Thomson Reuters MarketPsych Indices (TRMI) White Paper

Inside the Mind of the Market

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MarketPsych Data

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INTRODUCTION

> *"All economic movements, by their very nature, are motivated by crowd psychology."*
> ~ Bernard Baruch

Crowds move markets. Such crowds are made up of individuals - individuals who invest, trade, or manage portfolios. The decisions of these individuals are affected by the ebb and flow of news and rumor.[1,2] They are moved not only by what they read and hear, but often more so by their emotional reactions to such information.

Behavioral economics researchers have demonstrated that when new information provokes emotional responses such as joy, fear, anger, and gloom, individual trading behaviors are systematically biased.[3,4] And since individuals combine to form a market, their collective emotions manifest in observable market behavior. Indeed, financial researchers have demonstrated that news-derived sentiment metrics can be used to predict price movements.[5] As a consequence savvy investors are investigating how to measure the emotional pulse of the market in order to make better asset allocation and risk management decisions.

To meet this burgeoning need to monitor market moods, MarketPsych Data has partnered with Thomson Reuters to create the multi-dimensional Thomson Reuters MarketPsych Indices (TRMI). The software underlying the TRMI uses complex natural language processing to score sentiment-laden content in text. It scores content that pertains to specific companies, currencies, commodities, and countries. As of this writing, the entire content set includes over 2 million articles and posts daily from premium news wires, internet news sources, and social media.

In this document the TRMI are referred to as sentiment data, but the breadth of coverage is much wider than traditional bipolar positive/negative sentiment in three key ways. One, the TRMI score sentiment along a number of dimensions including specific emotions, expectations, uncertainty, and urgency. In addition, the TRMI include an array of one- and two-directional scores on asset-specific topics. Examples include Litigation and Layoffs in the Equities TRMI, Inflation and BudgetDeficit in the Country TRMI, ProductionVolume in the Commodities TRMI, and PriceForecast in the Currencies TRMI, as seen in Figure 4 below. Finally, MarketPsych's language processing can quantify complex sentiment-topic combinations such as GovernmentAnger (for Countries) and MarketRisk (for Countries and Equities).

TRMI data may be used for understanding and modeling price moves across a broad spectrum of assets, as well as economic activity from nations around the world. For example, quantitative funds may use TRMI to identify sentiment-driven mis-pricings across currencies and commodities. Value investors may use TRMI to identify pessimistic and optimistic countries and sectors where value and momentum factors differ in impact. Global macro investors may use TRMI to identify overlooked opportunities and arbitrage risk perceptions across international markets. Governments may monitor national business and economic sentiment using our country-level variables, and insurance companies may use it to quantify global risk perceptions and modify insurance pricing accordingly. Please refer to our Thomson Reuters MarketPsych Indices User Guide to learn more about researching this multi-dimensional dataset.

TRMI are unique in four ways:

1. The indices are derived from an innovative patent-pending system for extracting complex meaning from text. Developed over eight years, MarketPsych's text analytic techniques were designed to score business-specific language for quantitative financial applications.
2. The sentiment data is highly dimensional. The TRMI include scores on more than fifty sentiments and topics.
3. A broad range of entities are tracked. As of this publication, the TRMI deliver sentiments on 41 equity indices, 29 currencies, 34 commodities, and 119 countries.
4. The TRMI content collection, including tens of thousands of social media and news sources back to 1998, is unequalled in the sentiment industry.

This white paper consists of three sections. The first section addresses the theory and evidence that supports MarketPsych's innovative approach to language analytics. In the second section MarketPsych's lexical analytics software is described. In the third section the construction of the TRMI is explained.

MULTI-DIMENSIONAL SENTIMENT

Beyond One-Dimensional Sentiment

Traditional textual sentiment analysis typically yields only one dimension of output. Sentiment-laden references to an entity are scored on a valence scale ranging from positive to negative, with additional consideration for neutrality. Yet humans experience a broad range of emotions, and psychological research has demonstrated that more than just valence has predictable effects on investor behavior.

One common classification system of human emotion uses two dimensions commonly known as valence and arousal. Pleasantness and exuberance are positive in valence, while boredom and fury are of negative valence. As for arousal, pleasantness and boredom are low arousal states, while exuberance and fury are high arousal states. Researchers represent the valence and arousal dimensions in the affective circumplex model of sentiment,[6] depicted in Figure 1.

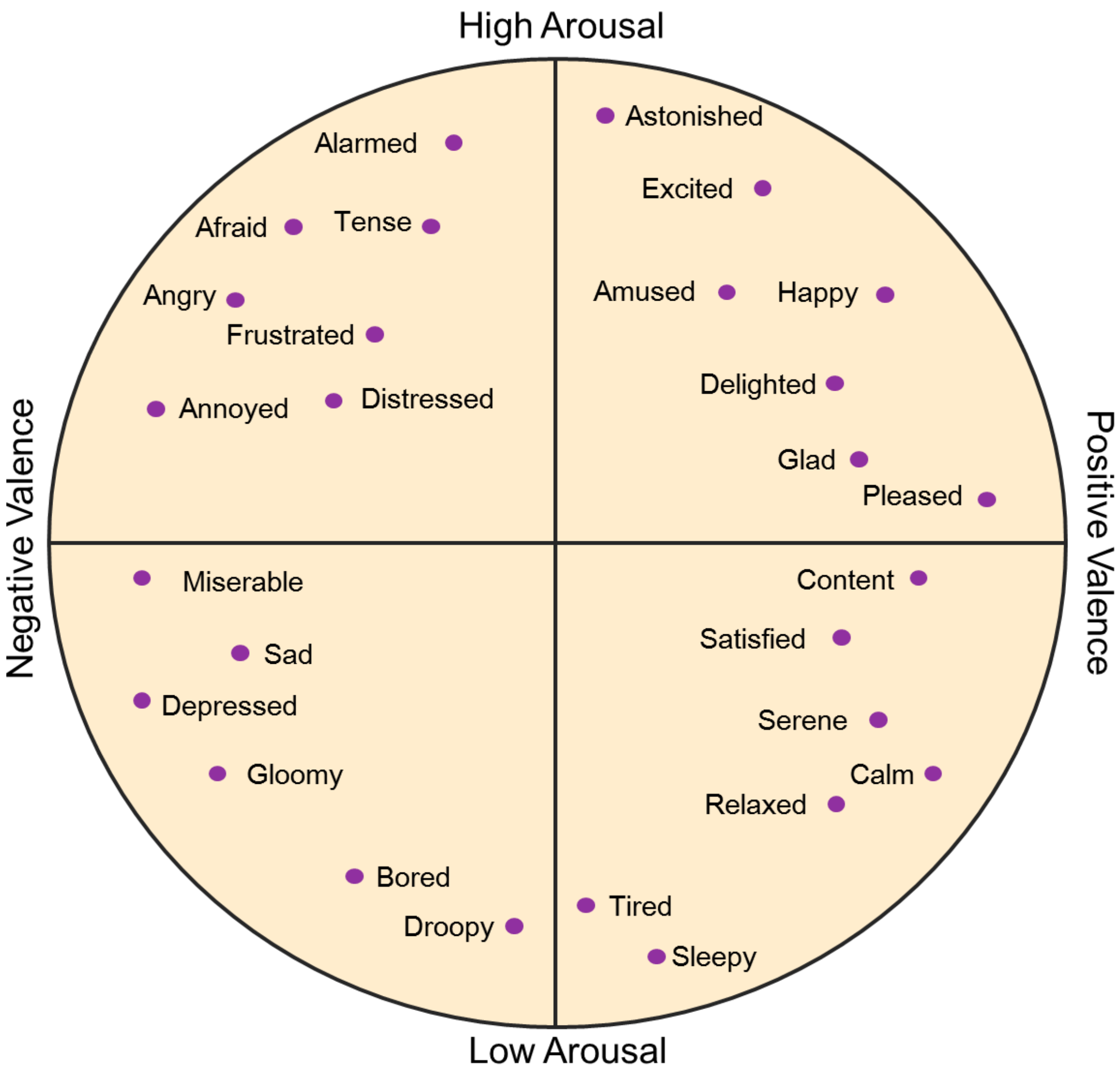

Figure 1. Common depiction of the affective circumplex with orthogonal valence and arousal dimensions.[7]

Arousal in Investing and the TRMI

Research has demonstrated that one's arousal level impacts decision-making. As background, varying levels of Stress have been shown to map to cognitive performance in an inverse-U curve called the Yerkes-Dodson Law.[8,9] When stress levels are very high, complex problem-solving performance drops and reliance on pre-existing habits increases.[10] On the other hand, low stress levels also lead to sub-par performance in complex decision-making environments due to inattention and slow reaction times. Thus decision-makers typically perform with optimal cognition when arousal is in the middle of its range.

The TRMI capture the arousal dimension in the specific indices for Stress (slightly negative valence) and Urgency (neutral valence). High TRMI Stress and Urgency scores are expected to correlate with decreased trader cognitive performance manifested in incomplete arbitrage of short-term price anomalies. As a result, high and low levels of arousal may predispose markets to exhibit price patterns such as momentum during low-arousal regimes and mean reversion during high-arousal regimes.[11]

Valence and arousal are only two dimensions out of many possible ones for describing emotions. The following sections describe research on how other emotions drive buying and selling decisions.

Anger, Fear, and Gloom

Research has shown that strongly negative emotions covered by the TRMI – Anger, Fear, and Gloom – have a unique and consistent effect in biasing how individuals set bid and ask prices in an experimental market.[12,13] Much of the modern research on this subject has been led by Professor Jennifer Lerner, now at Harvard University.

In a series of experiments, Professor Lerner induced emotional states of sadness, fear and disgust in subjects using short movie clips.[14,15] She then studied how the subjects placed bids and offers in a simulated marketplace.

Lerner found that participants in a disgusted emotional state were emotionally driven to "expel" or "get rid" of items they owned. They also had no desire to accumulate new possessions. As a result, they reduced both their bid and offer prices for consumer items.

The Anger TRMI encompasses angry sentiments ranging in intensity from disgust (low-level anger) to rage (intense anger). Based on Lerner's results, high TRMI Anger readings are expected to increase selling and reduce buying in affected assets.

Professor Lerner also studied the effects of fear. Compared to anger, fear is characterized by the combination of lower bid prices, higher ask prices, and pessimism about the future.[16,17] Fearful investors avoid transacting, paralyzed as prices slide until fear reaches an extreme level, marked by panic. Panic drives a purge of assets, an event which is termed "capitulation" colloquially and "over-reaction" in the behavioral finance literature.[18]

As for Gloom, Lerner found that behavioral responses to sadness are characterized by higher bid prices, lower ask prices, and overtrading. Lerner noted that, "Sadness triggers the goal of changing one's circumstances, increasing buying prices [bids] but reducing selling prices [asks]." Compared to people in neutral emotional states, people who had viewed sad movie clips subsequently valued items they owned *less*, and they valued items they did not possess *more*.[19] As a result of the increased willingness of sad people to transact, we expect that an equity sector with a high level of Gloom will experience higher relative trading volumes.

Uncertainty

"The future is never clear, and you pay a very high price in the stock market for a cheery consensus. Uncertainty is the friend of the buyer of long-term values."
~Warren Buffett [20]

In the first half of the 20th century Frank Knight developed the concept of Knightian uncertainty to differentiate between two types of uncertainty.[21] Knight noted that when potential future outcomes can be expressed probabilistically, they are called risk. When there is a lack of knowledge about potential probabilities, the outcomes are described as uncertain or ambiguous. The Uncertainty TRMI attempts to measure expressions of the latter type of uncertainty, a lack of knowledge about outcome probabilities.

Academic researchers identified a psychological process called *ambiguity aversion* that leads investors to mistakenly discount asset prices. Specifically, researchers found that high-uncertainty equities and country indices on average outperform their less ambiguous peers.[22] While high uncertainty typically creates discounted valuations (as Warren Buffett notes above), in speculative bubbles uncertainty magnifies the prevailing positive sentiment. During speculative bubbles, companies with valuation uncertainty outperform peers before earnings[23] and during IPOs.[24]

Additional TRMI Sentiments

Authors describing an asset may reference an event (topic), positive or negative impact (sentiment), outcome ambiguity (uncertainty), the importance of the event (magnitude), its immediacy (urgency), and specific emotions relating to it (emotive sentiments). Thus far, this paper has addressed the research behind TRMI representing Stress, Urgency, Anger, Gloom, Fear, and Uncertainty. The TRMI measure additional emotions and states. TRMI such as GovernmentAnger and MarketRisk encapsulate the relationship between sentiments and specific topics. Table 1 below summarizes the market research on a sample of the sentiment-based TRMI. A comprehensive listing of all sentiments and topical TRMI appears later in this document in Figure 4.

MarketPsych Data

TRMI COMMON NAME	ANTICIPATED MARKET IMPACT
Sentiment	There are several important research findings related to sentiment and price movement. Based on academic research on Thomson Reuters News Analytics sentiment scores, positive and negative sentiment in the news about individual stocks extend price momentum,[25] which is supported by additional evidence that traders collectively under-react to negative sentiment in news reports.[26] Another study finds that market sentiment improves factor weighting in some models.[27] In foreign exchange, news sentiment was found to influence volatility.[28]
Optimism	There is empirical evidence that proxies for optimism correlate with positive price behavior[29] and that bullish comments in financial social media precede higher trading volume.[30] Optimism in earnings press releases was found correlated with future stock price activity.[31]
Fear	Academic researchers who aggregated search terms they deemed reflective of economic fear found short-term mean reversion in prices when fear-related search terms spiked in volume.[32] In experimental markets, fear was found to decrease bid and increase ask prices, leading to less overall trading activity.[33] As a result, we expect wider bid-ask spreads when fear is high.
Joy	Joy is a marker of exuberance. Experimental markets demonstrate higher price peaks and larger collapses during bubble simulations if traders watched a positively exciting movie clip before trading begins.[34]
Trust	Trust was designed specifically for nations and banking and financial groups. Economists have found that national interpersonal Trust levels correlate with future economic growth.[35,36]
Conflict	The Conflict TRMI, which is intended to capture disagreement and dispute, is anticipated to correlate with price volatility. A study of international markets found that global conflicts significantly impact asset prices.[37]
Stress[*] and Urgency	Urgency and Stress are high-arousal indices that vary in valence. Based on evidence that arousal drives cognitive performance in an inverse-U shaped curve, we infer that pricing anomalies are more likely to emerge at low or high arousal values, as seen with both high positive and high negative arousal during research into experimental market bubbles.[38]
Uncertainty	Researchers found that high-uncertainty equities and country indices on average outperform their low-uncertainty peers.[39] In contrast, during speculative bubbles uncertainty amplifies the price momentum of positive sentiment.[40] In emerging fixed income markets, releases of macroeconomic data decrease future volatility.[41]
Gloom[*]	Traders in an experimental market offered lower ask and high bid prices when “sadness” was induced prior to trading, leading to increased transaction volume.[42] If this result transfers into larger market behavior, we expect increased trading volume during periods of high Gloom.[43] Researchers speculate that identified semi-annual variations in country stock index returns - which scale by latitude and reverse from northern to southern hemispheres - may be caused by seasonal changes in affect (the “winter blues”) among local traders.[44]
Anger[*]	Traders induced to feel anger in an experimental market decrease both average ask and bid prices.[45] As a result, we speculate that higher TRMI Anger readings should lead to increased selling and reduced buying in associated assets, leading to downward pressure on prices during high Anger periods.

Table 1. Academic and professional research measuring market responses for various TRMI sentiments.

[*] The Gloom, Anger, and Stress TRMI are only available for Equities, although GovernmentAnger is present in the Countries data set.

Figure 2 below depicts several of the above TRMI sentiments on the affective circumplex. Each dot corresponds to the emotion's location on the circumplex in Figure 1 above, noting that some of the TRMI are a hybrid of multiple emotions in the above circumplex. Note in Figure 2 that TRMI representing an emotion and its opposite are plotted with a thin grey line connecting the positive and negative poles.

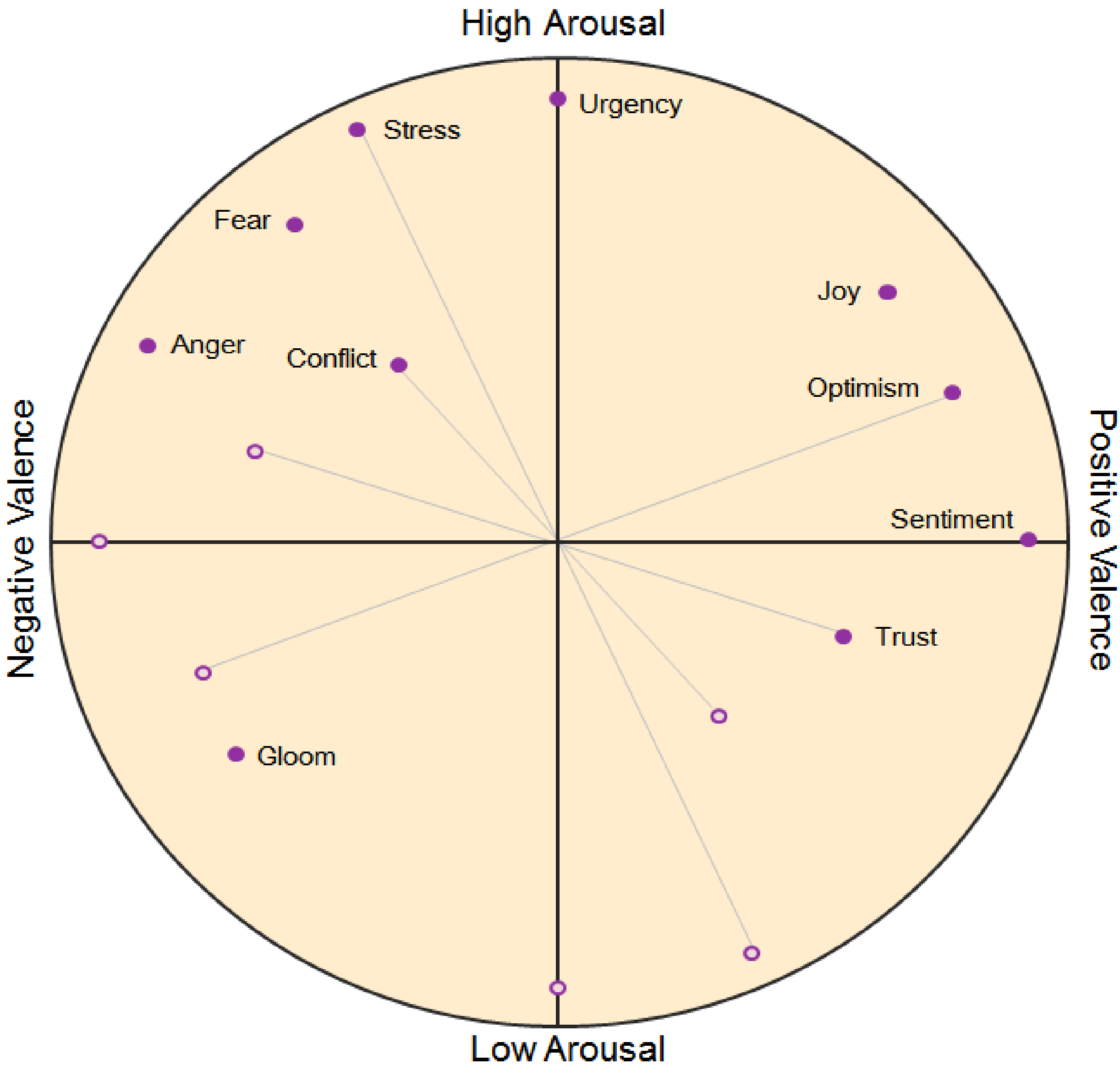

Figure 2. The sentiment-derived TRMI plotted on the affective circumplex.

MARKETPSYCH LEXICAL ANALYSIS

Over the past eight years MarketPsych honed its unique methodology for extracting detailed, relevant concepts from a variety of business and investment text. The MarketPsych lexicon is an extensive, expert-curated repository of simple and complex English-language words and phrases of potential interest for traders, investors, and economists. Used in conjunction with the MarketPsych lexicon, MarketPsych's natural language processing software employs grammatical templates customized to extract meanings from financial news, social media, earnings conference call transcripts, and executive interviews. The expertise MarketPsych amassed in extracting business-relevant concepts and psychological factors from multiple types of text stands as a key competitive advantage and asset.

Source Type Customization

We customize our analytics to each source type due to the vast differences in communication styles between social and news media. Compared to news, social media contains significant levels of sarcasm and irony, incomplete thoughts, misplaced or excessive punctuation, misspellings, non-standard grammar, case insensitivity, and crude language. Additionally, in social media many common words are used with colloquial meanings. A statement such as "That trade was the bomb!" with reference to a successful trade is far different from a reference to warfare, as would be interpreted by a historically-trained linguistic analysis engine.

Another significant difference between social and news media lies in how viewpoints are conveyed. In social media there is typically less editorial oversight and more leeway for a passionate author to unreservedly express his or her opinion or emotional state. In contrast, journalists are trained to offer multiple perspectives on the underlying story. In the news, emotion is typically conveyed by journalists whose role is to describe the emotional states of those they are reporting on. As a result, information obtained from social media is typically less inclusive of contrary viewpoints and more emotionally expressive from the first-person perspective than news information.

Direct expressions of emotion in news and social media also vary. In social media authors may utilize a complex array of emoticons (e.g., ">:-(") and acronyms (e.g., "LOL") that developed organically, with regional, industrial, and national differences. Furthermore, word context is much more important in social media than in news media for interpreting intended meaning.

As a result of all these differences between news and social media, sentiment scoring accuracy is improved by text analytic models calibrated to source type. MarketPsych currently uses differentiated models for news, social media forums, tweets, SEC filings, and earnings conference call transcripts.

Lexical Analysis

There are a variety of approaches used in sentiment analysis. The most common technique is called lexical analysis, and this approach is used in several recent academic studies of sentiment and stock returns.[46] Lexical analysis identifies explicit words and phrases in a body of text. Relevant content is organized and scored according to a hard-coded ontology. The simplest example of a lexical approach is called "bag of words." In the "bag of words" technique all words are counted according to their frequency, and no additional grammatical or relational post-processing is performed.

There are several known limitations to a purely lexical approach. The most significant one, for the purposes of producing TRMI, is that most lexical approaches are focused only on extracting one-dimensional sentiment. In cases where a variety of sentiment dimensions may be scored using lexical analysis, such as when using the Harvard General Inquirer dictionary, the word tokens representing specific sentiments are occasionally incongruent with meanings in contemporary business English. MarketPsych scores hundreds of business-relevant sentiments.

Another weakness of using uncurated dictionaries is lexical ambiguity across domains. For example, financial terms such as “investor” and “financier” are classified as negative sentiment terms in some open-source sentiment dictionaries. MarketPsych has overcome lexical ambiguity with extensive business-specific customization and curation of lexicons.

Insensitivity to grammatical structures is perhaps the most significant weakness of the lexical approach. In order to address this weakness, MarketPsych engineers embedded a complex grammatical framework with traits specific to different text sources such as social media, earnings conference call transcripts, financial news, and regulatory filings. The result is that customized lexicons, superior disambiguation, and optimized grammatical structures stand behind MarketPsych’s textual analytics.

Entity Identification and Correlate Filtering

Consider that entities such as IBM may be referred to as “IBM”, “Big Blue”, and “International Business Machines” in the press. Additionally, international press may or may not use accent marks on common location names such as Düsseldorf. In order to identify entities such as IBM and Düsseldorf that have multiple spellings or reference names, MarketPsych prepared a list of over 60,000 entity names with aliases. This list has been improved by human review, and it is updated quarterly with new entities including IPOs such as Zynga (ZNGA) and new location names such as South Sudan.

To improve entity name disambiguation, MarketPsych used supervised machine learning to identify correlate and anti-correlate words in proximity of ambiguous entity references. For example, gold and silver are commonly spoken of as both commodities and constituents of jewelry, but every two years they are frequently mentioned as Olympic medals. To prevent entity identification errors, anti-correlate filters are utilized to eliminate Olympic references such as “gold medal” and “won a silver.” Another example is the South Korean Won, which could be confused with a successful competition by a South Korean athlete who “won” an event. Anti-correlate filtering and case-sensitivity both improve precision of the scoring process and entity identification.

In addition to an anti-correlate filter to exclude irrelevant entities, for some entities MarketPsych software uses a correlate filter to ensure that only entities with the correct co-references are included in the entity identification. For example, when a Twitter user tweets that “I am enjoying my breakfast oats,” our software will not count that reference as applicable to the commodity Oats. References to Oats are counted only if they also contain key identification correlates such as “prices” and “futures.”

Temporal Classification

Accurate determination of expectations in text is an additional MarketPsych Data feature. In order to gauge time perspective, MarketPsych’s text-analytics software is calibrated to identify verb tenses in every phrase, including in instances when multiple verbs are present. This aspect of language processing is called MarketPsych’s “temporal classifier.”

This capability is essential for several emotional and topical TRMI. For example, the EarningsForecast TRMI requires that an earnings mention be both (a) future-oriented and (b) refer to earnings rising or falling. The difference between expectations of rising and falling earnings yields the net EarningsForecast value. As another example, the Optimism meaning is itself a net difference between future-oriented positive and future-oriented negative comments. Furthermore, the

Uncertainty TRMI excludes past-tense references to uncertainty, as those do not embody a current state of uncertainty.

Modifier Words

Modifier words change the meaning of a phrase or sentence by modifying its impact. For example, words or phrases that increase the significance of an adjective, such as “large”, e.g., “large loss”, are multiplicative on the weighting of the modified word. We call such words “Maximizers.” MarketPsych also has a lexicon of Minimizer expressions that reduce the score of a key term. MarketPsych created a lexicon of Maximizers and Minimizers specifically for use in business language in order to improve scoring of textual meanings.

In addition to the maximizing and minimizing operations, MarketPsych software also performs negations. For example, the phrase “I’m not worried about the earnings release” connotes that the author is not afraid, and as a result, the extracted fear score is negated (-1).

Linguistic Analysis Flow

When applied to text, the confluence of the various text processing described above generates over 400 psychological variables (PsychVars), each with the potential to be applied to a different entity. Alphabetically, the first few PsychVars are:

AccountingBad
AccountingGood
Ambiguity
Anger

Each PsychVar is then qualified by tense, such as the following:

AccountingBad_n: present-tense negative accounting news
AccountingGood_p: past-tense positive accounting news
Ambiguity_c: conditional-tense uncertainty
Anger_f: anger about anticipated events

Sentence-level Example

Using the principles outlined above, let’s now take a closer look at the MarketPsych software in action and see how it analyzes the following sentence:

"Analysts expect Mattel to report much higher earnings next quarter"

The language analyzer performs the following sequence:

1. Associates ticker symbol MAT with entity reference “Mattel.”
2. Identifies “earnings” as an *Earnings* word in the lexicon.
3. Identifies “expect” as a future-oriented word and assigns future tense to the phrase.
4. Identifies “higher” as an *Up-Word.*
5. Multiplies “higher” by 2 due to presence of the modifier word “*much.*”
6. Associates “higher” (*Up-Word*) with “earnings” (*Earnings*) due to proximity.

The analysis algorithm will report:

Date	Time	Ticker	PsychVar	Score
20110804	*15:00.123*	*MAT*	*EarningsUp_f*	*2*

In the example above, *2* is the raw score produced for EarningsUp_f.

THOMSON REUTERS MARKETPSYCH INDICES

The quantitative values generated by the above text scoring process are integrated into two products planned for distribution by Thomson Reuters. The first product is the currently available Thomson Reuters MarketPsych Indices (TRMI). The second product is a detailed sentiment add-in to the Thomson Reuters News Analytics product that is tentatively planned for late 2013.

The TRMI themselves derived from two groups of sources – news and social media – and the data feed itself consists of three feeds: a social media feed, a news media feed, and an aggregated feed of combined social and news media content. The TRMI are updated minutely. Over 2 million articles are processed daily and contribute to the TRMI feed within minutes of their publication. Each minutely value is a simple average of the past 24 hours (1440 minutes) of information about the target asset. The following sections further describe the construction of the TRMI, from raw content to PsychVars to published TRMI.

Source Text

The TRMI are derived from an unparalleled collection of premium news, global Internet news coverage, and a broad and credible range of social media. The TRMI social media feed consists of both MarketPsych and Moreover social media content. Moreover Technologies' aggregated social media feed is derived from 4 million social media sites and is incorporated into the TRMI from 2009-present. MarketPsych social media content was downloaded from public social media sites from 1998-present.

The TRMI News indices are derived from live content delivered via Thomson Reuters News Feed Direct and two Thomson Reuters news archives: a Reuters-only one from 1998-2002 and one with Reuters and select third-party wires from 2003-present. In addition, we incorporate Moreover Technologies aggregated news feed which is derived from 50,000 internet news sites and spans 2005-present. MarketPsych crawler content from hundreds of financial news sites is also included. MarketPsych-specific sources of text include *The New York Times*, *The Wall Street Journal*, *Financial Times*, *Seeking Alpha*, and dozens more sources widely read by professional investors.

Figure 3 below shows a graphic displaying the time course of each text feed within the TRMI.

HISTORICAL CONTENT EVOLUTION

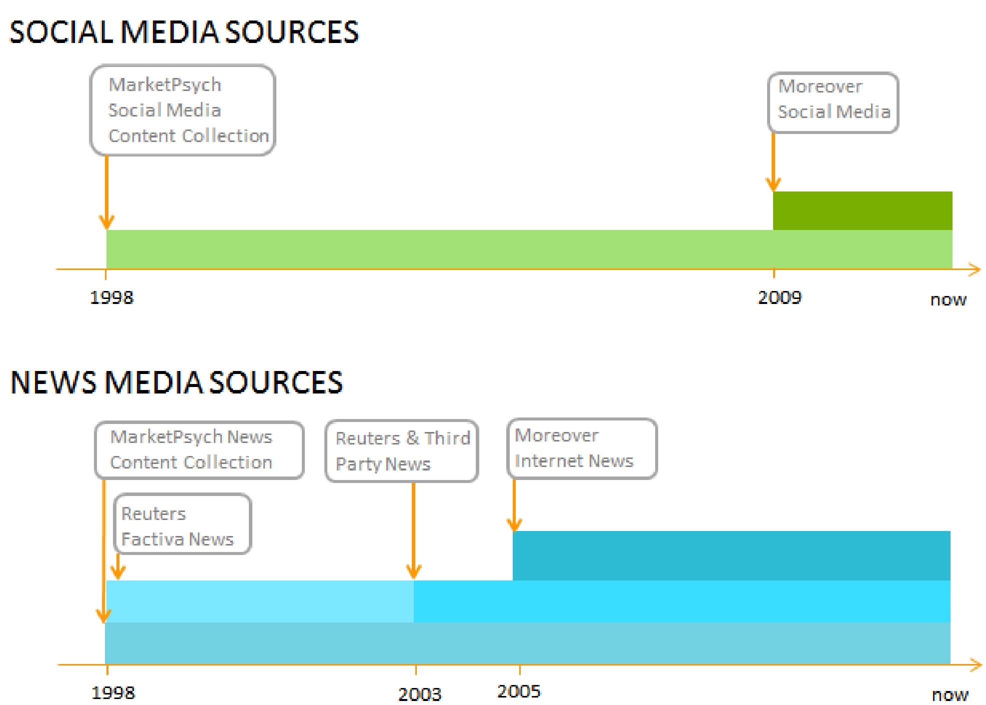

Figure 3. Timeline of textual content analyzed for the social and news media TRMI.

The TRMI thus cover the period 1998 through the present. Currently all source text for the MarketPsych sentiment products is English-language.

Index Construction

Each TRMI is composed of a combination of PsychVars. First we determine the absolute values of all TRMI-contributing PsychVars, for all asset constituents, over the past 24 hours. These absolute values are then summed for all constituents. We call this sum the "Buzz," and it is published in conjunction with each asset's TRMIs. More specifically, where *P* is the set of all PsychVars underlying *any* TRMI of the asset class, where *a* denotes an asset, and where *C(a)* is the set of all constituents* of *a*, we can define the Buzz of *a* as the following:

$$Buzz(a) = \sum_{c \in C(a), p \in P} \left| PsychVar_{c,p} \right|$$

* For example, Mattel is a "constituent" of MarketPsych's Nasdaq 100 index proxy asset (MPQQQ).

Each TRMI is then computed as a ratio of the sum of all relevant PsychVars to the Buzz. We define *P(t)* as the set of all PsychVars relevant to a particular TRMI *t*. Next we define a function to determine whether a PsychVar *p∈P(t)* is additive or subtractive to a TRMI as the following:

$$I(t,p) = \begin{cases} +1\, if\ additive \\ -1\, if\ subtractive \end{cases}$$

Thus the TRMI *t* of asset *a* can be computed as the following:

$$TRMI_t(a) = \frac{\sum_{c\in C(A),p\in P(t)} \left(I(t,p) \times PsychVar_p(c)\right)}{Buzz(Asset)}$$

It's worth noting that, particularly for Equities where the assets all correspond to indices and sectors, an individual constituent may contribute to multiple assets. For example, Mattel is a constituent of both the Consumer Goods sector and the Nasdaq 100 index proxies. As a result, Mattel's PsychVar scores will be incorporated into the TRMI for both.

Similarly, a single PsychVar can contribute to multiple TRMI. For example, the EarningsUp_f PsychVar noted in the "Sentence-level Example" section above is not only a constituent of EarningsForecast but also of the Sentiment, Optimism, and FundamentalStrength TRMI.

TRMI Numerical Ranges

Except for Buzz, all the TRMI may range from -1 to 1 or be NA. A TRMI value will be NA only if no relevant PsychVars are identified over the previous 24-hour period. NA values are expressed as blanks in the archives.

Unipolar TRMI such as Fear typically range between 0 and 1 but may fall below 1. When a unipolar emotion is expressed in the negative as in "I'm not afraid" or "I wouldn't worry about that," then the score weighting is inverted as mentioned above. When such negative expressions outweigh positive expressions of the same sentiment, the unipolar TRMI will display negative values. This phenomenon is more common at lower levels of Buzz.

Several of the TRMI are described as "bipolar," because by definition they consist of the net difference between PsychVar values of equivalent meaning but opposite valence. For example, Sentiment is the net difference between Positive and Negative PsychVars. As a result, median sentiment values are at or near zero and the range of such a bipolar TRMI is -1 to 1.

A list of typical value ranges for each TRMI is available in the Thomson Reuters MarketPsych Indices Output Image Format Guide.

TRMI Content

The Thomson Reuters MarketPsych Indices consist of several different sentiments, nine of which are common to all five scored asset classes. Macroeconomic and topic TRMI vary by asset class. See Figure 4 below for a listing of all TRMI by asset class.

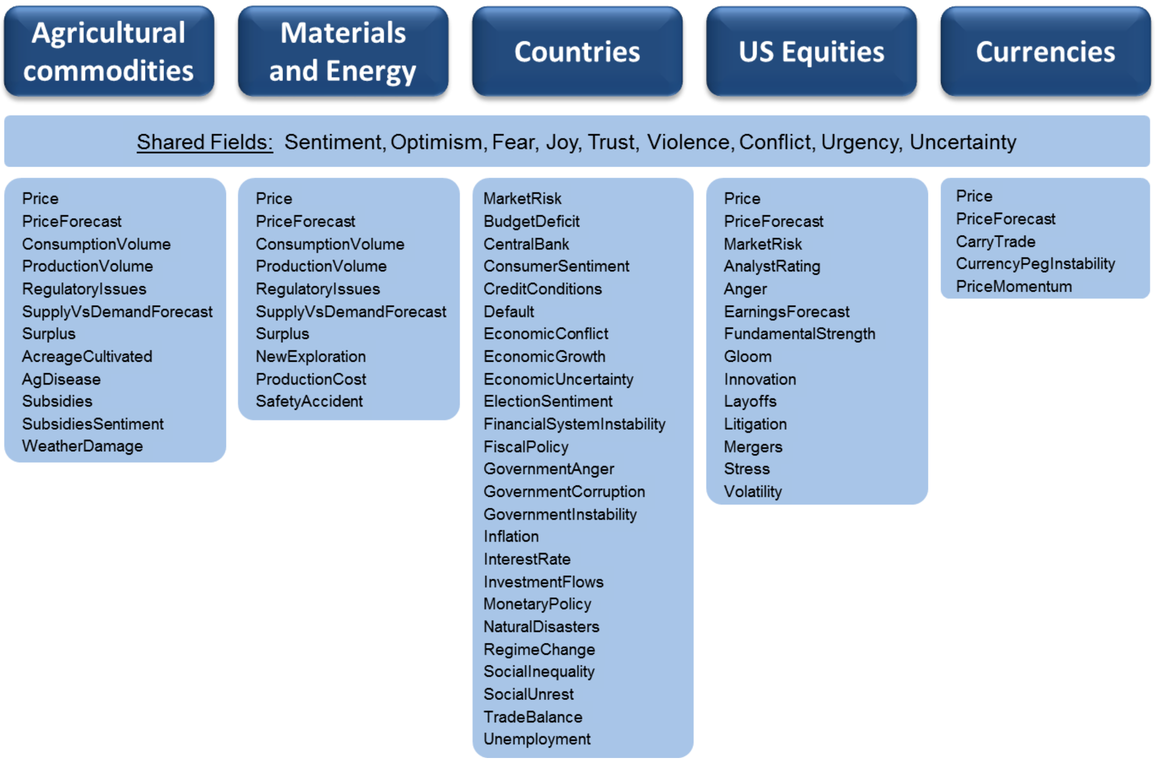

Figure 4. The TRMI include sentiments and topics covering five asset classes.

The TRMI themselves are produced for 34 commodities, 119 countries, 41 equity groups, and 29 currencies. More documentation about the individual assets and indices covered is available in the [Thomson Reuters MarketPsych Indices User Guide]().

CLOSING

From Baron Rothschild to Keynes to Baruch to Buffett, investor emotion has long been suggested to impact market prices, but until now there has been no means to measure such emotions quantitatively. We believe that the introduction of the TRMI – representing nine years of technological development – will help you to leverage investor emotions in forecasting economic activity and market price movement.

The TRMI consist of over 18,000 minutely indices representing news, social media, and an aggregate feed. The TRMI represent composite scores from 2 million relevant daily articles, downloaded from tens of thousands of blogs, chat rooms, and news feeds. Articles whose scores are incorporated into the TRMI are downloaded within minutes of posting on the web and analyzed within 500 milliseconds. Article scores reach the TRMI only minutes after information was published. 100,000 articles are analyzed and incorporated into the TRMI in the time it takes a human to read two such articles. In creating the historical TRMI archive, we used up to 3,000 servers on a Hadoop architecture to achieve speed efficiencies.

The TRMI that are delivered to users are aggregates of hundreds of underlying constituent sentiments. Each constituent sentiment is scored in relation to thousands of companies, currencies, and commodities (entities) and cities and regions (locations). As a result, our coverage is among the most extensive in the industry.

We encourage you to test a sample of TRMI data with your own hypotheses. For a data sample, please contact your Thomson Reuters account manager or submit an inquiry here: https://forms.thomsonreuters.com/qed/.

We hope you will find the data interesting and useful. If you have any questions or comments about our data or analytics process, please inquire to info@marketpsychdata.com.

Sincerely,
Richard L. Peterson, M.D.
Managing Director
MarketPsych Data

ENDNOTES

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