 26, 9), \alpha = \frac{2}{n+1}.

\[
\text{MACD}(n_1, n_2) = V_{n_1} - V_{n_2}
\]

- the strength of up trend

\[
S = V_{n_3}[\text{MACD}(n_1, n_2)]
\]

- the strength of change in trend
Relative Strength Index

- Divide the dataset \( \{ C_n \} \) into two sets, Gain and Drop.

\[
\{ G_t \} = \frac{C_t - C_{t-1}}{C_t} , \quad C_t > C_{t-1} \\
\{ D_t \} = \frac{C_{t-1} - C_t}{C_t} , \quad C_t < C_{t-1}
\]

Calculate the Average,

\[
\bar{G}_t = V_n[G_t] , \\
\bar{D}_t = V_n[D_t] .
\]

The index is given by

\[
RSI = 100 - \frac{100}{1 + \frac{\bar{G}_t}{\bar{D}_t}} .
\]

- Measures the relative strength of gains and drops.
Wilcoxon Signed Rank Test

Consider dataset \( \{x_i\} \) and hypothesized median \( \tilde{x} \). To compare the distribution on both sides, rank the difference and compute the sum. Formally, the statistic \( W \) is

\[
W = \sum sgn(d_t)R(d_t),
\]

where \( R(\cdot) \) is the rank and

\[
sgn(d_t) = \begin{cases} 
1, & d_t > 0 \\
-1, & d_t < 0 \\
0, & d_t = 0 
\end{cases}
\]