‘Return’ and ‘volatility’ of prices and ‘sentiments’

Khurshid Ahmad,
Chair of Computer Science
Trinity College, Dublin, IRELAND
kahmad@cs.tcd.ie
Economics and Finance

Three states of matter: solid, liquid and gases;

Three kinds of randomness: mild, slow, and wild.

Benoit Mandelbrot (1963) has argued that the rapid rate of change in prices (the *flightiness* in the change) can and should be studied and not eliminated – ‘large changes [in prices] tend to be followed by large changes –of either sign- and small changes tend to be followed by small changes’.

The term *volatility clustering* is attributed to such clustered changes in prices.

Mandelbrot’s paper drew upon the behaviour of commodity prices (cotton, wool and so on), but volatility clustering’ is now used in for almost the whole range of financial instruments (see Taylor 2007 for an excellent and statistically well-grounded, yet readable, account of this subject).
Dan Nelson (1992) ‘recognized that volatility could respond asymmetrically to past forecast errors. In a financial context, negative returns seemed to be more important predictors of volatility than positive returns. Large price declines forecast greater volatility than similarly large price increases. This is an economically interesting effect that has wide ranging implications’
‘Why it is natural for news to be clustered in time, we must be more specific about the information flow’ (Engle 2003:330)

<table>
<thead>
<tr>
<th>Volatility Clustering Type</th>
<th>Clustering Cycle</th>
<th>Information Flow</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slow</td>
<td>Several years or longer</td>
<td>Single inventions or unique events that may benefit firms in the longer term</td>
</tr>
<tr>
<td>High Frequency</td>
<td>Few days or minutes</td>
<td><strong>Price Discovery</strong>: When agents fail to agree on a price and suspect that other agents have insights/models better than his or her. Prices are revised upwards or downwards quite rapidly.</td>
</tr>
<tr>
<td>Medium Duration Volatility</td>
<td>Weeks or Months</td>
<td><strong>Clustered events</strong>: Many inventions streaming in; global summits; governmental inquiries;</td>
</tr>
</tbody>
</table>

Bounded Rationality

Herbert Simon (Nobel Prize in Economics 1978)

Rational Decision Making in Business Organisations:

Mechanisms of Bounded Rationality – failures of knowing all of the alternatives, uncertainty about relevant exogenous events, and inability to calculate consequences.

Daniel Kahneman (Nobel Prize in Economics 2002)

Maps of bounded rationality – intuitive judgement & choice:

Two generic modes of cognitive function: an intuitive mode: automatic and rapid decision making; controlled mode deliberate and slower.
Volatility and Information Arrivals

The set of ten announcements provides a fairly complete characterization of the macro economy, in that it describes:

1. the inflationary process by the consumer price index (CPI) and producer price index (PPI);
2. the situation in the labor market by the civilian unemployment rate (CUR) and non-farm payrolls (NFP);
3. the dynamic of consumption by the retail sales (RS);
4. the state of the economy by the industrial production (IP);
5. the perceived state of the economy by consumer confidence (CC) and the national association of purchasing managers index (NAPM);
6. the conditions of the money market by the Federal Open Market Committee federal funds target rate (FOMC) and
7. the situation in the real estate market by housing starts (HS)

Quantitative Sentiment Analysis?

Firm-level Information Proxies:

- Closed-end fund discount (CEFD);
- Turnover ratio (in NYSE for example) (TURN);
- Number of Initial Public Offerings (N-IPO);
- Average First Day Returns on R-IPO;
- Equity share S;
- Dividend Premium
- Age of the firm, external finance, ‘size’(log(equity))

Each sentiment proxy is likely to include a sentiment component and as well as idiosyncratic or non-sentiment-related components. Principal components analysis is typically used to isolate the common component.

A novel composite index built using Factor Analysis:

\[
\text{Sentiment} = -0.358\text{CEFD}_t + 0.402\text{TURN}_{t-1} + 0.414\text{NIPO}_t + 0.464\text{RIPO}_t + 0.371 S_t - 0.431 P_{t-1}
\]

Affective Content and Text Analysis: Return & Volatility

Definitions of Returns:
Statistical analysis of market prices is more difficult than analysis of changes in prices. [...] Consecutive prices are highly correlated but consecutive changes have very little correlation, if any.

Three widely used definitions involve the price $p_t$ and the dividend $d_t$. The dividend is set to a constant or zero ($!$).

$$r_t^* = p_t + d_t - p_{t-1}$$

$$r'_t = \frac{(p_t + d_t - p_{t-1})}{p_{t-1}}$$

$$r_t = \log(p_t + d_t) - \log(p_{t-1})$$
Definitions of Volatility:
Volatility is a measure of price variability over some period of time. It typically describes the standard deviation of returns over a given period. The standard deviation of a time series is expected to be a constant indefinitely – changes in volatility are called structural breaks and are used to calculate risk associated with an instrument like shares or currencies.

\[ \nu = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} (r_{t-k} - \bar{r})^2} \]
Affective Content and Return & Volatility

The two parameters of performance of instruments in a way relate to the original observations made by Herbert Simon, Daniel Kahnemann and Amos Tversky, in the context of the notions of bounded rationality.

\[
\begin{align*}
\hat{r}_i &= p_i + d_i - p_{t-1} \\
\ddot{r}_i &= \frac{(p_i + d_i - p_{t-1})}{p_{t-1}} \\
r_i &= \log(p_i + d_i) - \log(p_{t-1})
\end{align*}
\]

The structural break perhaps occurs in the period when humans enter into a risk-taking mode which cannot be rationalised and leads to booms and busts.

\[
\nu = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} (r_{t-k} - \bar{r})^2}
\]
More importantly, perhaps, the sentiment may be expressed through action:
(a) panic buying and selling of financial instruments by the investors and traders, and
(b) the sometimes complacent attitude of the regulators, are good examples of economic, social and political action by individuals and groups.

Quantitative Sentiment Analysis?

Symmetric case

Asymmetric case

The News Impact Curve

\[ R_t = c + \epsilon_t \]
\[ \sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \]

\[ \log \sigma_t^2 = \hat{\omega} + \hat{\beta} \log \sigma_{t-1}^2 + \hat{\alpha} |z_{t-1}| + \hat{\gamma} z_{t-1} \]

As time goes by, we get more information on these future events and re-value the asset. So at a basic level, financial price volatility is due to the arrival of new information. Volatility clustering is simply clustering of information arrivals. The fact that this is common to so many assets is simply a statement that news is typically clustered in time.

Quantitative Sentiment Analysis?

Volatility and Information Arrivals

- News Effects
  - I: News Announcements Matter, and Quickly;
  - II: Announcement Timing Matters
  - III: Volatility Adjusts to News Gradually
  - IV: Pure Announcement Effects are Present in Volatility
  - V: Announcement Effects are Asymmetric – Responses Vary with the Sign of the News;
  - VI: The effect on traded volume persists longer than on prices.

It has been argued by Robert Engle, the 1993 co-winner of the Nobel prize in economics, that ‘[a]s time goes by, we get more information on these future events and re-value the asset. So at a basic level, financial price volatility is due to the arrival of new information. Volatility clustering is simply clustering of information arrivals. The fact that this is common to so many assets is simply a statement that news is typically clustered in time.’ (1993:330).
My argument is rather naïve and suggests that if we look at how markets are reported, especially the usage of sentiment bearing words, one may find clusters again: good news cannot suddenly be followed by bad news unless we have a kind of breakdown.

The other point is this: if we look at the notion of information arrivals in terms of the quantity and quality of linguistic units, then how will we relate these to market indices: cannot compare numbers in different units – frequency with aggregates of prices.

Return and volatility are dimensionless numbers and we can compare the return of prices with return of (frequency of) words.
The annual number of stories published in the New York Times from 1980-2008 (left vertical axis), and the percentage change in returns \( r_t \) (dashed line) and volatility \( \nu \) (solid triangle) are on the right. The changing volatility sends a negative signal.
Much of the work in information extraction deals with the discourse about the events (in blogs, newspapers) at different levels of linguistic description – lexical, syntactic, ‘semantic’- without reference to the quantitative details related to the events – price movements, election results, death tolls, population dynamics.
One of the pioneers of political theory and communications in the early 20th century, Harold Lasswell, has used sentiment to convey the idea of an attitude permeated by feeling rather than the undirected feeling itself. (Adam Smith’s original text on economics was entitled *A Theory of Moral Sentiments*).
Laswell and colleagues looked at the Republican and Democratic party platforms in two periods 1844-64 and 1944-64 to see how the parties were converging and how language was used to express the change.

Laswell created a dictionary of affect words (*hope*, *fear*, and so on) and used the frequency counts of these and other words to quantify the convergence.
Ole Holsti (1969) offers a broad definition of content analysis as "any technique for making inferences by objectively and systematically identifying specified characteristics of messages."

http://en.wikipedia.org/wiki/Content_analysis
‘Modern’ day dictionaries of affect: Emotion as dimension and emotion as ‘finite category’

— **good–bad axis**: termed the dimension of valence, evaluation or pleasantness
— **active–passive axis**: termed the dimension of arousal, activation or intensity
— **strong–weak axis**: termed the dimension of dominance or submissiveness
Computing affect: The use of ‘universal’ dictionaries

‘Modern’ day dictionaries of affect are used in computing the frequency of sentiment words in a text and the attempt usually is ensure that one picks up sentences that pick up the ‘correct’/unambiguous sense of the sentiment word

—General Inquirer [Stone et al. 1966];
—Dictionary of Affect [Whissell 1989];
—WordNet Affect [Strappavara and Valitutti 2004];
—SentiWordNet [Esuli and Sebastiani 2006].
The **General Inquirer** is a software system for analysing texts for ascertaining the psychological **attitude/orientation/behaviour** of the writer of a text as implicit in his or her writing.

The system has a large database of words and each word is tagged primarily in terms of whether the word is generally used *positively* or *negatively*.

But there are many fine gradations within the tags – ranging from tags to describe *active/passive* orientation and whether the word belongs to a specific subject category like *economics*, or that the word is used usually by *academics* or found in *legal documents*.
Automatic Analysis of Texts: Natural Language Processing
General Inquirer Categories

<table>
<thead>
<tr>
<th>Name</th>
<th>No. of Words</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positiv</td>
<td>1,915</td>
<td>positive outlook.</td>
</tr>
<tr>
<td>Negativ</td>
<td>2,291</td>
<td>negative outlook</td>
</tr>
<tr>
<td>Pstv</td>
<td>1045</td>
<td>positive outlook</td>
</tr>
<tr>
<td>Affil</td>
<td>557</td>
<td>affiliation or supportiveness.</td>
</tr>
<tr>
<td>Ngtv</td>
<td>1160</td>
<td>Negative outlook</td>
</tr>
<tr>
<td>Hostile</td>
<td>833</td>
<td>an attitude or concern with hostility or aggressiveness</td>
</tr>
<tr>
<td>Strong</td>
<td>1902</td>
<td>implying strength</td>
</tr>
<tr>
<td>Power</td>
<td>689</td>
<td>Positive</td>
</tr>
<tr>
<td>Hostile</td>
<td>833</td>
<td>concern with hostility or aggressiveness</td>
</tr>
<tr>
<td>Weak</td>
<td>755</td>
<td>Negative</td>
</tr>
<tr>
<td>Submit</td>
<td>284</td>
<td>submission to authority or power, dependence on others, vulnerability to others, or withdrawal.</td>
</tr>
</tbody>
</table>
Tetlock et al (2005, forthcoming) have examined whether a simple quantitative measure of language can be used to predict individual firms’ accounting earnings and stock returns:

The three findings suggest that linguistic media content captures otherwise hard-to-quantify aspects of firms’ fundamentals, which investors quickly incorporate in stock prices.


A regression analysis suggests the (lagged) correlation between the Dow-Jones Average and *bad news* and *traded volume*. The ‘bad news’ index depends upon the count of words that are included in the ‘negative’, ‘weak’ and ‘pessimistic’ categories in the General Inquirer dictionary.

\[
\begin{align*}
Dow_t &= \alpha_1 + \beta_1 \cdot L5(Dow_t) + \gamma_1 \cdot L5(BdNws_t) + \delta_1 \cdot L5(Vlm_t) + \lambda_1 \cdot Exog_{t-1} + \varepsilon_{1t}, \\
BdNws_t &= \alpha_2 + \beta_2 \cdot L5(Dow_t) + \gamma_2 \cdot L5(BdNws_t) + \delta_2 \cdot L5(Vlm_t) + \lambda_2 \cdot Exog_{t-1} + \varepsilon_{2t}, \\
Vlm_t &= \alpha_3 + \beta_3 \cdot L5(Dow_t) + \gamma_3 \cdot L5(BdNws_t) + \psi_3 \cdot L5(|BdNws_t|) + \delta_3 \cdot L5(Vlm_t) + \lambda_3 \cdot Exog_{t-1} + \varepsilon_{3t}.
\end{align*}
\]

Tetlock studied the impact of negative words in all *Wall Street Journal (WSJ)* and *Dow Jones News Service (DJNS)* stories about individual S&P 500 firms from 1980 to 2004.
Tools for Sentiment Analysis?
To tools for Sentiment Analysis?

Reuters Sentiment Analysis Workflow

1. News stories collected in realtime
2. Stories are standardized
3. Word sense disambiguation performed on each story
4. Linguistic analysis performed on each story to produce sentiment
5. Sentiment feature vector produced to describe each document
6. Feature vector matched against machine learning vector in order to classify story sentiment
7. Analysis results delivered to clients
Tools for Sentiment Analysis?

Dow Jones Newswires

Dow Jones News Analytics

Transform News for Trading Strategies

Algorithmic traders and quantitative analysts can now discover new ways to create profitable market opportunities with Dow Jones' News Analytics, a flexible solution suite that combines a unique content set of news and sentiment with powerful interface tools. Dow Jones, a leader in financial news, partnered with RavenPack, an innovator of advanced news analytics for algo trading, to develop Dow Jones News Analytics. This cutting-edge application and toolkit enable buy- and sell-side firms to build, test and deploy news-based trading models.

Unique Synergy - Dow Jones Deepest News Source & RavenPack Sentiment Data

All Dow Jones' news and archives, plus RavenPack's proprietary sentiment analysis are available via a web-based desktop application or the Dow Jones News Analytics Developer's Kit.

- Dow Jones Newsfeeds - Real-time news feed covering all asset classes, includes all editions of The Wall Street Journal and Barron's.
- Dow Jones 20-year Archives - More than 20 years of historical news and metadata of over 10,000 company symbols and news category codes.
- RavenPack Sentiment Data - Sentiment analysis, using multiple classification techniques, is applied to both real-time and historical Dow Jones news covering all major asset classes.
Cornerstone of Fast, Actionable News – Robust News Sentiment Analytics

RavenPack's underlying RavenSpace® proprietary computational linguistics and artificial intelligence technologies transform the news into actionable data in real-time.

- Sentiment analysis of each news story utilizes classification techniques (Expert Consensus, Key Word, Market Response) is added to the news item in real-time.
- News and sentiments are exposed as time series data
- The deep data collection along with high-performance tools facilitate trend discovery, correlations with marketplace activity, and algorithm back testing
I have used a corpus of texts, 2.6 million words in total, retrieved from the Irish Times Digital Archive and published between 1995-2005 and used the *Harvard Dictionary of Affect* to compute the frequency of the so-called positive and negative affect words in the Dictionary.
The ‘return’ and ‘volatility’ of sentiments: An attempt to quantify the behaviour of the markets? The use of General Inquirer Categories in Sentiment Analysis

### Distribution of stories in our *Irish Times Corpus*

<table>
<thead>
<tr>
<th>Year</th>
<th>No. of Stories</th>
<th>No. of Words</th>
<th>Year</th>
<th>No. of Stories</th>
<th>No. of Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>296</td>
<td>165937</td>
<td>2001</td>
<td>562</td>
<td>360026</td>
</tr>
<tr>
<td>1997</td>
<td>395</td>
<td>259748</td>
<td>2002</td>
<td>367</td>
<td>256613</td>
</tr>
<tr>
<td>1998</td>
<td>465</td>
<td>296531</td>
<td>2003</td>
<td>377</td>
<td>250415</td>
</tr>
<tr>
<td>1999</td>
<td>447</td>
<td>295873</td>
<td>2004</td>
<td>377</td>
<td>250376</td>
</tr>
<tr>
<td>2000</td>
<td>462</td>
<td>306063</td>
<td>2005</td>
<td>327</td>
<td>234101</td>
</tr>
<tr>
<td>TOTAL</td>
<td>2065</td>
<td>1324152</td>
<td>2010</td>
<td>1351531</td>
<td></td>
</tr>
</tbody>
</table>
The return and volatility of the distribution of **positive** affect words over 10 years.
The return and volatility of the distribution of negative affect words over 10 years.
Automatic Analysis of Texts: Natural Language Processing
The use of General Inquirer Categories in Sentiment Analysis

Changes in the historical volatility in the affect series and in the ISEQ Index
One observation based on my own study of polar words in corpora comprising genre-varied texts in topics as diverse as finance, ethnic conflicts, Nobel prize lectures, that the positive sentiment words exceed the negative sentiment words almost invariably.

I suppose it is a way we have in dealing with ‘grief’ (market failures, ethnic riots) that we ‘move on’.

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