Trading indicators with information-gap uncertainty

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Abstract
Purpose – This paper aims to provide a new quantitative methodology for predicting turning points and trends in financial markets time series based on information-gap decision theory.

Design/methodology/approach – Uncertainty in future returns from financial markets is modelled using information-gap decision theory. The robustness function, which measures immunity to uncertainty, yields an additional time series whose turning points anticipate and reflect those of the underlying financial market time series.

Findings – The robustness function falling above or below certain thresholds is shown to provide a new reliable technical indicator for predicting highs and lows in financial markets. In addition, iterates of the robustness function are shown in certain cases to predict trends in financial markets.

Research limitations/implications – In the analysis and application presented here we have only considered a special case of the robustness function. Stricter performance requirements and alternative process model estimates for future returns could be included in the information-gap model formulation and analysis.

Practical implications – An additional technical trading tool for applying Information – Gap theory to financial markets has been provided.

Originality/Value – This paper provides a new reliable methodology for constructing technical indicators for use by traders and fund managers in financial markets.

Keywords Technical trading indicators, Information gaps, Uncertainty, Robustness, Financial modelling

Paper type Research Paper

Introduction
Trading in financial markets is a huge business with literally trillions of dollars changing hands world-wide on a daily basis based on beliefs about future movements of prices of traded entities such as stocks, bonds, property, commodities, futures, options and so on. Much of the growth in trading can probably be attributed to the increasing rise by market players of computer-based trading models and the availability and transfer of data and information through the internet.

Underpinning much of the recent computer-based trading strategies are various technical indicators, many of which have been known, developed and used by the traders long before the advent of trading software (see Murphy, 1986) for a comprehensive review). These include point and figure charts, support and resistance lines, channels, head and shoulders, trend lines and breakout patterns, Elliot waves, Fibonacci cycles and the more technical oscillators and momentum indicators such as the RSI and the crossing of two or more moving averages. More recently the technical traders have been exposed to more sophisticated mathematical techniques based on chaos theory (Peters, 1991), fractals (Peters, 1994) and genetic algorithms (Bauer Jr, 1994), to name a few, all with limited success.

Our purpose here is to present an alternative approach to technical trading based on Information-Gap Decision Theory (Ben-Haim, 2006). This theory aims to model true Knightian uncertainty (Knight, 1921) where underlying probability distributions of future outcomes, such as price movements in financial markets are unknown and subject to (possibly severe) uncertainty. For some background on applications of Info-Gap Theory to financial markets and risk management the reader is referred to Ben-Haim (2005) and Beresford-Smith & Thompson (2007).

In the following section we present a general Info-Gap framework for constructing technical indicators for turning points in future price movements. A particular example is developed in section 3 and applied to real financial market time-series data. In section 4 we show how two-dimensional patterns obtained from iterates of
our simple Info-Gap indicator can be used to detect upward and downward trends as well as turning points in financial market time series. Our main results are summarised and discussed in the final section.

An info-gap framework for technical trading

For a particular traded entity we define

\[ p_j = \text{the closing (or clearing) price at time } j. \quad (1) \]

The traded entity in question could be any one of a number of financial instruments such as equities, bonds, property trusts, derivatives and so on. We take “time” in (1) to be in discrete unit intervals \((j = 0, 1, 2, \ldots)\) which could be seconds, minutes, days, weeks etc. depending on traders’ practices and time frames.

We take \( j = n \) in (1) to represent “now” so that the \( p_j \) are known for \( j = n, n-1, n-2, \ldots \). The problem for traders of course is that \( p_j \) is unknown and subject to uncertainty when \( j > n \).

To model the uncertainty of future prices we use Info-Gap Decision Theory (Ben-Haim, 2006) which has several key ingredients. Firstly there is an uncertainty model \( U \) for the unknowns, in our case the \( p_j \) for \( j > n \), which in general is a family sets defined in terms of nominal or process model values \( \hat{p}_j \) for the unknowns and a horizon of uncertainty \( \alpha \geq 0 \) which in principle is unknown and unbounded. There are many possible uncertainty models \( U = U(\hat{p}, \alpha) \) but all should satisfy two axioms:

\[ \alpha < \alpha' \implies U(\hat{p}, \alpha) \subseteq U(\hat{p}, \alpha') \quad \text{(Nesting)} \]

\[ U(\hat{p}, 0) = \{ \hat{p} \} \quad \text{(Contraction)} \]

Nesting says that as the horizon of uncertainty increases the range of uncertain variation in the \( p_j \) increases. Contraction simply says that in the absence of uncertainty \( (\alpha = 0) \) the nominal values \( (\hat{p}) \) are in fact correct.

In the present application we propose the so-called envelope-bound uncertainty model (Ben-Haim, 2006):

\[ U(\hat{p}, \alpha) = \{ j = n : |p_j - \hat{p}_j| = \alpha \hat{\sigma}_j, j > n \} \quad \alpha \geq 0 \quad (3) \]

with nominal values \( p_j \) having “variability” \( \hat{\sigma}_j \) in their estimate of \( p_j, j > n \). In simple language (3) says that the unknown future prices \( p_j (j > n) \) are assumed to lie in an interval of length \( 2\alpha \hat{\sigma}_j \) centred on the nominal estimates \( \hat{p}_j \) with interval sizes increasing as the horizon of uncertainty \( \alpha \) increases in proportion to the nominal relative variability \( \hat{\sigma}_j \). The choice of \( \hat{p}_j \) and \( \hat{\sigma}_j \) is left to individual traders who could base their estimates on any number factors, including computer-based models, intuition, consensus opinion (of analysts), fundamentals or even gut feeling and rumours. In the following section we give examples of possible choices for \( \hat{p}_j \) and \( \hat{\sigma}_j \). Note that in general Info-Gap uncertainty models such as (3) make no assumptions of underlying probability distribution functions for the unknown (prices) and are thus models of true uncertainty in the sense of Knight (1921).

The second key ingredient in Info-Gap Theory is a performance requirement, usually expressed as an inequality involving the unknowns. From a trading perspective one would, ideally, like to predict price movements or at least turning points such as highs and lows over some time frame of \( T \) (units) from “now” \((n)\). For example if our trading horizon is \( T \) we might decide to sell at a (local) high if

\[ p_{n+T} \leq (1 - \varepsilon)p_n, \quad 0 \leq \varepsilon \leq 1 \quad (4) \]

i.e. if the actual price \( T \) units from now is some fraction \( \varepsilon \) less than the last traded price \( (p_n) \).
Similarly we would buy (at a local ‘low’) if our investment horizon were \( T \) units, when
\[
p_{n+T} \geq (1 + \varepsilon')p_n, \quad \varepsilon' \geq 0
\] (5)
i.e. if our profit aspirations were a fractional gain of \( \varepsilon' \) over the current price. Eqns (4) and (5) are examples of performance requirements. The problem of course is that we don’t know \( p_{n+T} \)!

The final ingredient in Info-Gap Theory is the concept of robustness \( \hat{\alpha} \) which is defined to be the largest horizon of uncertainty \( (\alpha) \) for which performance requirement(s) are met for all realizations of the unknown quantities in the underlying uncertainty model \( U \). Thus for the performance requirements (4) (for a sell), robustness is defined mathematically by
\[
\hat{\alpha}(s) = \max \{\alpha | \max_{p_{n+T} \in U} p_{n+T} \leq (1 - \varepsilon) p_n\} \] (6)

For the uncertainty model (3)
\[
\max_{p_{n+T} \in U} p_{n+T} = \tilde{p}_{n+T} + \alpha \bar{\sigma}_{n+T} \] (7)

It then follows from (6) that (recalling \( \alpha \geq 0 \))
\[
\hat{\alpha}(s) = [(1 - \varepsilon)p_n - \tilde{p}_{n+T}] / \hat{\sigma}_{n+T} \] (8)
provided the numerator is positive (i.e. provided the performance requirement (4) is met for the nominal values \( \tilde{p}_{n+T} \)) and zero otherwise. Similarly for the buy performance requirement (5) the robustness is given by
\[
\hat{\alpha}(b) = \max \{\alpha | \min_{p_{n+T} \in U} p_{n+T} \geq (1 + \varepsilon') p_n\} \]
\[
= [\tilde{p}_{n+T} - (1 + \varepsilon')p_n] / \hat{\sigma}_{n+T} \] (9)
provided the numeration is positive and zero otherwise.

In general terms robustness \( \hat{\alpha} \) is a measure of how wrong one can be in estimating future prices and yet still satisfy performance requirements. It follows that larger values of \( \hat{\alpha} \) are preferable to smaller values. Note, however, from (8) and (9) that this implies a trade-off between performance and robustness. That is, if one strives for better performance by requiring larger \( \varepsilon \) (or \( \varepsilon' \)) one does so by sacrificing some immunity to uncertainty by reducing robustness \( \hat{\alpha}(s) \) (or \( \hat{\alpha}(b) \)). This trade-off between performance and robustness is a general feature of Info-Gap Theory.

From a trading perspective the robustness functions \( \hat{\alpha}(s) \) eqn (8) and \( \hat{\alpha}(b) \) eqn (9) could be used as technical trading indicators. Thus for given nominal or process the model estimates \( \tilde{p}_{n+T} \) and \( \bar{\sigma}_{n+T} \) and profit aspirations \( \varepsilon(\varepsilon') \) we might say that a sell (buy) is indicated at time \( n \) for a trading horizon of \( T \) units if \( \hat{\alpha}(s) \) (\( \hat{\alpha}(b) \)) exceeds a predetermined threshold (determined for example by back-testing on historical data). It would of course be up to individual traders to decide on what process models, parameters, aspirations, trading horizons and thresholds to use in this Info-Gap model framework for technical trading. An example with application to real market data is presented in the following section.

**An info-gap model indicator**

Here we consider the Info-Gap model of the previous section with minimal performance aspirations \( \varepsilon = \varepsilon' = 0 \) in eqns (4) and (5). Comparison of (8) and (9) in this case lends us to define
\[ \hat{\alpha}_{n,T} = (p_n - \hat{p}_{n+T}) / \hat{\sigma}_{n+T} \]

which is the sell robustness (8) when positive and the negative of the buy robustness (9) otherwise. \( \hat{\alpha}_{n,T} \) can then be taken as a single buy/sell indicator with large positive values indicating a sell and large (in magnitude) negative values indicating a buy.

To proceed we need nominal or process model estimates for \( \hat{p}_{n+T} \) and \( \hat{\sigma}_{n+T} \). For simplicity we base our estimates on the moving-average of prices over the previous \( M \) time-steps from now \( (n) \) defined by

\[ \hat{p}_n = \frac{1}{M} \sum_{j=n-M+1}^{n} p_j \]

(11)

For \( \hat{p}_{n+T} \) we take the convex combination

\[ \hat{p}_{n+T} = \lambda_T \hat{p}_n + (1 - \lambda_T)p_n \]

\[ = p_n - \lambda_T (p_n - \hat{p}_n) \quad ; \quad 0 \leq \lambda_T \leq 1 \]

(12)

which is in accord with conventional wisdom regarding crossing of moving averages and “reversion to the mean”. Thus, when \( p_n > \hat{p}_n \) (\( p_n < \hat{p}_n \)) prices will tend to fall (rise) at some later time.

For variability \( \hat{\sigma}_j \) when \( j > n \) we take the standard deviation of (known) prices prior to \( n \) relative to the \( M \)-step prior moving averages. That is

\[ \hat{\sigma}^2_j = \hat{\sigma}^2_n = \frac{1}{M} \sum_{k=n-M+1}^{n} (p_k - \hat{p}_k)^2 ; j > n \]

(13)

where \( \hat{p}_k \) is defined by (11) with \( n \) replaced by \( k \).

We stress that the simple process model choices for \( \hat{p}_j \) and \( \hat{\sigma}_j \) for \( j > n \) in eqns (12) and (13) make no assumptions about probability distribution functions for the unknown \( p_j \), \( j > n \). In (13) the variability of future prices is assumed to be independent of the investment horizon \( T \) and is thus in essence the implied (or historical) volatility relative to the moving (arithmetic) averages of previously known prices. In other words \( \hat{p}_j \) and \( \hat{\sigma}_j \) for \( j > n \) are derived from known (historical) values of \( p_j \) (\( j \leq n \)).

When we substitute (12) and (13) into (10) we obtain

\[ \hat{\alpha}_{n,T} = \lambda_T (p_n - \hat{p}_n) / \hat{\sigma}_n \]

(14)

so that in terms of robustness the process model (12) and (13) leads to separability of the \( T \) and \( n \) dependence.

In practical terms \( \lambda_T \) is itself subject to some degree of uncertainty, particularly for increasing \( T \), which poses problems if one wants reasonable estimates for \( p_{n+T} \) (from eqn (12)). From a trading perspective however, we can simply scale the robustness (14) by \( \lambda_T \) and take

\[ I_n = (p_n - \hat{p}_n) / \hat{\sigma}_n \]

(15)
to be the trading indicator. A sell would then be signalled when \( I_n \) exceeds some positive threshold and a buy would be signalled when \( I_n \) is less than some negative threshold. Optimal thresholds, which will presumably depend on the investment horizon, could for example be determined by back testing on historical data. In this regard we note that the model indicator (15) has only one adjustable (free) parameter, namely the window size \( M \) of the moving average (11).

As a practical application of the Info-Gap Indicator (IGI) \( I_n \) eqn (15) we have shown in Table I the daily closing values of the Australian All Ordinaries Index (\( p_n \)) and corresponding values of \( I_n \), for window size \( M = 50 \) (days), over 69 consecutive trading days commencing on 14/12/89 (\( n = 1 \)) and ending on 20/3/90 (\( n = 69 \)). In order to obtain the values for \( I_n \) in Table I we have used known values for \( p_j \) for \( j \leq n \) to calculate \( \hat{p}_n \) from (11) [and similarly \( \hat{p}_k \)] and then \( \hat{\delta}_n \) from (13). The values of \( I_n \) for successive values of \( n \) are then determined from (15). Note that from (11) and (13) one in general needs the previous 2M known values of \( j \) prior to \( j = n \) in order to calculate \( I_n \). In other words to compute the \( I_n \) values in Table I we actually used known values of \( p_j \), 100 days (\( M = 50 \)) prior to 14/12/1989 (\( n = 1 \)).

In Table I with prior sell and buy thresholds set at +3.0 and –3.0 we would have had a sell signal at \( n = 15 \) where \( I_n \) rises above the sell threshold and a buy signal at \( n = 53 \) when \( I_n \) falls below the threshold. If however we had set the sell threshold at +2.5 we would have had two consecutive sell signals (\( n = 15 \) and \( n = 22 \)) all it will be noted giving significant gains by taking appropriate short and long positions in the market. This is in contrast with most technical indicators where a sell signal is followed by a buy signal and vice versa.

In Table I for example, \( I_n \) changes from being negative to positive at \( n = 6 \) i.e, from (15) \( p_n \) rises from below to above the 50-day moving average (\( \hat{p}_n \)) at \( n = 6 \) signalling a buy (in a simple “crossing a moving average” strategy), and then falls below the 50-day moving average at \( n = 40 \) signalling a sell. Following this simple crossing a moving average strategy we would have then made a gain of \( p_{40} - p_6 = 6 \) index points. On the other hand following the IGI strategy by short selling at \( n = 15 \) and closing out the position at \( n = 53 \) we would have made a gain of \( p_{15} - p_{33} = 140 \) index points. One could, of course, legitimately argue that the simple crossing of the 50-day moving average strategy above is suboptimal and that one could do much better with carefully chosen crossings of two moving averages perhaps in combination with other technical indicators such as RSI or even the IGI \( I_n \). Since there are many possible choices for parameter values, thresholds, exit and entry strategies etc in the many technical indicators (including IGI) we make no attempt here to quantify the performance of IGI relative to other technical indicators (see Murphy, (1986) for discussion of comparatives).

We merely wish to point out that the main differences and advantages of IGI over other technical indicators is that a signal is not always followed by a contrary signal and more importantly that a signal for a turning point using IGI typically occurs before or at (rather than after) the actual turning point. In the following section we show how the latter can be utilised to signal trends as well as turning points.
defined recursively by 

\[ \text{define } \]

historical data needed to compute higher-order indicators. As time evolves we thus generate another time series \( \{I_j\} \) with highs and lows which in turn we would like to predict into the future \( j > n \). Clearly we can repeat the Info-Gap modelling process to derive an indicator for the indicator and so on infinitum (or at least until we run out of the historical data needed to compute higher-order indicators).

For the simple indicator \( I_n \) eqn (15) we can simply iterate the Info-Gap process as follows. First we define \( I_n \) in (15) to be the first iterate \( I_n^{(1)} \) obtained from the zeroth iterate \( I_n^{(0)} = p_n \). The \( k^{th} \) iterate is then defined recursively by

\[
I_n^{(k+1)} = \begin{cases} 
\text{high signal if } I_n^{(k)} > \text{threshold} \\
\text{low signal if } I_n^{(k)} < \text{threshold} \\
\text{no signal if } I_n^{(k)} = \text{threshold}
\end{cases}
\]

Table I. The Australian All Ordinaries Index (AOI) \( (p_n) \) and the basic indicator \( (I_n) \) with window size \( M = 50 \) for 69 consecutive trading days from 14/12/1989 \( (n = 1) \) to 20/3/1990 \( (n = 69) \). High signals occur at \( n = 15, 16 \) (for a threshold of +3.0) and at \( n = 22 \) (for a threshold of +2.5) and a low signal occurs at \( n = 53 \) (threshold – 3.0).

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<th>( I_n )</th>
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\[ I_n^{(k)} = \left[ I_n^{(k-1)} - \hat{I}_n^{(k-1)} \right] / \hat{\sigma}_n^{(k-1)} \quad k = 1, 2, \ldots \]

(16)

where, on comparison with (11), (13) and (15)

\[ \hat{I}_n^{(l)} = \frac{1}{M} \sum_{j=n-M+1}^{n} I_j^{(l)} \quad l = 0, 1, \ldots \]

(17)

And

\[ [\hat{\sigma}_n^{(l)}]^2 = \frac{1}{M} \sum_{j=n-M+1}^{n} (I_j^{(l)} - \hat{I}_j^{(l)})^2 \quad l = 0, 1, \ldots \]

(18)

so that, in particular eqn(16) reduces to eqn(15) when \( k = 1 \).

As noted in the previous section, the basic indicator \( I_n^{(1)} \) typically signals a turning point prior to the actual event. It follows that turning points of higher-order iterates \( I_n^{(k)} \) may signal turning points of lower-order iterates. Turning points for the iterated indicators could thus signal upward and downward trends as well as turning points in the financial time series from which they are generated. An example where this actually happens is given in Table II. The underlying time series in this case consists of closing daily prices of shares in a major Australian bank.

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<td>-0.72</td>
</tr>
<tr>
<td>4</td>
<td>334</td>
<td>-0.16</td>
</tr>
<tr>
<td>5</td>
<td>344</td>
<td>0.66</td>
</tr>
<tr>
<td>6</td>
<td>350</td>
<td>1.15</td>
</tr>
<tr>
<td>7</td>
<td>366</td>
<td>2.31#</td>
</tr>
<tr>
<td>8</td>
<td>376</td>
<td>2.78#</td>
</tr>
<tr>
<td>9</td>
<td>371</td>
<td>2.26#</td>
</tr>
<tr>
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</tr>
<tr>
<td>18</td>
<td>377</td>
<td>1.39</td>
</tr>
</tbody>
</table>

Table II: Iterated indicators \( I_n^{(k)} \), \( k = 1, 2, 3, 4, 5, 6 \)...for 18 consecutive trading days (\( n = 1 \) corresponds to 10/4/91 and \( n = 18 \) to 6/5/91) with closing daily prices \( p_n \). The moving average window in this case is \( M = 44 \).

In the table we have highlighted iterated indicator values exceeding +2.0 with a #. Several features are worthy of note. Firstly as stated above large higher order iterates can signal an up trend (eg at \( n = 2 \) the 6th iterate exceeds +2.0 signalling a possible uptrend). A wave pattern of iterates exceeding +2.0 develops from higher to
lower order iterates reaching the primary indicator $I_n^{(1)}$ at $n = 7$. The emerging wave pattern and the additional dimension of iteration suggest some alternative signals for turning points to the idea of (exceeding) a threshold for the basic indicator ($k = 1$) described previously. We have found that situations where $I_n^{(1)}$ exceeds some threshold (eg 2.5) and the iterates “line-up” in the sense that at $n$

$$I_{n^*}^{(k)} > I_{n^*}^{(k+1)} \quad k = 1,2,\ldots,5$$

(19)

generally provide a good reliable signal for the end of the uptrend (at a local high). Eg in Table II an uptrend is signalled at $n = 2$, $k = 6$ ($p_2 = 327$) and the iterates line up as in (19) with $n = 13$ and $I_{n^*}^{(1)} = 2.91$, signalling the end of the uptrend at a (local) high of $p_{13} = 398$.

Similarly, patterns of negative iterates (say less than –2.0) washing across to the primary indicator typically signal a downtrend which ends at a (local) low when the primary indicator is say less than –2.5 and the iterates line up in the opposite directions to (19).

The situation shown in Table II does not of course always occur. Occasionally the wave pattern ends before it reaches the primary indicator. Such pattern may or may not signal a trend. Other patterns are possible and occasionally fake signals appear. We have made no attempt at this stage to classify the various patterns that are generated by iterated indicators or to quantify the statistical significance of various signalling hypothesis (for trend and turning points) such as those mentioned above.

Discussion

In this paper we have presented a methodology for deriving new technical trading indicators for financial markets based on the concept of robustness in Info-Gap Decision Theory (Ben Haim, 2006). In this theory robustness is a measure of how wrong one can be in estimating future price movements and yet still satisfy performance requirements for future turning points. Large values of robustness are thus preferred and these could in principle be used as signals for turning points. A general framework for constructing indicators based on Info-Gap robustness was developed in section 2. A simple basic version of robustness indicator was developed and applied to a real financial time series in section 3.

The basic indicator in Section 3 has essentially only one adjustable parameter, namely the choice of a moving-average window in the underlying process model. In applications, however, one needs to specify threshold values for turning point signals, which will depend on trader’s profit aspirations and investment or trading time frames. Determination of optimal windows and thresholds from historical data analysis may, of course, due to Info-Gap uncertainty, be suboptimal for signalling turning points in the future.

Unlike most other technical trading indicators where a sell signal is followed by a buy signal and vice versa, our basic indicator, depending on threshold parameter values, can have consecutive sell (or buy) signals as shown in the Table I example. This can be problematic since in the absence of a contrary signal one could be caught out by an unexpected reversal unless one has an additional holding time threshold for closing out a position when there is no contrary signal from the indicator. Exit time thresholds could of course be determined from historical back testing but again there is no guarantee they will give optimal results in the future.

In section 4 we showed that iteration of the basic indicator provides an additional dimension in which patterns can develop in higher order iterates and spread to lower order iterates over time to signal trends as well as turning points. Not all patterns however evolve as shown in the example in Table II. Some come to an abrupt end and trends and turning points can occur with no apparent signal from the indicator or its iterates. Again, due to inherent Info-Gap uncertainties, there is no guarantee that patterns and thresholds that worked well in the past will work in the future. In real-time applications, however, we have found that when strong patterns emerge as in Tables I and II the basic indicator and its iterates yield correct signals and significant returns.

In this paper we have made no attempt to classify patterns, specify particular (optimal) thresholds and exit strategies or to quantify the statistical significance of various signals for trends and turning points. We have also made no attempt to quantify the performance of our indicator relative to the performance of other technical indicators. We have also yet to explore the more general forms of robustness in eqns (8) and (9) as technical
trading indicators using alternative process model estimates of the nominal returns \( \tilde{p}_j \) and variabilities \( \tilde{\sigma}_j \), and including positive aspiration \( (\varepsilon, \varepsilon' > 0) \) for excess returns. It would also be of interest to investigate possible applications of the Info-Gap concept of opportuneness for windfall profits.

References