Using Media-Based Emotion for Predicting Commodity Prices

Abstract

Emotion plays a significant role in consumer decision making through affecting an individual's perception of risk and the person's assessment of monetary value. Based on valence-arousal framework and cognitive appraisal theory, the existing marketing emotion research indicated that emotion influences consumers' purchase decision making and post-purchase responses, yet there is lack of research to examine market-level emotion effect on demand of goods and services, and how managers can utilize established emotion indices to predict prices of those goods and services.

The development of big data analytics in textual analysis provides opportunities to study market-level emotion from a collection of contents from the news and social media sources. Thomson Reuters MarketPsych Indices (TRMI) is built on the comprehensive textual analysis of sources from news wires, internet news sources, and social media and can be a valuable resource for big data analytics in business research. The authors implement TRMI commodity emotion indicators in a fourteen-year analysis of market emotion effects on twelve energy and material commodities' prices. The empirical results suggest that high-arousal emotion from all groups of individuals tend to reach consensus at the market level in its effect on commodity price. Furthermore, the research also provides evidence that there is a short term predictive relationship between the media-based emotion indices and the following five days' commodity prices. This study shed light on big data analytics of media-based emotion and its implication in business valuation creation and risk management.

JEL classification: C22 D80 D87 M15 M30

Keywords: Market emotion; Big data econometrics; Commodity; Neuro-marketing; TRMI

*"Commodities usually end in a very big...wave. Unlike the stock market, commodities usually have their extensions in the [final] wave. It's usually some kind of blow off and that's because it is associated with a different kind of emotion than a stock market peak. A stock market peak is built on hope, which is very slow to build and very slow to dissipate. Commodity tops are built on fear, so they tend to be very dramatic and they tend to be spiky."**

- Robert Prechter, Elliott Wave International

I. Introduction

Media plays an essential role to diffuse information in modern days' business world. Recently, academic researchers and industrial practitioners have adopted content analysis and data mining algorithms to detect aggregated business and financial markets' sentiment and emotions manifested on news media and social media (Tetlock, 2007; Kothari, Li & Short, 2009; Culnan, McHugh & Zubillaga, 2010; Chen, De, Hu and Hwang, 2014; Sun, Najand, Shen, 2015). In this research, the authors are interested to know how media-based information of aggregated market emotion influence the consumers' expected demand of commodities, and further how business can use media-based emotion indices to predict commodity prices.

The development of neuroscience over the last two decades has shown that human behaviors, including economic behaviors are strongly influenced by our finely tuned affective processes operated in our brain system. (Elster, 1998; Lowenstein, 2000; Camerer, Loewenstein and Prelec, 2005) Emotion, as a major part of reflection on our affective processes, can produce a transient but significant impact on economic decision makings and activities in both individual and society level. (Lowenstein, 2000; Camerer, Loewenstein and Prelec, 2005) Neuro-economists in their experiments also detected that human's emotion and cognitive thinking are intertwined together all the time. (Lo, Repin and Steenba, 2005; Fenton-O'Creevy, Soane, Nicholson and Willman, 2010)

We utilized market-level emotion indices of commodities from Thomson Reuters MarketPsych Indices (TRMI), which is built on the comprehensive textual analysis of sources from news wires, internet news sources, and social media. Then we ran time series analysis to test significance of emotion on twelve energy and material commodities' prices. Furthermore, we examined the short term predictive power of media-based emotion indices on the following five days' commodity prices, consistent with short term predictive model of media-based sentiment on the next five days' stock return (Tetlock, 2007; Garcia, 2013). Comparing previous time series studies of media-based sentiment, we expand the single dimension of consumer or investor sentiment index to multiple dimensions of emotion indices. More

** Comments made at the **2010 Legends of Trading Forum in** Chicago as reported in an ElliottWave blog by Bob Strokes, "Spike in Silver: Watching Emotion in Action", 01/25/2011 18:15 pm, accessed 01/07/2016 09.59 am. http://www.elliottwave.com/freeupdates/archives/2011/01/25/Spike-in-Silver-Watching-Emotion-in-Action.aspx#axzz3wmjS50f0

importantly, our emotion indices are built on a collection of media sources covered from news wires, internet news sources, and social media, which includes over two million news articles and posts every day (Peterson, 2013), where most of the prior textual analysis studies of media contents exclusively rely on a single source. The collective media sources approach are more likely to reflect the information of the aggregated individual consumer emotion, in that aggregated level, the consensus of the information from all single sources further contribute to cancel out noisy opinion, and rumors from some unreliable sources.

In the field of marketing studies utilizing media information, the existing research documented evidences regarding the effects of positive and negative online customer reviews on product sales, brand strength, and converting site visitors into paying customers (conversion rates). (Ludwig, De Ruyter, Friedman, Brüggen, Wetzels & Pfann, 2013; Ho-Dac, Carson & Moore, 2013) Those studies further suggested that managers can identify and promote the positive reviews in a given product category, then to further promote their product, and increase the conversion rates. A negative online consumer review prevent consumers from buying the product, so researchers (Ullrich & Brunner, 2015) suggested that high quality products, brands should encourage their customers to write reviews, however, weak brands should be very careful about their customers' reviews. Another recent research (Du, Hu & Damangir, 2015) explored how Google search pattern of product feature-related keywords can affect the corresponding feature's development trend, and further suggested that managers may make decision to improve their effectiveness of market response by monitoring feature search trends and leveraging those trends. At this stage, there is no documented empirical evidence providing suggestions on how managers from companies in high energy and material consuming sector can utilize information of market emotion manifested on the collection of all news and social media sources to predict commodity prices. We provide the first paper to implement time series econometrics in big data analysis of a fourteen year daily observations of twelve major energy and material commodity (Aluminum, Copper, Crude Oil, Gold, Heating Oil, Jet Fuel, Gasoline, Natural Gas, Nickel, Palladium, Platinum, Silver) prices and five the market-level emotion indices (buzz, sentiment, optimism, fear and joy).

The rest of the paper is organized as follows. The next section introduces the emotion theories in business and marketing and how to constructed market level emotion indices. A subsequent section describes big data analytics and how businesses apply it for their decision making. Then the following section provides a description of research data, and time series econometric models in this big data analysis. Further followed by a section to provide empirical evidence on the effects of media-based emotion indices on energy and material commodity price and short term predictive power of emotion indices on the following days' commodity prices. The discussion section provides a summary of media-

based emotion effects on commodity market and their implications in managing companies' risk exposure to commodity price fluctuation. The paper concludes with a list of several main contributions, and a suggested future research avenue.

II. Emotional Theories in Business Research

Psychologists suggested individual's emotion plays an important role in a person's information processing and decision making. (Feldman, 1995; Lerner and Keltner, 2000; Tiedens and Linton, 2001) Valence-arousal approach and cognitive appraisal approach are two main dominated emotion theories in psychology studies. According to valence-arousal model, emotions can be mapped out on a two-dimensional circular space constructed by arousal in the vertical axis (mild to intense) and valence in the horizontal axis (unpleasant to pleasant) (Feldman, 1995). Cognitive appraisal theorists contend that emotions can be distinguished at a more fine-grained level as a person's appraisal or cognitive response to a specific situation. (Lerner and Keltner, 2000; Tiedens and Linton, 2001)

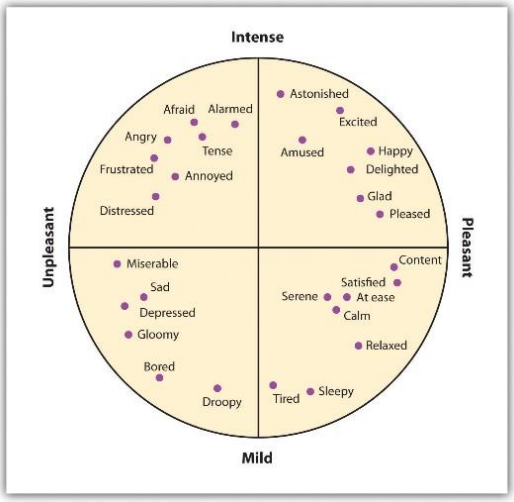


Figure 1. Valence-Arousal Circumplex Adapted from Russell, J. A. (1980)

Emotion is considered as one of the major influence in consumer behaviors, such as purchase decision making, and customer satisfaction. (Bagozzi, Gopinath & Nyer, 1999; Watson and Spence, 2007) Di Muro and Murray (2012) investigated how consumers' purchasing preferences are affected by the level of arousal and the valence of their affective state and they proposed a hypothesis that consumers in a pleasant mood tend to choose products that are congruent with their level of arousal at that moment, while those in an unpleasant mood are more likely to choose products that are incongruent with their level of arousal at the moment. Zeelenberg and Pieters (2004) empirically showed emotions have a direct impact on dissatisfied consumers' responses on a product, such as complain to customer service, switch to the other products, and talk about their dissatisfaction with others. While many consumer behavior have

documented evidences that emotions influence consumers' purchase decision making and post-purchase responses, there is still lack of research to examine how market-level emotion affect commodity pricing, and whether managers can utilize collective media emotion indices to predict commodity prices.

Market-level emotion effect research has attracted tremendous amounts of interests in financial studies. Financial analysts agreed that a big part of the financial market anomalies caused by investors' psychological bias. There is a Wall Street motto "Buy on fear, sell on greed" shown that financial professionals aware emotion can affect investors' trading behaviors. Academic researchers (Kuhnen and Knutson, 2011; Hirshleifer and Shumway, 2003) have found evidence to support that emotion states influence investors' risk taking and their trading performance. Kuhnen and Knutson (2011) found that positive emotional states motivate investors to take risky investment portfolios, while negative emotional states hinder them to do so. Hirshleifer and Shumway (2003) documented that sunshine is strongly significantly correlated with stock returns. That is because "*sunlight affects mood, and that people tend to evaluate future prospects more optimistically when they are in a good mood than when they are in a bad mood*."

In this research, the authors focus on each dimension of emotion manifested in collective media sources and their impact on commodity pricing in market level. According to appraisal-tendency hypothesis (Lerner and Keltner, 2000; Han, Lerner and Keltner, 2007), specific emotions carry over from past situations to guide future judgments and choices. The emotional carryover effects is related to individual's perception of risk and the person's assessment of monetary value. Because risk perception and value assessment are fundamental psychological processes, understanding them has essential implications for consumer judgment and decision making. Our research focus on five basic dimensions of emotion, buzz, sentiment, fear, optimism, and joy, rather than in individual level, they are in a collective market level. We are interested to know whether cognitive appraisal of emotions in a collective market level have similar effects with those in individual level.

III. Literature Review: Big Data Analytics and Its Applications

The market level emotion indices of commodities from Thomson Reuters MarketPsych Indices (TRMI) is built on the comprehensive big data-based text analysis of sources from news wires, internet news sources, and social media, which includes over 2 million news articles and posts every day (Peterson, 2013). Thus, we would like to provide a review of the big data analysis. The Big Data phenomenon has attracted a lot of attention because vast amounts of data are becoming available across a wide range of application domains. The importance of big data has been increasingly recognized by

industries, governments, and academia. Paulo B. Goes, Editor-in-Chief of MIS Quarterly, points out that the IS field has been moving along the hierarchy Data -> Information -> Knowledge -> Intelligence. After proposing a simplified taxonomy to describe big data analytics (see figure 1), Goes defines analytics to be the upper stages of the hierarchy: the generation of knowledge and intelligence to support decision making and strategic objectives (Goes, 2014). Therefore, big data analytics can be referred to the process of examining massive amounts of data in an effort to uncover hidden patterns, unknown correlations and other useful knowledge and intelligence for better supporting decision making and strategic objectives (Shanmuganathan, 2014; Chen, Chiang, & Storey, 2012; Wu et al., 2014). Figure 1 shows the simplified taxonomy of big data analytics proposed by Goes (2014), which includes the common analytics methods and techniques. The big data world is moving from yearly, monthly, weekly, hourly toward real-time or close to real-time decision making. A description of these analytics methods and techniques can be found in articles such as Gandomi & Haider (2015) and Chen, Chiang, & Storey (2012).

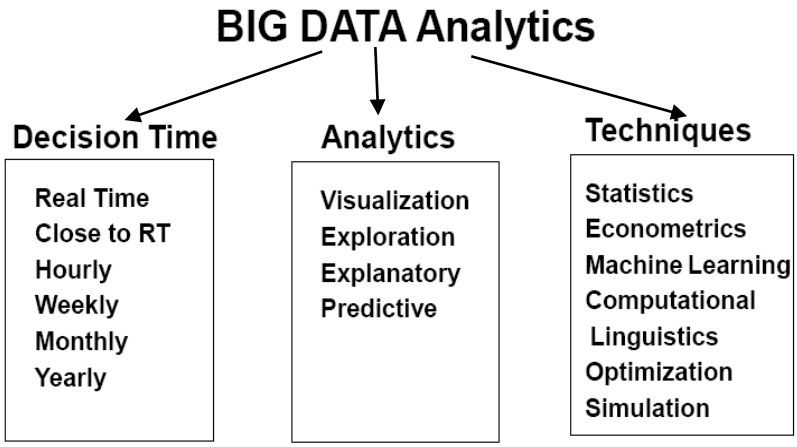


Figure 2. A Simplified Taxonomy of Big Data Analytics Adapted from Goes, P.B. (2014)

Big data is usually characterized by the four Vs — that is, volume, velocity, variety and veracity (Zikopoulos & Eaton, 2011). Volume is referred to as the amount of data. Millions of users use social media such as Facebook, Tiwtter, YouTube and Pinterest today. For example, Twitter has over 140 million active users and generates over 340 million tweets every day. Variety means that data can be represented by very different formats, for example, structured data and unstructured data. Structured data reside in traditional relational databases where data are correlated to each other. Unstructured data often mean data without obvious correlations, for example, random text streaming to social media, emails, video, audio and log files, etc. The challenging comes in managing, merging, and handling different varieties of data. Velocity is often referred to as the speed of data that are generated and processed. As millions of people use social media every day, social media spread their voices in a speed and scale we never saw before. Veracity refers to the quality or trustworthiness of the data. Social media data contains

both useful information and lots of noise. For example, Twitter contains numerous spambots and untrustworthy tweets (Zikopoulos et al, 2012). Different from traditional transaction data, social media data have several unique characteristics. First, social media cover general users' opinions about almost every aspect of our life. Second, there are always fresh content on social media and the content are updated consistently and timely by numerous online users. Third, social media contents are associated with metadata in various attributes such as user, location, likes, time, dislikes, etc. Fourth, social media data have quality issues and contain a lot of noise and spams, which need to be sifted through to figure out what data can be trusted. Real benefit can be obtained by analyzing massive social media data in real time and gaining trustworthy insights while social media data are continuously coming in high speed. The New York Stock Exchange announced to provide investors with real-time information about trade-related public sentiment in 2013 (NYSE, 2013). Bollen et al. (2011) did sentiment analysis on a large corpus of tweets and found that the mood of the Twitter population can be used to predict the movement of the Dow Jones Industrial Average (DJIA) on the following day with a claimed accuracy of 87.6%. Risius and Beck (2015) conducted a multilevel analysis of approximately five million tweets regarding the main Twitter accounts of 28 large global companies and identified different social media activities in terms of social media management strategies, account types (broadcasting or receiving information), and communicative approaches (conversational or disseminative). However, the rapid increase of social media data evolves into a big data problem because most organizations do not have the capability and skills to process such huge amounts of data in a timely manner, identify trustworthy data, and gain values from these massive data to enhance their business such as marketing, products, sales, and online commerce.

So far a lot of efforts have been made by academics and practitioners to improve the technologies and methodologies with regards to big data analysis. For example, Cao, Chychyla and Stewart (2015) used big data analytics to improve the efficiency and effectiveness of financial statement audits. The National Science Foundation in the U.S. had several program solicitations regarding Big Data in the past three years and has been inviting proposals that focus on the development of novel techniques and methodologies in order to "*advance state-of-the-art core technologies needed to collect, store, preserve, manage, analyze, and share huge quantities of data*" (NSF, 2015).

Effective big data analytical tools should have the capability of automatically analyzing a huge amount of data. Applying automatic methods to quickly analyze massive content is increasingly needed by organizations. Although text mining and sentiment analysis were developed before big data technology, both are commonly used techniques in conducting big data analytics (Gandomi & Haider, 2015). Text mining focuses on finding useful models, trends, patterns, or rules from unstructured textual data (Aggarwal & Zhai, 2012). Different from traditional content analysis, its main purpose is to

automatically extract knowledge, insights, useful patterns or trends from a given set of text documents and can dramatically reduce cost and increase knowledge discovery of analyzing public opinions, compared with the conventional survey approach (Zhong, Li, & Wu, 2012; Tsytsarau & Palpanas, 2012). A wide range of tools such as IBM SPSS Modeler, Lexalytics, Leximancer, Clarabridge and SAS Enterprise Miner can be used for text mining and analytics. Sentiment analysis is the computational detection and study of opinions, sentiments, emotions, and subjectivities in text (Pang & Lee, 2004). As a special application of text mining, sentiment analysis is concerned with the automatic extraction of positive or negative opinions from text (Pang & Lee, 2004). As texts often contain a mix of positive and negative sentiment, it is useful to identify the polarity of sentiment in text (positive, negative, or neutral) and even the strength of sentiment expressed (Thelwall, Buckley, & Paltoglou, 2011). Sentiment analysis mainly relies on machine learning techniques such as Support Vector Machine (SVM), Naive Bayes, Maximum Entropy and Matrix Factorization to classify texts into positive or negative categories (Pang, Lee & Vaithyanathan, 2002; Li & Wu, 2010).

Big data research is mainly concerned with three key challenges: storage, management and processing (Kaisler et al. 2013). Business researchers are mainly interested in the management aspect of big data, which emphasizes creating value based on big data analysis (Zhao, Fan, & Hu, 2014). Organizations must invest in big data infrastructure to deal with new business opportunities and challenges in order to compete and succeed in the era of big data. Many industries such as e-commerce, marketing, retail, health care, logistics and financial services generate massive amounts of data that need deep analysis to gain critical business values. Some organizations had success in using these big data technologies to analyze big data. For example, Lansdall-Welfare et al. (2012) used big data technology to analyze 484 million tweets posted by more than 9.8 million users over a period of three years and revealed changes in public mood and associated mood changes with important events. Chevron analyzed 50 terabytes of seismic data to refine their advanced computer models. As the result, Chevron has improved the odds of drilling a successful well to nearly 1 in 3 and saved a lot of cost in drilling (Watson, 2014). Perrey et al. (2013) found that retailers can achieve up to 15–20% increase in ROI by putting big data into analytics. When big data analytics is used in health care, it can help predict the impact of disease, prevent medical malpractice, reduce healthcare costs and detect fraud in health insurance claims (Levy, 2013; Li, Bagheri, Goote, Hasan, & Hazard, 2013; Srinivasan & Arunasalam, 2013). The U.S. Geological Survey (USGS) monitors Twitter messages containing the word "earthquake" to detect identify possible earthquakes events because people begin sending tweets with in tens of seconds after feeling shaking (Earle, Bowden, & Guy, 2012). Big data analytics has been used as an efficient tool to analyze huge amounts of astronomical data for scientific discoveries (Garrett, 2014). Duan & Xiong

(2015) point out that big data analytics is very useful in terms of identifying and detecting bank fraud, insurance fraud, securities and commodities fraud and other related financial fraud.

IV. Data and Methodology

In this research, we mainly incorporate twelve energy and material commodities' price data and five dimensions of their market-level emotion data. The twelve energy and material commodities are Aluminum, Copper, Crude Oil, Gold, Heating Oil, Jet Fuel, Gasoline, Natural Gas, Nickel, Palladium, Platinum, Silver. The five dimensions of market emotion are buzz, sentiment, optimism, fear and joy. We retrieved our daily commodity data from Bloomberg Commodity Database and Global Financial Database. Bloomberg Database is a leading business commercial data powerhouse encompassing both current and historical financial information on individual equities, stock market indices, fixed-income securities, currencies, commodities, and futures for both US and international markets. Global Financial Database Provides an extensive collection of financial and economic data covering more than 200 countries extending back to centuries ago.

We obtain our daily commodity emotion data from Thomson Reuters MarketPsych Indices (TRMI). TRMI's entire content set includes millions of articles and posts each day from various sources such as news wires, internet news sources, and social media. TRMI utilizes contents derived both from news and social media to reflect market emotion from a group of customers, analysts, journalists, and economists, etc.. A collection of MarketPsych sources covers The New York Times, The Wall Street Journal, Financial Times, Seeking Alpha, Google News among other major business news channels and over 2 million social media sites. MarketPsych employs lexical analysis to extract market level emotion indices by sweeping through all sources minutely, which includes over 2 million news articles and posts every day. (Peterson, 20136). TRMI emotion measures provide the 24 hour rolling average score of total references in news and social media. The scores are normalized so that their value ranges from -1 to 1.

In the empirical analysis, we employ a time series of study of the fourteen years' daily observations among twelve energy and material commodities. We implement Ordinary least squares (OLS) model and Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model to measure the relationship between commodity's price and market emotion (buzz, sentiment, optimism, fear, and joy).

OLS model is widely used in academia for estimating the parameters in a linear regression. For each commodity, we conduct the following OLS regression to test whether commodity price is affected by different dimensions of market emotion:

$$Price_i = \alpha + \beta_1 * BUZZ_i + \beta_2 * SNTMENT_i + \beta_3 * OPTIMSM_i + \beta 4 * FEAR_i + \beta 5 * JOY_i + \varepsilon_i$$

where $Price_i$ is the daily log commodity *i*'s price, BUZZ is the daily media attention of this commodity, SNTMENT is the daily market sentiment level, OPTIMSM is the daily optimism level of this commodity, FEAR is the daily fear level of this commodity, and JOY measures the daily joy level of this commodity.

Next, we use GARCH model to capture the lagged effects with a few parameters. The reason we use this model is to deal with the variance changes over time and it comes from the Auto Regressive Conditional Heteroskedasticity (ARCH). GARCH models have become important tools in the analysis of time series data in academic research. These models are especially useful when the goal of the study is to analyze and forecast volatility. For example, one of the main stock market indexes, S&P 500 index experienced a stable period from 1992 to 1996, but it became more volatile from 1996 till now. In that case, normal OLS model cannot analyze the data accurately due to this time-varying volatility. The basic GARCH model contains three equations. The first equation is a linear regression function that contains a constant and possibly some other variables. In the examples below, the regression function contains only an intercept.

$$y_t = \beta + \varepsilon_t$$

In this case we expect the time series to vary randomly on its mean. If the mean of the time series drifts over time or is explained by other variables, these would be added to the regression equation. The error term is conditionally normal with variance that depends on information available in the previous period.

The second part is the variance equation, which describes how the error variance changing by time. The equation is showing below:

$$h_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1}$$

where h_t is the error variance for time t. The variance in the current period is a function of a constant term and the lagged squared error and lags of the conditional variance. This is a well-developed model to deal with historical price volatility's effect on current price.

The last method we use is the vector autoregressive (VAR) model, which is a general framework used to describe the dynamic interrelationship among variables. VAR models have become increasingly popular in recent decades. The VAR model is based on OLS model, but this model can be used to study the information transition within several variables, and this is why VAR model have an important role in econometrics. The VAR model here is used to capture the spillover effects of one commodity's market emotion to other ones. In addition, this model is also employed to test the predictive power of market emotions to the future commodity price.

The basic VAR(p) model can be shown as below:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + \varepsilon_t$$

Where each y_t is a vector of length k and each A_i is a k × k matrix. k is the number of variable in this analysis. Clearly, the model tests how one variable, y_i, is influenced by the historical value of itself and the historical values of other variables. In addition, this can be used to test the predictive power of other variables on this one.

V. Empirical Results

V(I). Data summary

The summary table and historical price for 12 commodities are given by **Table 1** and **Figure 3**. The lowest price standard division is given by Aluminum, which is 0.265, and the highest price standard division is given by Copper, which is 0.671. **Figure 3** clearly shows that there is fairly high co-movements among all commodities' price during January 1998 to December 2011, but the correlation is not strong during economic expansion, however, all commodities' prices went down together during 07-09 financial crisis. To support that, we also calculate the correlation coefficients between 12 commodities' prices, and the results are reported in **Table 2**.

Table 1

Summary of all 12 commodities' prices

Variable	N	Mean	Std Dev	Minimum	Maximum
Aluminum	3432	7.486751	0.264962	7.0387835	8.0940731
Copper	3642	5.060323	0.671344	4.1475693	6.1485751
Crude Oil	3587	3.736406	0.662117	2.2082744	4.969466
Gold	3642	6.239954	0.583306	5.5306189	7.5490774
Heating Oil	3515	4.781598	0.641451	3.3456847	6.0120757
Jet Fuel	3509	0.195132	0.652005	-1.2658482	1.5715283
Gasoline	3514	4.776538	0.606005	3.2958369	6.1887773
Natural Gas	3513	1.426903	0.461495	0.076961	2.9678471
Nickel	3475	9.417125	0.638464	8.2228221	10.89955
Palladium	3646	5.851205	0.449788	4.9870254	6.9893353
Platinum	3654	6.7269	0.526251	5.8081425	7.7286358
Silver	3601	2.169563	0.634782	1.3999507	3.8825942

Figure 3

12 Energy and Material Commodities' Prices during January 1998 to December 2011

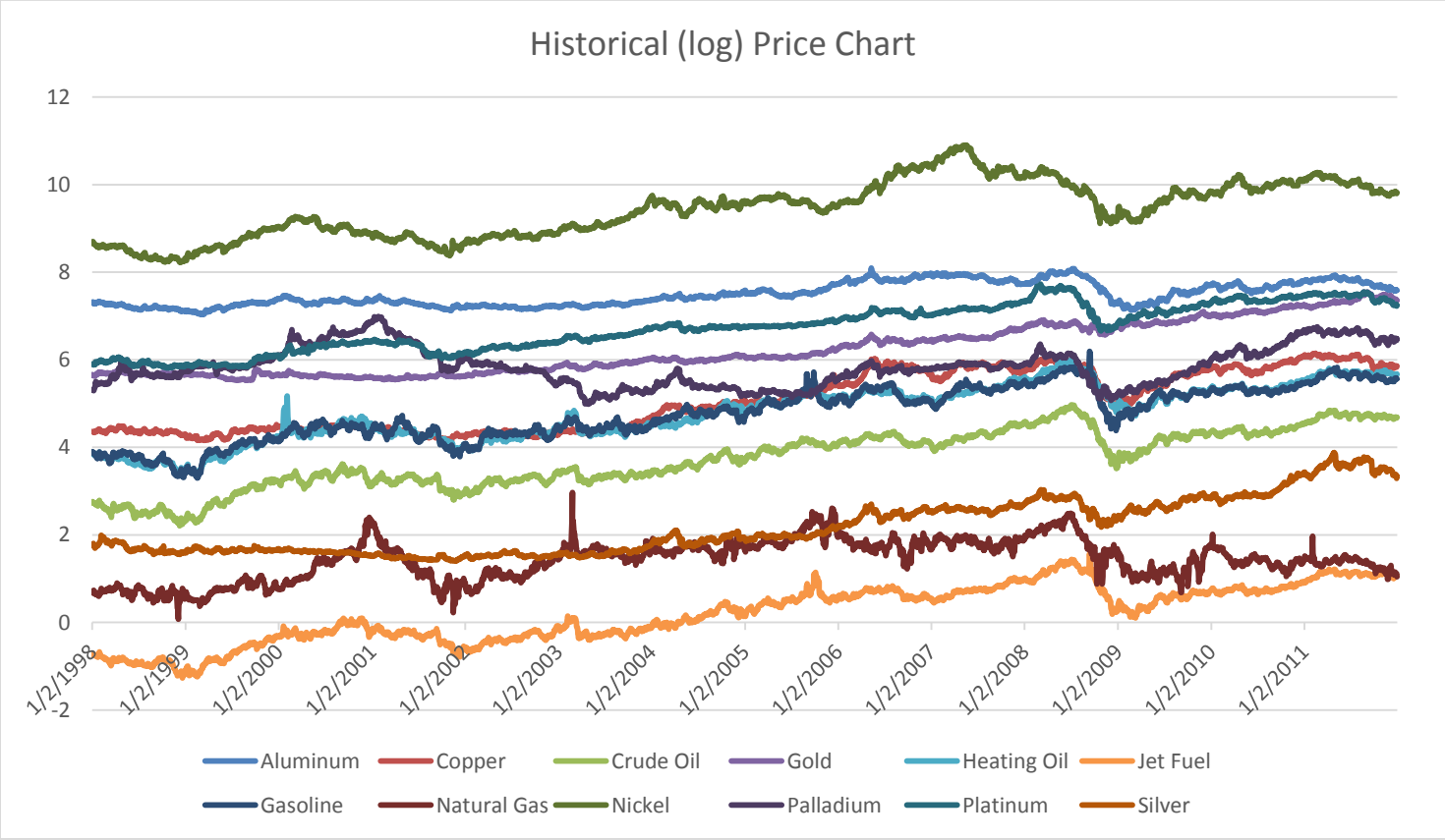


Table 2

Pearson Correlation Coefficients of 12 Energy and Material Commodities

	Aluminum	**Copper**	**Crude Oil**	**Gold**	**Heating Oil**	**Jet Fuel**	**Gasoline**	**Natural Gas**	**Nickel**	**Palladium**	**Platinum**	**Silver**
Copper	0.91826	1										
Crude Oil	0.86415	0.93077	1									
Gold	0.72291	0.91346	0.87627	1								
Heating Oil	0.86616	0.92312	0.99252	0.86354	1							
Jet Fuel	0.87546	0.92898	0.99236	0.85872	0.99684	1						
Gasoline	0.86573	0.92254	0.98835	0.84871	0.98271	0.98627	1					
Natural Gas	0.6351	0.51389	0.63291	0.31427	0.66801	0.67237	0.66702	1				
Nickel	0.91209	0.91204	0.88815	0.76684	0.88153	0.8866	0.8945	0.64514	1			
Palladium	0.22943	0.20425	0.20884	0.21488	0.19026	0.18151	0.18772	-0.0734	0.09541	1		
Platinum	0.84858	0.94428	0.96464	0.91373	0.95851	0.9567	0.95626	0.61845	0.90236	0.18859	1	
Silver	0.78009	0.92881	0.85982	0.9731	0.84459	0.8423	0.83432	0.28914	0.78127	0.31771	0.88703	1

V(II). OLS results

The results of OLS model are reported in **Table 3**. First of all, based on the variance inflation factor (VIF), we are confident that the OLS model is not suffered from multicollinearity. The correlation between commodity price and media buzz indicates that when a commodity is increase its news exposure on media, its price level will increase (all commodities are with P value less than 0.1 and 9 out of 12 commodities are with P value less than 0.01). From **Table 3**, one can see 10 out of 12 correlations between commodity price and market sentiment level is positive and significant. This result goes alone with our expectation that high sentiment level will increase the commodity price due to increased demand of the commodity on the market. The majority results of optimism and fear are also supporting our hypothesis that market optimism (fear) level will increase (decrease) the market demand because customers assume the price will go up in the future, which in return increase the commodity price. The above findings are consistent with appraisal-tendency hypothesis (Lerner and Keltner, 2000; Han, Lerner and Keltner, 2007) even in a collective market-level emotion research setting. The emotional carryover effects of sentiment, optimism and fear influence the collective market's assessments of risk and monetary value of commodities. Also, we noticed that all these three emotions, sentiment, optimism and fear are high arousal emotions on the valence-arousal circumplex (Russell, 1980), so one can also explain that for high arousal emotions, a collective market groups of individuals' feelings tend to have consensus effects on evaluation of commodity price consistent with their feelings. However, the correlations between price and fear are positive and statistically significant for CPPR, CRU, and NGS. Our guess is that the positive relationship between fear and commodity price is the result of customers' protection activity on future expectation. This protection activity will increase current market demand for this commodity and increase the current price. When there is a fear of shortage on the supply of a natural resource on the market, the price of the natural resource will run high. An example could be during Iraq Wars, the fear of shortage on supply of crude oil on global petroleum market caused Crude Oil and Natural Gas price jumped up. Lastly, according to appraisal-tendency hypothesis, we are expected to see a positive effect of market joy on commodity price, however, we only found joy has positive effect on Crude Oil and Gold. More surprisingly, 8 out of the rest 10 correlations between commodity price and market joy level are significant but negative. What we noticed is that joy is a low arousal emotion, we may explain the inconsistent findings on joy as for low arousal emotions, a collective market groups of individuals' feelings cannot reach consensus to evaluate commodity price consistent with their feelings. From a methodological perspective, the inconsistent finding of market joy effect on commodity may be caused by the uncertain information and volatility on commodity market, so we would like to take a further investigation of the market-level collective emotion effects in a GARCH model that control for past errors and past volatilities.

Table 3

OLS regression results of Market Emotion Effects on Commodities' Prices

	Aluminum	Copper	Crude Oil	Gold	Heating Oil	Jet Fuel	Gasoline	Natural Gas	Nickel	Palladium	Platinum	Silver
Intercept	7.74671	4.78635	3.04403	5.75349	4.94866	0.78318	4.6535	1.77701	9.56413	6.06862	6.93312	2.26004
P Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
VIF	0	0	0	0	0	0	0	0	0	0	0	0
BUZZ	1.61E-05	0.000277	0.000153	8.17E-05	0.00024	0.000274	0.000126	-8.8E-06	0.000747	0.000375	0.000361	0.000189
P Value	0.0356	<.0001	<.0001	<.0001	<.0001	0.019	<.0001	0.0563	<.0001	<.0001	<.0001	<.0001
VIF	1.05266	1.11975	1.23035	1.13252	1.02948	1.07519	1.15917	1.04994	1.11173	1.0557	1.05818	1.00817
SNTMENT	0.43068	0.70597	0.45244	0.21122	-0.42093	0.42398	-0.39212	0.49869	0.75146	0.189	0.32007	1.13108
P Value	<.0001	<.0001	<.0001	<.0001	0.0039	0.0824	<.0001	<.0001	<.0001	0.0412	<.0001	<.0001
VIF	1.38937	1.422	1.22622	1.35092	1.08643	1.1534	1.23074	1.28271	1.1979	1.15552	1.23876	1.25163
OPTIMSM	-0.05249	2.36176	1.34925	2.81844	0.48445	0.60132	0.41337	0.52385	0.24411	-0.27165	0.41747	1.15541
P Value	0.7669	<.0001	<.0001	<.0001	0.3323	0.5163	0.2957	0.0988	0.3832	0.4065	0.0384	0.0004
VIF	1.32004	1.30783	1.1718	1.39362	1.08411	1.08981	1.14623	1.22969	1.15041	1.14078	1.16649	1.17721
FEAR	-2.86374	4.69408	5.14229	-3.41029	-2.21334	0.42821	-2.37015	4.7202	-4.37814	-1.31439	-5.08209	-8.86029
P Value	<.0001	<.0001	<.0001	<.0001	0.0331	0.861	0.0005	<.0001	<.0001	0.1601	<.0001	<.0001
VIF	1.06784	1.19504	1.06368	1.09598	1.04402	1.03517	1.06367	1.01079	1.03446	1.09012	1.08256	1.02924
JOY	-3.60606	-13.8654	15.91973	10.0975	-3.57632	-7.37072	-7.50244	-28.1909	-4.37132	-0.9767	-3.99575	-3.53428
P Value	<.0001	<.0001	<.0001	<.0001	0.1401	0.0117	0.001	<.0001	<.0001	0.4887	<.0001	0.0008
VIF	1.10416	1.10351	1.17499	1.15491	1.02979	1.1524	1.02404	1.04262	1.13509	1.05161	1.09906	1.05753
Monday	0.03511	0.13108	0.10528	0.07467	0.02451	-0.11904	0.2282	0.0223	0.08765	0.04725	0.04077	0.05171
P Value	0.0639	<.0001	<.0001	<.0001	0.7202	0.3337	<.0001	0.2528	0.0061	0.4221	0.055	0.0164
VIF	1.01169	1.01363	1.0175	1.01192	1.04724	1.05181	1.05221	1.02809	1.00772	1.01465	1.00754	1.00715
Adj R2	0.1164	0.597	0.6447	0.8093	0.0797	0.0671	0.3714	0.111	0.2947	0.0501	0.3745	0.5451

V(III). GARCH (1,1) results

The results of GARCH (1,1) model are exhibited in **Table 4.** First of all, the results of CARCH (1,1) model are consistent with the OLS model results after controlling for the effect of historical price volatility. Specifically, based on the P value of GARCH model, the model structured based on market emotion level can explain the commodity price changes appropriately (9 out of 12 P values are smaller than 1%). Furthermore, the P values for copper and natural gas are also significant within 5% confidence level. However, when we use the model explain the price change of jet fuel, the generated result is not accurate.

Comparing the ARCH and GARCH elements, we can draw the results that commodity prices are affected more by past error, rather than past volatility. If we consider the error term as news information intercepted into the commodity price evaluation, we can see a clear tendency that unpredictable information will influence the price for a long time.

In addition, the explanation power of several dimensions of market emotion—optimism, fear, and joy, is decreasing. As we mentioned before, our finding on the strong negative relationship between joy and commodity price in the OLS regression results is not consistent with the evaluation of joy in appraisal-tendency hypothesis. When we control the past volatility and error, the negative relationship vanishes. Within those 12 commodities, only 3 of them show strong negative relationship (with P value less than 1%). More interestingly, 2 within those 12 commodities, gold and crude oil shows significant positive relationship between price and market joy, assigned with the evaluation of joy in appraisal-tendency hypothesis. Interestingly, even in the GARCH model, the Monday dummy variable is still significant.

As we shown above, in a framework based on market-level emotion in explaining commodity price, the empirical results shown that commodity market emotion indices are relative reliable and persistent indicators to explain commodity price dynamic changes. The emotion effects on commodity price changes can be further explained by collective emotion in the market drives the market demand fluctuations in shifting or rotating commodity demand curves in demand-supply mechanism.

Table 4

GARCH (1,1) results of Market Emotion Effects on Commodities' Prices

	Aluminum	Copper	Crude Oil	Gold	Heating Oil	Jet Fuel	Gasoline	Natural Gas	Nickel	Palladium	Platinum	Silver
Intercept	7.7971	4.7685	3.157	5.6276	5.1452	0.655	5.277	1.7074	9.7159	6.2093	7.3202	1.7488
P Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
BUZZ	3.42E-07	0.000275	0.000167	0.000105	-6.25E-06	8.03E-05	1.14E-05	-4.9E-05	0.000131	6.83E-05	1.54E-05	0.00043
P Value	0.8339	<.0001	<.0001	<.0001	0.3123	<.0001	<.0001	<.0001	<.0001	0.0024	<.0001	<.0001
SNTMENT	0.0294	0.2534	0.1504	0.0969	0.00181	0.2006	0.147	0.0671	0.0512	0.1238	0.0265	0.2775
P Value	0.0052	<.0001	<.0001	<.0001	0.9455	0.0211	<.0001	0.0115	0.0284	<.0001	<.0001	<.0001
OPTIMSM	-0.0427	0.833	0.127	0.131	0.1163	0.4031	-0.0803	0.006806	-0.2088	-0.3403	-0.0228	0.2544
P Value	0.3252	<.0001	0.2818	0.0233	0.197	0.2628	0.3336	0.9526	0.0039	0.0218	0.433	0.0411
FEAR	-0.0356	-0.1635	1.6232	-1.2872	-0.0715	-0.2381	0.6089	0.4252	-0.4879	-0.3816	0.0163	-3.2942
P Value	0.8114	0.712	<.0001	<.0001	0.6831	0.7746	<.0001	0.3232	0.1811	0.3148	0.8238	<.0001
JOY	-0.052	-3.3416	6.9659	0.6748	-0.0925	-1.8052	-0.6181	-4.1163	-0.8747	-0.7363	0.0216	-0.4976
P Value	0.7571	0.0005	<.0001	<.0001	0.8538	0.0928	0.1917	<.0001	0.0021	0.0485	0.8503	0.2382
Monday	-0.00048	0.0915	0.0393	0.0153	-0.009	-0.0245	0.0186	-0.0252	0.0168	0.001246	0.000391	0.0574
P Value	0.8745	<.0001	<.0001	<.0001	0.4711	0.6347	0.001	0.0004	0.0304	0.9295	0.8753	<.0001
ARCH0	0.000118	0.000268	0.000203	3.17E-05	0.000222	0.000352	0.000294	0.001194	0.000546	0.000574	6.91E-05	0.000392
P Value	<.0001	0.0096	0.0002	<.0001	0.0034	0.0926	<.0001	<.0001	0.0005	0.0204	0.0063	<.0001
ARCH1	1.0006	0.2038	0.2052	0.225	1.0043	0.9992	0.6024	0.5734	0.7731	0.9981	0.902	0.2664
P Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
GARCH1	0	0.7995	0.803	0.7937	0	0	0.3954	0.4214	0.2266	0	0.0985	0.7319
P Value	.	<.0001	<.0001	<.0001	.	.	<.0001	<.0001	0.008	.	0.3452	<.0001
Pr > ChiSq	<.0001	0.0247	<.0001	<.0001	<.0001	0.3161	<.0001	0.0017	<.0001	<.0001	<.0001	<.0001

V(IV). VAR results

The results of VAR model are in **Table 5**. These results show a strong predictive power of different dimensions of market emotion on commodity's future price, but the power is in relative short term, and high-arousal emotion (such as optimism and fear) has prediction effect last longer than low-arousal emotion (such as joy). The predictive powers of buzz, sentiment, optimism, and fear are still significant with 90% confidence level for some commodities.

First, for all the commodity prices, the past one day prices have a very strong predictive power of current prices. However, the prediction effect decreases when the historical prices go back further in the time line, but even back to 5 days before the current day, historical commodity prices can still affect the current prices of heating oil, natural gas, platinum, and silver.

Overall, higher media buzz predicts a higher price percentage change of those commodities. However, the predictive power, based on our VAR model, is not clear. For example, the predictive power of market buzz for copper can go back to 5 days, and still in 5% significant level; but for aluminum, there is no predictive power at all.

Commodity market sentiment has a pretty strong prediction effect to predict future price. The sentiment level in past 2 periods can predict 4 out of 12 current commodity prices with 5% significant confidence level. Combine with the results of GARCH model, we can assume that unpredicted information will trigger the increase of sentiment, which in return will influence the future price.

As we discussed before, joy, which is a sample of low arousal emotion, has the relative low predictive power of future commodity price.

To further test the prediction power of the market emotion, we conduct an out-of-sample analysis to predict future one-week commodity price for all 12 commodities. The results are shown in **Figure 4.** We compare the predicted price and real price, along with the 95% confidence boundary. The result confirms the strong predictive power of the market emotion on commodity price. Based on our analysis, we see that market emotion model can provide a robust forecasting on following days' commodity prices. Even though, the forecasting of our model would be more accurate if there is less new information adjusted into the price. As shown by the charts in **Figure 4**, the model fits very well to forecast the price of heating oil, natural gas, and platinum, which commodities with less volatilities in the prediction period. On the other hand, commodities with high volatility will have a higher diversion between the real price and the predicted price.

Table 5

VAR results of Market Emotion Indices in Predicting Future Commodities' Prices

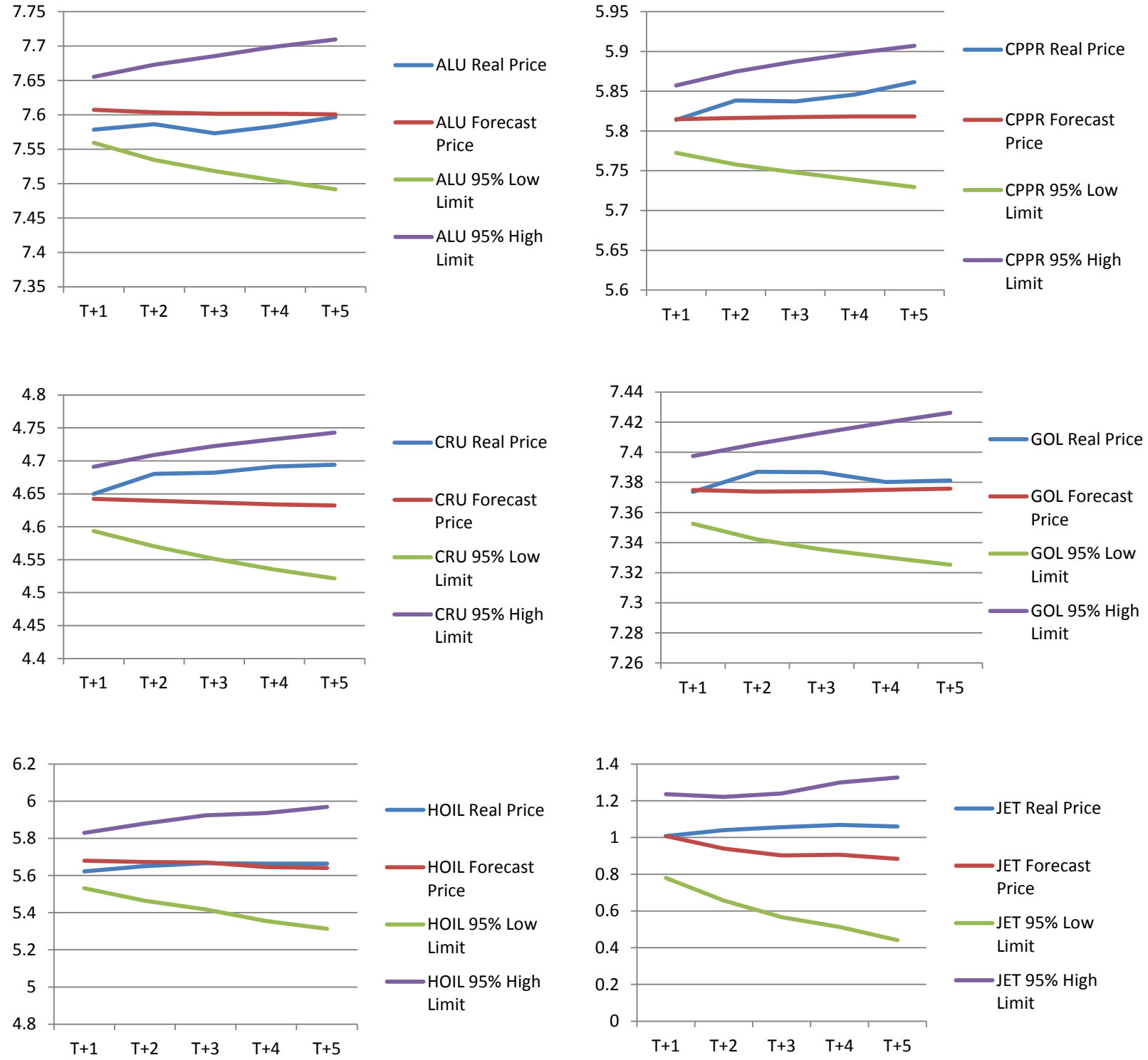
Variable	Aluminum	Copper	Crude Oil	Gold	Heating Oil	Jet Fuel	Gasoline	Natural Gas	Nickel	Palladium	Platinum	Silver
(t-1)	1.02562	0.88476	0.95328	0.99716	0.97473	0.6727	1.02842	0.82972	0.98248	1.04975	1.06008	1.0077
P Value	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
buzz(t-1)	0	0	0	0	0	0.00002	0	0	0	0.00001	0	0
P Value	0.5807	0.0001	0.2465	0.1359	0.9311	0.5317	0.6478	0.0229	0.2294	0.5554	0.3865	0.0247
SENTMENT(t-1)	0.00223	0.01948	0.02542	-0.00097	0.00072	0.09518	-0.01107	0.02362	-0.00093	-0.00455	0.00145	0.00337
P Value	0.7323	0.0001	0.0001	0.7575	0.9778	0.1594	0.2843	0.2643	0.896	0.7983	0.6925	0.5301
OPTIMSM(t-1)	0.05591	0.00207	-0.01969	0.02655	-0.0294	0.17203	0.00192	0.09444	-0.00758	0.13394	-0.002	-0.00269
P Value	0.007	0.9032	0.3656	0.0243	0.7311	0.5002	0.9612	0.1448	0.7185	0.0178	0.8804	0.881
FEAR(t-1)	-0.076	-0.01373	-0.02784	-0.0267	0.13256	0.17313	-0.19879	0.15338	0.06759	0.10305	0.02389	-0.07711
P Value	0.3842	0.7652	0.52	0.3984	0.4765	0.7937	0.0169	0.5124	0.3953	0.5338	0.5266	0.2497
JOY(t-1)	-0.07192	-0.04274	-0.10655	0.06819	0.49271	0.01977	-0.1612	0.42177	0.11487	0.02683	-0.07475	0.00866
P Value	0.4303	0.6168	0.1133	0.1018	0.2364	0.9799	0.4755	0.2756	0.1215	0.9132	0.122	0.8793
(t-2)	-0.09583	-0.02668	0.06045	-0.00998	-0.01113	0.28761	-0.02803	-0.03017	-0.01387	0.08273	-0.03619	-0.02424
P Value	0.0413	0.3327	0.0272	0.6951	0.8764	0.0176	0.3524	0.2779	0.6874	0.2838	0.3508	0.4083
buzz(t-2)	0	0	0	0	-0.00002	-0.00004	0	0	0.00001	0	0	0
P Value	0.1738	0.0056	0.9447	0.6594	0.0472	0.2509	0.8707	0.1015	0.0198	0.8485	0.0403	0.0391
SENTMENT(t-2)	0.00873	0.01244	-0.01154	-0.00184	0.02598	-0.00289	0.01586	0.05531	0.00344	0.00021	-0.00722	0.00261
P Value	0.1868	0.0044	0.0351	0.5699	0.3203	0.9659	0.1328	0.0121	0.6339	0.9906	0.0496	0.6308
OPTIMSM(t-2)	-0.00982	0.01173	0.02054	0.00836	-0.0358	-0.12726	-0.01328	-0.0234	0.00635	-0.01593	0.0088	-0.00368
P Value	0.6354	0.4925	0.3514	0.4824	0.6774	0.6162	0.7398	0.7208	0.7625	0.7788	0.5102	0.8365

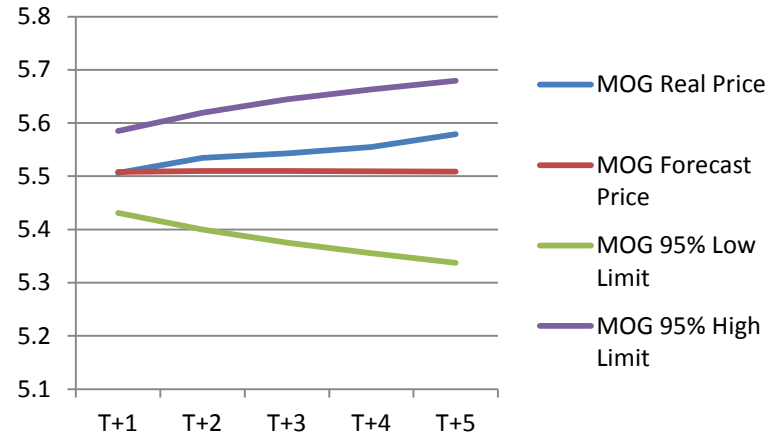
FEAR(t-2)	-0.07039	0.01714	0.00325	0.01853	0.29475	0.24168	-0.13384	0.19763	-0.07078	-0.01974	-0.05709	0.09075
P Value	0.4204	0.7137	0.9436	0.5712	0.1182	0.7159	0.1264	0.4051	0.3737	0.9072	0.1362	0.177
JOY(t-2)	-0.10572	-0.17048	-0.05141	-0.02559	1.20674	0.56962	-0.11118	-0.10614	0.08224	0.59765	0.06156	0.01668
P Value	0.2471	0.0462	0.4578	0.5429	0.004	0.4693	0.6231	0.788	0.2677	0.0168	0.1999	0.7705
(t-3)	0.10198	0.11286	-0.02542	0.02727	0.02546	0.07741	-0.04425	0.11867	0.05472	-0.26279	-0.01328	0.00208
P Value	0.0287	0.0001	0.3581	0.3187	0.7225	0.5128	0.144	0.0001	0.113	0.0006	0.7321	0.9442
buzz(t-3)	0	0	0	0	0	0	0	0	0	0.00001	0	0
P Value	0.6021	0.6516	0.1429	0.8955	0.6817	0.9979	0.9048	0.1737	0.2277	0.5003	0.0256	0.3692
SENTMENT(t-3)	0.00519	-0.00383	-0.00035	-0.00034	-0.00682	0.11819	0.00292	-0.02799	0.01094	0.00283	0.00011	0.01172
P Value	0.4356	0.3795	0.9491	0.9175	0.7943	0.0777	0.7809	0.2052	0.1278	0.8766	0.9761	0.0303
OPTIMSM(t-3)	0.03472	0.00598	0.00897	0.00497	-0.06934	0.01446	-0.03059	-0.07305	0.01692	-0.06118	-0.01646	-0.01415
P Value	0.0937	0.7256	0.6837	0.6765	0.4195	0.9539	0.4439	0.264	0.4221	0.2863	0.2186	0.4256
FEAR(t-3)	0.15831	-0.08976	-0.03147	0.00677	-0.24904	1.40567	0.15884	0.3862	0.08188	-0.02836	-0.03239	0.0923
P Value	0.0711	0.0541	0.4936	0.8362	0.1878	0.0399	0.0691	0.1031	0.3052	0.866	0.3944	0.171
JOY(t-3)	0.12778	0.0401	0.13399	0.06619	0.47101	-2.17981	0.23954	0.27659	-0.17203	0.08109	-0.07709	-0.09161
P Value	0.1619	0.6392	0.0544	0.116	0.2547	0.0055	0.2891	0.4823	0.0202	0.744	0.1067	0.1089
(t-4)	-0.05534	0.01441	-0.00907	0.01121	0.11139	-0.00879	0.03113	0.03044	-0.03848	0.10969	-0.0912	-0.02602
P Value	0.2316	0.6071	0.7414	0.6795	0.1204	0.939	0.3036	0.2752	0.2641	0.1538	0.0188	0.3805
buzz(t-4)	0	0	0	0	0.00001	-0.00001	0	0.00001	0	0	0	0
P Value	0.0145	0.7813	0.6078	0.8909	0.5937	0.8351	0.9002	0.0001	0.3619	0.9343	0.119	0.6705
SENTMENT(t-4)	0.00154	0.00411	0.00564	0.00054	-0.06377	-0.13719	0.00892	0.02322	0.00518	0.01142	0.00264	-0.00536
P Value	0.8171	0.326	0.2947	0.8542	0.0151	0.0482	0.3962	0.293	0.4682	0.5251	0.4725	0.3118
OPTIMSM(t-4)	-0.00575	-0.00616	-0.00785	-0.01168	0.02492	0.14912	-0.03797	0.0193	0.00204	-0.01341	0.01388	-0.0069
P Value	0.7804	0.7175	0.7214	0.325	0.7717	0.5596	0.3408	0.7671	0.9224	0.8141	0.3014	0.6976

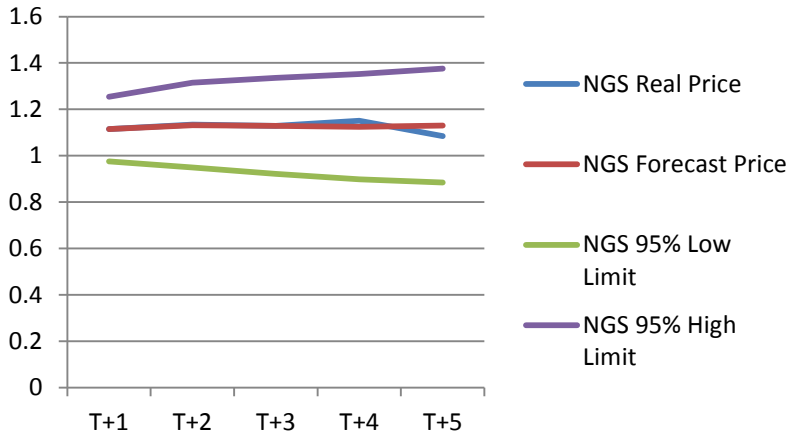
FEAR(t-4)	0.16071	0.02577	-0.08587	-0.00673	0.08182	0.32118	-0.0126	-0.11352	-0.02533	-0.15129	-0.02364	0.01199
P Value	0.0652	0.5815	0.0619	0.8357	0.664	0.6461	0.8856	0.632	0.75	0.3693	0.5357	0.8589
JOY(t-4)	-0.13617	-0.10156	-0.01007	-0.00823	0.46464	-0.54816	0.1177	0.06687	0.01812	0.00549	-0.10352	0.06606
P Value	0.1353	0.2351	0.8845	0.8444	0.2594	0.493	0.6033	0.8653	0.8072	0.9823	0.0307	0.2485
(t-5)	0.00963	0.01232	0.01953	-0.02595	-0.12161	-0.09701	0.0098	0.03718	0.01036	0.00283	0.07407	0.041
P Value	0.7629	0.5754	0.345	0.2125	0.0161	0.2939	0.6515	0.0825	0.6789	0.9583	0.0066	0.0574
buzz(t-5)	0	0	0	0	0.00001	0.00001	0	-0.00001	0	-0.00001	0	0
P Value	0.5946	0.0331	0.8315	0.6721	0.1514	0.8068	0.4818	0.0001	0.6967	0.4462	0.6992	0.5316
SENTMENT(t-5)	0.00169	-0.00714	-0.00372	-0.00105	0.03652	-0.03989	0.00037	0.01294	-0.00096	0.00521	0.00518	0.00312
P Value	0.7953	0.0662	0.4116	0.6935	0.1524	0.56	0.9703	0.5301	0.8895	0.7551	0.1289	0.5285
OPTIMSM(t-5)	0.01274	-0.00172	0.06618	-0.01844	0.03411	0.07189	0.03201	-0.03777	0.00613	0.00554	0.00514	-0.00319
P Value	0.5348	0.9187	0.0023	0.1169	0.6923	0.7698	0.4155	0.5574	0.7696	0.9221	0.7	0.8575
FEAR(t-5)	0.01281	-0.08909	0.0692	-0.04611	-0.15989	0.22437	-0.00742	-0.28243	-0.13603	-0.12438	-0.03403	-0.11566
P Value	0.8834	0.0526	0.1094	0.1411	0.3848	0.726	0.9289	0.227	0.0861	0.4519	0.3674	0.0843
JOY(t-5)	-0.03552	0.1117	0.03029	0.04295	-0.27371	-0.62613	0.07584	-0.30203	0.07227	-0.12444	-0.05141	-0.00801
P Value	0.6964	0.1904	0.6529	0.3006	0.5045	0.433	0.7367	0.434	0.3313	0.6139	0.2817	0.8886

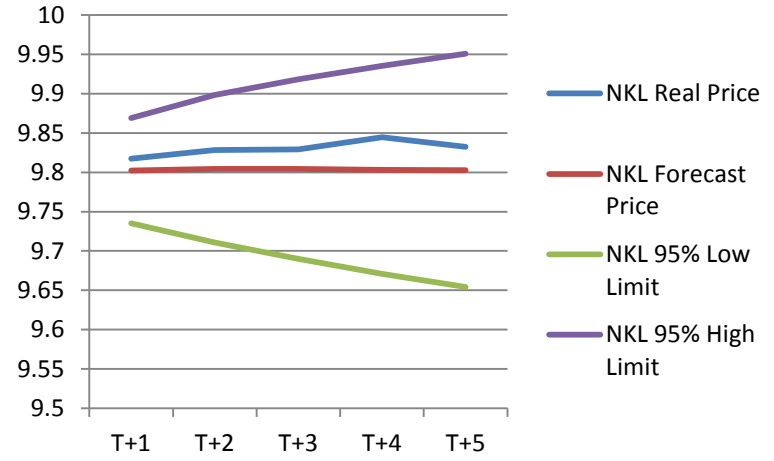
Figure 4

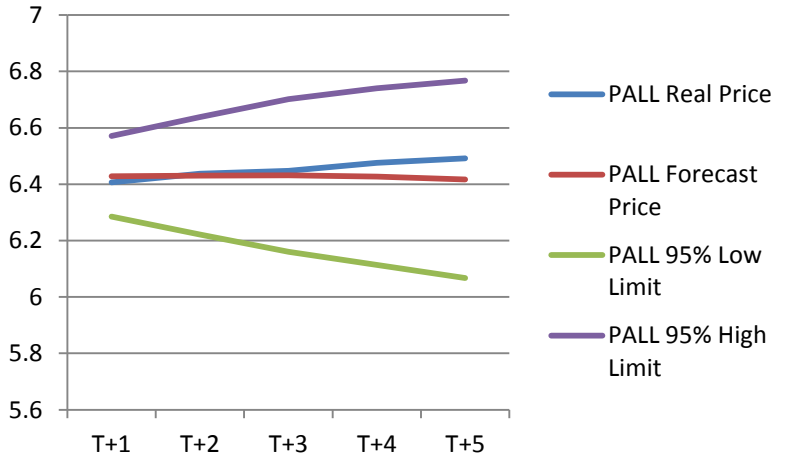
Forecasting Model of Market Emotion Indices on Future Commodities' Prices

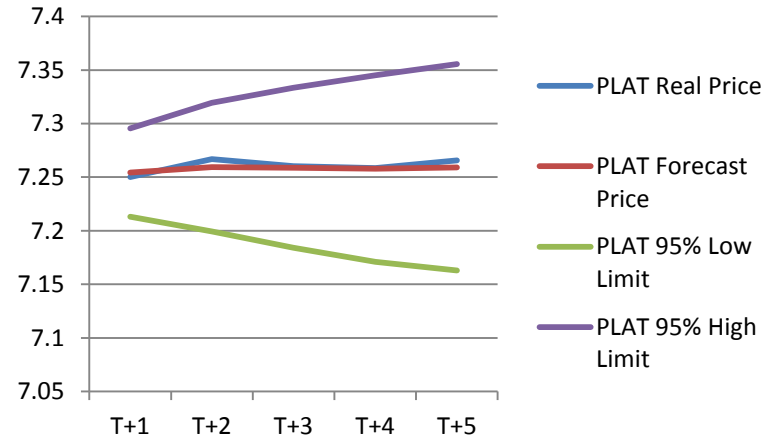


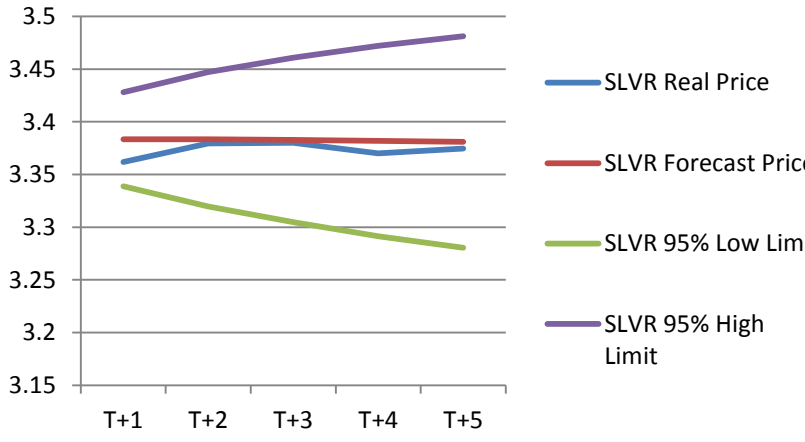

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MOG Real Price
MOG Forecast Price
MOG 95% Low Limit
MOG 95% High Limit


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NGS Real Price
NGS Forecast Price
NGS 95% Low Limit
NGS 95% High Limit


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NKL Real Price
NKL Forecast Price
NKL 95% Low Limit
NKL 95% High Limit


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PALL Real Price
PALL Forecast Price
PALL 95% Low Limit
PALL 95% High Limit


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PLAT Forecast Price
PLAT 95% Low Limit
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SLVR 95% High Limit

V(V).Business cycle

As we discussed before, the commodity price can be influenced by business cycle. We also conduct analysis to answer the question whether the relationship of market emotion with commodity price will be affected by business cycle. The indicator we use to capture the business cycle is the Chicago Fed National Activity Index (CFNAI). The CFNAI is a coincident indicator of national economic activity comprising 85 existing macroeconomic time series. It is constructed to have an average value of zero and a standard deviation of one. We use the headline three-month moving average. If the indicator is larger than 0 we consider this month is in business expansion, and if the indicator is smaller than 0 we consider this month is in business recession. The results are reported in **Table 6**, which using both OLS model and GARCH (1,1) model.

There is no major difference found in market-level emotion effects on commodity prices between economic recession and expansion. However, the coefficients between commodity price and market buzz, fear, and joy are relative larger during expansion than during recession. The coefficients between commodity price and sentiment and optimism are relative smaller during expansion than during recession.

Table 6

Business cycle analysis of Market Emotion Effects on Commodities' Prices

OLS Model

	Aluminum	Copper	Crude Oil	Gold	Heating Oil	Jet Fuel	Gasoline	Natural Gas	Nickel	Palladium	Platinum	Silver
Expansion												
Intercept	7.70287	4.705	2.91925	5.76469	4.7213	0.52658	4.51606	1.72801	9.30156	6.14265	6.78856	1.98072
P Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
BUZZ	0.00007058	0.00031178	0.00016304	0.00007133	0.00029196	0.0001851	0.00013311	0.00000525	0.00115	0.00038043	0.00050175	0.00028265
P Value	<.0001	<.0001	<.0001	<.0001	<.0001	0.1347	<.0001	0.4538	<.0001	0.0021	<.0001	<.0001
SNTMENT	0.24126	0.73403	0.47842	0.30518	-0.4567	-0.15528	-0.86539	0.0785	0.4208	-0.07233	0.29601	0.54573
P Value	0.0028	<.0001	<.0001	<.0001	0.0139	0.6557	<.0001	0.5407	0.0008	0.5799	0.0001	<.0001
OPTIMSM	-0.26897	1.6235	1.06829	2.70761	0.6096	0.25127	1.34003	-0.30984	0.4333	-0.99218	0.20998	0.96554
P Value	0.2561	<.0001	0.0343	<.0001	0.3222	0.8757	0.033	0.4737	0.2553	0.0201	0.4508	0.0076
FEAR	-3.3891	1.30836	6.93601	-1.4214	0.33346	1.72585	-1.44157	4.03232	-1.92097	-0.70362	-4.92877	-5.98656
P Value	0.0003	0.2518	<.0001	0.0962	0.7757	0.5703	0.1206	0.0129	0.164	0.6322	<.0001	<.0001
JOY	-2.40695	-5.78432	17.33479	9.52019	-6.4323	-4.7317	-3.14063	-31.27198	-0.48662	-0.39717	-1.87463	-0.94918
P Value	0.0228	0.006	<.0001	<.0001	0.0262	0.2261	0.3619	<.0001	0.728	0.8163	0.0833	0.3981
Monday	0.02681	0.11921	0.08117	0.04918	-0.05109	-0.10721	0.20574	0.05442	0.1064	-0.07764	0.05561	0.06217
P Value	0.3152	<.0001	0.0022	0.0008	0.5435	0.4894	<.0001	0.0561	0.0259	0.2885	0.0867	0.0106
Adj R2	0.1491	0.6565	0.6071	0.7991	0.1883	0.0137	0.3509	0.1309	0.396	0.0969	0.4686	0.7244
Recession												
Intercept	7.76348	4.91735	3.20395	5.70906	5.06112	0.85021	4.8262	1.8232	9.76044	6.05838	7.02139	2.47008
P Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
BUZZ	0.00000224	0.00024412	0.00013949	0.00009223	0.00029902	0.00078566	0.00011867	-0.00001755	0.00053123	0.00024499	0.00029605	0.0001516
P Value	0.8125	<.0001	<.0001	<.0001	0.0003	0.009	<.0001	0.0045	<.0001	0.0615	<.0001	<.0001

SNTMENT	0.50513	0.74347	0.38512	0.07959	-0.26609	1.11049	0.15725	0.80306	0.90247	0.33653	0.33337	1.6659
P Value	<.0001	<.0001	<.0001	0.2806	0.1796	0.0007	0.186	<.0001	<.0001	0.0071	<.0001	<.0001
OPTIMSM	0.24736	3.08016	1.78741	2.62825	0.69033	1.53792	-0.23696	1.34526	0.07753	0.26436	0.54134	1.10173
P Value	0.3349	<.0001	<.0001	<.0001	0.318	0.16	0.6314	0.0029	0.8425	0.5739	0.0534	0.0205
FEAR	-2.0968	6.08743	2.51758	-4.30517	-4.21856	1.63976	-3.75434	4.82116	-8.04311	-1.23137	-4.71496	-11.18094
P Value	0.0535	<.0001	0.0007	<.0001	0.009	0.6589	0.0003	0.0017	<.0001	0.297	<.0001	<.0001
JOY	-4.41879	-20.32351	14.58192	9.89867	5.31347	-6.75294	-10.71	-24.61061	-6.8884	-0.88314	-5.80461	-5.95333
P Value	<.0001	<.0001	<.0001	<.0001	0.134	0.1242	0.0003	<.0001	<.0001	0.6771	<.0001	0.0001
Monday	0.04098	0.13037	0.11548	0.10557	0.10765	-0.07334	0.23273	-0.00731	0.07704	0.12337	0.03472	0.04262
P Value	0.1131	<.0001	<.0001	<.0001	0.255	0.6859	<.0001	0.7806	0.0635	0.1515	0.203	0.1601
Adj R2	0.13	0.5268	0.6728	0.8273	0.0832	0.2099	0.3727	0.1227	0.2656	0.0565	0.3306	0.5057

Table 6 (Continued)

Business cycle analysis of Market Emotion Effects on Commodities' Prices

GARCH (1,1) Model

	Expansion											
	Aluminum	Copper	Crude Oil	Gold	Heating Oil	Jet Fuel	Gasoline	Natural Gas	Nickel	Palladium	Platinum	Silver
Intercept	7.7662	4.7533	3.166	5.6384	5.136	0.5286	4.7851	1.7989	9.5386	6.3153	6.9698	1.8049
P Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
BUZZ	2.40E-06	0.000273	0.000182	0.000113	-2.59E-06	0.000108	0.0000646	-0.000059	0.0003	-9.27E-06	0.00028	0.000282
P Value	0.3053	<.0001	<.0001	<.0001	0.6891	<.0001	<.0001	<.0001	<.0001	0.8342	<.0001	<.0001
SNTMENT	0.0146	0.201	0.1161	0.1108	0.008672	0.0221	-0.1255	0.0143	-0.0751	0.059	0.1449	0.1209
P Value	0.4314	<.0001	0.0048	<.0001	0.7261	0.878	0.0052	0.813	0.0294	0.3171	0.0003	<.0001
OPTIMSM	0.051	0.5267	0.2719	0.0937	0.065	0.5242	0.1832	0.0339	-0.0851	0.0789	-0.1424	0.1441
P Value	0.538	0.003	0.1479	0.2633	0.4887	0.2162	0.3375	0.8769	0.3289	0.7009	0.35	0.2087
FEAR	0.0147	-1.0019	2.5132	-1.3192	-0.1441	0.1864	-0.2093	0.8237	0.2218	-1.1022	-0.5306	-1.4911
P Value	0.9333	0.0354	<.0001	<.0001	0.4052	0.8536	0.4465	0.3593	0.5784	0.0047	0.3994	0.0034
JOY	-0.0153	-0.2754	7.9596	0.9565	-0.046	-0.8381	0.7527	-8.6249	0.3859	-1.0965	0.8452	-0.1433
P Value	0.9489	0.7987	<.0001	<.0001	0.922	0.5826	0.4776	<.0001	0.2575	0.2017	0.0369	0.7373
Monday	0.001782	0.0781	0.0395	0.009414	-0.00717	0.000397	0.055	-0.0203	0.0201	0.002434	0.034	0.0312
P Value	0.7739	<.0001	<.0001	0.0165	0.5728	0.9928	<.0001	0.1151	0.1018	0.929	0.0301	0.0004
ARCH0	0.000137	0.000207	0.000513	0.0000332	0.000196	0.00041	0.000409	0.001219	0.000284	0.000666	0.000838	0.000257
P Value	0.0044	0.0187	0.0023	0.0178	0.0243	0.1528	0.0067	<.0001	0.0084	0.0037	0.0156	0.0022
ARCH1	1.0006	0.228	0.2676	0.2688	1.0071	0.9829	0.4416	0.4835	0.5451	0.9989	0.5042	0.3367
P Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
GARCH1	0	0.7761	0.7424	0.7562	0.000101	0.0148	0.5588	0.5127	0.4524	0	0.4936	0.659
P Value	.	<.0001	<.0001	<.0001	0.9988	0.8887	<.0001	<.0001	<.0001	.	<.0001	<.0001
Pr > ChiSq	<.0001	0.0004	<.0001	<.0001	0.0066	0.8761	<.0001	<.0001	<.0001	0.0079	0.0005	<.0001

	Recession											
Intercept	7.8245	5.855	3.1735	5.5644	5.3389	1.1765	5.3002	1.7005	9.8446	6.0608	7.2726	2.4198
P Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
BUZZ	-0.000012	3.41E-06	0.000161	0.000109	0.000025	0.0000149	7.25E-06	-0.000036	4.64E-07	0.0000661	0.0000565	0.000142
P Value	<.0001	0.0085	<.0001	<.0001	0.2541	0.8798	<.0001	<.0001	0.967	0.0784	<.0001	<.0001
SNTMENT	0.0435	0.0604	0.158	0.0399	0.0774	0.2934	0.1704	0.0152	0.057	0.0355	0.0798	0.1792
P Value	0.0319	<.0001	<.0001	0.0298	0.0006	<.0001	<.0001	0.7529	0.0125	0.1185	<.0001	<.0001
OPTIMSM	0.0138	-0.0423	-0.0693	0.1042	-0.3113	0.3473	-0.1376	0.2332	-0.0532	-0.2257	0.3018	-0.1085
P Value	0.7809	0.5664	0.6119	0.1451	0.0299	0.2267	0.1671	0.1989	0.4319	0.1251	<.0001	0.4554
FEAR	-0.7852	-0.6479	1.0489	-0.3725	-0.1536	-0.8146	0.9495	-0.3276	0.0724	-0.2629	-0.4577	0.6998
P Value	0.0006	0.0001	<.0001	0.0344	0.7308	0.4588	<.0001	0.6118	0.8225	0.4516	0.0026	0.3072
JOY	0.0184	-0.3384	3.4092	0.3755	-0.8371	-3.468	-0.3193	-3.2383	-0.3057	-0.2661	0.403	0.0744
P Value	0.9488	0.4884	<.0001	0.1691	0.166	0.0029	0.5655	<.0001	0.2515	0.5885	0.0428	0.8835
Monday	-0.005438	0.00181	0.0387	0.0188	0.003711	0.0129	0.0131	-0.0297	0.005732	0.0214	0.001963	0.04
P Value	0.4041	0.6772	<.0001	<.0001	0.8183	0.7976	0.0681	0.0043	0.4923	0.0521	0.762	<.0001
ARCH0	0.0003	0.000236	0.000161	0.0000196	0.000206	0.000301	0.000652	0.003204	0.000295	0.000221	0.000151	0.000579
P Value	<.0001	<.0001	0.0154	0.0172	0.0139	0.1821	<.0001	<.0001	0.0096	0.1832	0.0574	<.0001
ARCH1	0.999	0.8234	0.3545	0.2253	0.9938	1	0.9845	0.8472	0.9408	0.9668	0.5835	0.4732
P Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
GARCH1	0	0.1713	0.6721	0.7981	0.005149	0	0.008254	0.1299	0.0596	0.0327	0.4135	0.5304
P Value	.	0.0175	<.0001	<.0001	0.9247	.	0.8218	<.0001	0.4191	0.8247	0.0014	<.0001
Pr > ChiSq	<.0001	<.0001	0.0038	<.0001	0.0001	0.7879	<.0001	0.1002	<.0001	<.0001	<.0001	<.0001

VI. Discussion and implications

Customers, analysts, journalists, and economists often share their knowledge, experience and opinions about common goods and services and those products' pricing on media including news media and social media. As Barrett, Lindquist, and Gendron (2007) proposed that language functions provide a context to study the individual's emotion perception, the content appearing in the media sources contains certain linguistic tone indicating the authors' emotion. With a collective market level of the overall media sources, the aggregated emotion index of all groups of individuals can represent the market-level emotion on a certain topic. Because the collective media sources approach are more likely to reflect the information of the aggregated individual consumer emotion, in that aggregated level, the consensus of the information from all single sources further contribute by canceling out noisy opinion, and rumors from some unreliable sources.

Comparing to previous marketing research of emotion on an individual customer level, we utilized an established market level emotion manifested in a collective sources of news wires, internet news sources, and social media to examine the market emotion predictive power in commodity prices. Through a time series studies of 12 energy and material commodity price (Aluminum, Copper, Crude Oil, Gold, Heating Oil, Jet Fuel, Gasoline, Natural Gas, Nickel, Palladium, Platinum, Silver) on five market level emotion (buzz, sentiment, optimism, fear and joy), we found evidence that market emotion indices are relative reliable and persistent indicators to explain commodity price dynamic changes. The effects of buzz, sentiment, optimism and fear on commodity price are generally consistent with the evaluation of emotion effect in appraisal-tendency hypothesis (Lerner and Keltner, 2000; Han, Lerner and Keltner, 2007), whereas the effect joy on commodity price is rather confounding. Additionally, we provide evidence that our market emotion model provide a relative accurate forecast of future commodity price up to five days, and the model fits better to forecast commodity prices with less volatile changes over time. From another major mainstream perspective, valence-arousal framework (Feldman, 1995), to looked at our emotion indices, we can group our emotion indicators into high arousal indicators (buzz, sentiment, optimism, fear) and low arousal measure (joy) based on intensity of the emotion. The high arousal emotion tend to reach a market consensus in their effects on commodity pricing, whereas the low arousal emotion, such as joy, is more difficult to cause an information consensus in the market to influence commodity prices that could be a possible explanation for the confounding effect of joy on commodity price. The summary of the empirical results also indicate that high arousal emotion, such as buzz, sentiment, optimism, fear tend have a stronger predictive power in future commodity prices that last longer as well, whereas the low arousal emotion, such as joy, has a weaker prediction effect on future commodity prices that also last shorter. This paper provided evidence of the existence of relationship

between market level emotion fluctuation and commodity price change and demonstrated the value of media-based information including news media and social media in affecting business performance.

The findings of this research provide significant managerial implications, specifically highlighting the value of media-based emotion in reflecting and forecasting commodity price. Researchers and managers should pay more attention to the valuable information contained in media-based information. Since the market level emotion has proven to be effective in predicting short term commodity price changes, business managers from high energy and material commodity consuming sector should implement emotion content analysis tools or subscribe established market level emotion indices to track longitudinal reactions of public opinions and emotions toward a commodity price changes. Based on collective media-based emotion data, managers from those companies can construct strategies to store resources in low prices, or use financial futures to hedge the emotion based bias in commodity pricing. Furthermore, companies from high commodity consuming sector are recommended to deploy real time surveillance and big data analytics and streaming mining technology to analyze various media sources and examine how market level emotion fluctuation influences real time commodity price change. Companies should monitor and respond quickly to messages with high arousal emotion by taking corrective actions to mitigate the potential adverse effects on future performance.

VII. Conclusion

This paper contributes to the media-based customer emotion and big data analytics literature in several important ways. First, the authors conducted a market-level emotion research to investigate collective groups of individuals' emotion effects on commodity market demand and prices. The empirical evidence of the market emotion effects are generally consistent with two mainstream emotion theories - valence-arousal framework and appraisal-tendency hypothesis, and further enrich the customer emotion studies from individual level to market level. Secondly, we brought market-level emotion indices of commodities from Thomson Reuters MarketPsych Indices (TRMI) into media-based research. TRMI is built on the comprehensive textual analysis of sources from news wires, internet news sources, and social media and can be a valuable resource for big data analytics in business research. In particular, TRMI emotion indices are constructed on a collection of media sources covered over two million news articles and social media posts every day (Peterson, 2013) where most of the prior textual analysis studies of media contents exclusively rely on a single source. Thirdly, we ran time series analysis to test significance of emotion on twelve energy and material commodities' prices and examined the short term predictive power of media-based emotion indices on the following five days' commodity prices, consistent with the short term predictive model of media-based sentiment on the next five days' stock return (Tetlock, 2007;

Garcia, 2013). Comparing previous time series studies of media-based sentiment, we expanded the single dimension of consumer or investor sentiment index to multiple dimensions of emotion indices. Last, but not least, by employing a real-world data set, this study empirically identified patterns of relationships between market emotion fluctuation and commodity price change.

The media-based market level emotion research shed light on several future avenues of different business subjects. In the marketing area, one may be interested in investigating whether marketing agencies can exploit favorable consumer emotion on media to build up the demand of their products; another intriguing question could be whether customer services can utilize media-based emotion to facilitate their dynamic responses to avoid conflicts with customers and gain beneficial feedback from them. In finance investors may like to know whether it is going to be profitable to hedge the emotion based behavioral-bias related risks in financial markets. In the information technology area, one practical question is whether engineers can develop an app to improve the cyber security for an organization by monitoring the real time streaming emotion appearing on the internet.

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