Emotional Fluctuations and Consumer Desire: An Exploration from Psychology to Economics

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Abstract

As the information age continues to advance, the influence of emotions on consumer decision-making is increasingly strengthening. In recent years, emotion regulation has gradually become a crucial factor in shaping consumer behavior, particularly among younger cohorts. This paper examines the relationship between emotional fluctuations and consumer desire from psychological and economic perspectives. Grounded in emotion regulation theory, the study investigates the impact of emotions on total retail sales of consumer goods by expanding the emotion lexicon and analyzing large-scale Weibo data. First, this research integrates existing emotion lexicons with Tencent AILab Chinese word vector data, employs large models to screen candidate words, and constructs an emotion lexicon that better reflects contemporary online language. Subsequently, panel data analysis is performed on Weibo emotion data from 2010 to 2020 using this lexicon, revealing that positive emotions (such as pleasure and well-being) significantly promote consumption growth, while anger and sadness drive consumption levels through impulsive or compensatory consumption. In contrast, fear emotions exert a certain inhibitory effect on consumption behavior. The findings not only enrich theoretical research on the relationship between emotions and consumer behavior but also provide important references for marketing and policy-making.

Full Text

Emotional Fluctuations and Consumer Desire: An Exploration from Psychology to Economics

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Abstract

With the continuous advancement of the information age, the influence of emotions on consumer decision-making has grown increasingly significant. In recent years, emotional regulation has gradually emerged as a crucial factor shaping consumer behavior, particularly pronounced among younger demographics. This paper examines the relationship between emotional fluctuations and consumer desire from both psychological and economic perspectives. Grounded in emotional regulation theory, the study investigates the impact of emotions on total retail sales of consumer goods by expanding an emotion lexicon and analyzing large-scale Weibo data. First, by integrating existing emotion lexicons with Tencent AI Lab's Chinese word vector data and leveraging large models to screen candidate words, we construct an emotion dictionary better aligned with contemporary online language. Subsequently, panel data analysis of Weibo emotional data from 2010 to 2020 reveals that positive emotions (such as joy and well-being) significantly promote consumption growth, while anger and sadness drive consumption levels through impulsive or compensatory mechanisms. By contrast, emotions of surprise and fear exert a suppressive effect on consumer behavior. The findings not only enrich theoretical research on the emotion-consumption relationship but also provide important references for marketing strategies and policy formulation.

Keywords: Emotion, Consumption, Large Models, Panel Data Analysis

Introduction

As socioeconomic development accelerates, people's consumption levels have risen year by year. Concurrently, with the continuous advancement of network technology in the information age, consumption patterns have become increasingly diversified, drawing growing attention from researchers regarding consumption motivations. In May 2024, the China Consumers Association's Annual Report on the State of Consumer Rights Protection in China noted that beyond pursuing cost-effectiveness, emotional release would become a crucial factor influencing the decision-making of young consumers and would represent a new consumption hotspot in the coming period.

Emotion constitutes an immediate, perceptual psychological response generated during individuals' perception of external events. As the primary platform for modern information acquisition and emotional expression, social media has become particularly prominent for emotional dissemination within social networks. Mainstream social media platforms in China include WeChat, QQ, and Weibo, which people utilize for interpersonal relationship building and strengthening social connections. Netizens can share and disseminate their lives, thoughts, and experiences through text, emoticons, images, or videos to express their emotions (Zang et al., 2021).

Consumer behavior, through extensive exploration, has been defined as the specific actions people exhibit to satisfy their needs during product or service acquisition processes. Engel et al. (1985) conceptualized consumer behavior as the interaction between emotional and cognitive processes, encompassing specific actions such as comparison, selection, purchase, use, evaluation, and disposal. Emotion plays a vital role in consumer decision-making processes. Kahneman (2011) noted that individuals are often subconsciously driven by emotions when making decisions. Positive emotions can enhance consumers' information processing capabilities, thereby increasing their acceptance of new products. Conversely, negative emotions may lead consumers to rely on simple decision rules while ignoring potential information (Lerner et al., 2015). For instance, Rucker and Galinsky (2008) found that consumers experiencing positive emotions are more prone to impulsive consumption, whereas negative emotions may inhibit consumer behavior (Mandel et al., 2017). Dunn and Norton (2013) demonstrated that positive emotions elicited by holidays and promotional events can significantly enhance consumers' purchase intentions. Meanwhile, negative emotions may trigger consumer reactance, manifesting as hesitation and negative responses toward purchases (Mandel et al., 2017).

The emotion-as-information model posits that people's current emotional states directly influence their behaviors or responses with minimal attention to the source of emotions (Schwarz et al., 1981). Consequently, even when emotions originate from factors unrelated to the current task, individuals still interpret them as task-relevant. This makes emotions important information and cues that can significantly impact decision-making and behavior. Existing research demonstrates that emotions can substantially influence consumer responses through emotion regulation mechanisms. Emotion regulation theory assumes that consumers regulate their current emotional states through their behaviors or responses (Andrade, 2005). Specifically, the theory postulates that consumers integrate their current emotional state, anticipated emotional state, and desired emotional state to guide their behaviors and reactions. Negative emotional states drive consumers to regulate and repair their emotional states to achieve positive ones, whereas consumers in positive emotional states tend to protect these states and actively avoid negative emotions. Therefore, individuals in negative emotional states are more likely to take mood-boosting actions compared to those in positive states (Salerno, 2014). In Chuang et al.'s (2008) study, consumers in different emotional states were compared by priming emotions through films, dividing participants into positive emotion, negative emotion, and control groups. Participants were then asked to imagine purchasing five hedonic products at a supermarket and finally select the types of products to purchase. The study found that consumers primed with negative emotions exhibited greater diversity in their product choices.

In emotion analysis of text, researchers currently employ two primary methods:

supervised learning and emotion lexicon analysis. However, since supervised learning requires extensive data annotation to constitute training data, it consumes substantial researcher resources. Consequently, some researchers utilize word-count-based text analysis tools, though such tools are constrained by the lexicon's vocabulary. With the rapid development of social media and online language, popular internet slang and emerging emotional expression methods among younger populations render traditional emotion lexicons inadequate for accurate identification. Therefore, this study considers expanding existing emotion lexicons to align with the dynamic evolution of contemporary online language and enhance the applicability of emotion analysis tools for Weibo text.

Thus, based on emotion regulation theory, Study 1 focuses on expanding the emotion lexicon using word vector large models and large language models, while Study 2 conducts panel data analysis using obtained Weibo data and macroeconomic indicators to deeply explore the relationship between emotions and consumption. Through quantitative analysis of the emotion-consumption relationship, this research aims to provide scientific evidence for merchants' marketing strategies and product design while offering references for policymakers to understand consumption trends, thereby helping fill theoretical research gaps and providing new perspectives for practical applications.

2. Study 1: Emotion Lexicon Expansion

With the rapid development of internet technology and the proliferation of social media, a large number of new internet slang terms and innovative vocabulary continue to emerge. These linguistic changes challenge the applicability of existing emotion lexicons in emotion recognition, particularly since many lexicons were constructed relatively long ago and may struggle to accurately capture users' emotional expressions on social media. To address this issue, Study 1 expands existing emotion lexicons to capture the dynamic evolution of contemporary online language and enhance the applicability of emotion analysis tools for Weibo text.

2.1 Theoretical Basis of the Dictionary

This study's lexicon foundation comprises the Emotion Lexicon Ontology and the Weibo Basic Emotion Lexicon (Xu et al., 2008; Dong et al., 2015). The Emotion Lexicon Ontology is an emotion dictionary created by Lin Hongfei's team at Dalian University of Technology's School of Computer Science and Technology. Building upon six major emotion categories from international research, the ontology added "good" to "joy" to provide more nuanced characterization, as the original six categories only included "joy" for positive emotions, which was insufficiently detailed. The team extracted emotional information from corpora through manual emotional classification and automatic intensity acquisition methods. The Weibo Basic Emotion Lexicon was created by Chen Hao's team in the Psychology Department at Nankai University. Compared to other emotion lexicons, it additionally incorporates internet slang with emotional connotations from Weibo, categorizing emotions into happiness, anger, sadness, fear, and disgust.

2.2.1 Merging Existing Dictionaries

This study proposes to use the seven emotion categories from the Emotion Lexicon Ontology as the lexicon foundation, supplementing them with the five emotion categories from the Weibo Basic Emotion Lexicon to form a base dictionary. This base dictionary categorizes emotions into joy, good, sadness, anger, surprise, fear, and disgust, comprising a total of 27,804 words. The word counts for each emotion category are shown in Table 1 .

2.2.2 Dictionary Expansion

This study utilized Tencent AI Lab's large model to expand the emotion lexicon. Tencent AI Lab's publicly available Chinese word vector data, released on December 24, 2021, contains over 8 million Chinese vocabulary entries, with each word corresponding to a 200-dimensional vector. Compared to existing Chinese word vector data, Tencent AI Lab's Chinese word vectors specifically improved coverage, freshness, and accuracy, substantially enhancing quality and usability over various existing Chinese word vectors (Song et al., 2018).

For all words under each emotion category, we input them into the Tencent word vector model and used its constructed Annoy index to identify five nearest neighbor words as candidate replacements. Figure 1 [Figure 1: see original paper] illustrates the schematic diagram of word vector expansion. Subsequently, we conducted statistical analysis on all expanded candidate words under each word category. If an expanded word appeared with a frequency of two or more, we considered it highly likely to be an innovative or omitted word within that category and classified it as a candidate inclusion word list.

In previous lexicon construction or updating, researchers often employed manual evaluation methods to assess candidate inclusion words, which consumed considerable human and time resources. With the rapid development of deep learning and artificial intelligence, a new problem-solving paradigm—large models—has gradually demonstrated extraordinary capabilities. Large models refer to "large-parameter" models trained using massive datasets and powerful computing capabilities. These models typically exhibit high generality and generalization ability, applicable to natural language processing, image recognition, speech recognition, and other domains. Through their vast parameter scale, deep network architecture, and extensive pre-training capabilities, large models can capture complex data patterns and demonstrate exceptional performance across multiple fields. They can not only understand and generate natural language but also process complex visual and multimodal information, adapting to various changing application scenarios. Large models possess powerful learning and generalization abilities, showing commendable performance in areas such as text revision, information recognition, and sentiment analysis.

In this study, we aimed to employ large models to replace manual evaluation, reducing time and labor costs. We selected four open-source large models as evaluators to replace manual coding: qwen2.5:7b, qwen2.5:72b, gemma2:9b, and gemma2:27b. We constructed prompts to enable large models to replace human judgment in determining whether specified words belong to particular emotion categories. For output rules, if a large model determined that a specified word belonged to the category, it output Y; otherwise, it output N. To ensure the reliability of large model outputs, we tallied five outputs from the large models for each word. If four out of five outputs indicated that the word belonged to the emotion category, the word was placed on the proposed inclusion word list. Figure 2 [Figure 2: see original paper] shows the schematic diagram of large model judgment.

To assess and quantify the reliability of large models, we calculated Fleiss' Kappa consistency for their five evaluations of all words. The results indicated that the large models' multiple outputs demonstrated good internal reliability. Table 2 presents the internal rating consistency of large models: qwen2.5:7b, qwen2.5:72b, gemma2:9b, gemma2:27b.

For the obtained proposed inclusion word list, if a particular combination of word category and word appeared three or more times in this list—meaning three or more large models considered the word to belong to the emotion category—we regarded it as a validated expansion word and added it to the previously merged base dictionary. To examine whether large models replacing manual screening demonstrated good validity, we randomly selected 20 words from each of the seven expanded emotion categories for manual evaluation. Using manual evaluation results as the gold standard, we constructed a confusion matrix for validity verification.

A confusion matrix is a square matrix where rows represent actual categories and columns represent predicted categories, dividing the entire matrix into four quadrants: True Positives (TP)—the number where the model's judgment was 1 and the actual coding was also 1; False Positives (FP)—the number where the model's judgment was 1 but the actual coding was 0; True Negatives (TN)—the number where the model's judgment was 0 and the actual coding was also 0; and False Negatives (FN)—the number where the model's judgment was 0 but the actual coding was 1. Figure 3 [Figure 3: see original paper] illustrates the schematic diagram of the confusion matrix.

2.2.3 Results Analysis

Comparing large model evaluation results with manual evaluation yielded 72 true positives, 3 false negatives, 22 false positives, and 43 true negatives. The validity verification results indicate that large models performed excellently in emotion category judgment tasks. Specifically, the large models achieved a precision rate of 0.77 and a remarkably high recall rate of 0.96, demonstrating particularly outstanding capability in identifying positive cases with almost no omissions. This high recall rate indicates that the model can effectively capture the majority of emotional words. Additionally, the large models' accuracy rate of 0.82 further shows that the model can maintain high overall reliability while correctly judging emotion categories and reducing misjudgments. Moreover, the F1 score of 0.85 reflects that the large models maintained an ideal balance between precision and recall. The F1 score, as the harmonic mean of precision and recall, indicates that the model can optimize identification of both positive and negative cases while balancing the trade-off between them. These validation metrics collectively demonstrate the model's excellent performance in emotion category judgment tasks.

Ultimately, we expanded the base emotion lexicon with 1,209 emotional words. Table 3 shows the number of expanded words by emotion dimension.

3. Study 2

Study 2 delves into the intrinsic relationship between emotions and consumption from a macro-level societal perspective. Using the expanded emotion lexicon from Study 1, this research employs big data word frequency statistics to assess the overall emotional tendency trends exhibited by the public from 2010 to 2020. Furthermore, it constructs an analytical model combining public emotions with total retail sales of consumer goods to explore potential quantitative relationships between the two.

3.1 Data Sources

The research text is based on Weibo data from 2010-2020. Web scraping technology was used to calculate emotional tendencies across 31 provincial-level administrative units during this period. The group consumption indicator adopts the total retail sales of consumer goods macroeconomic indicator published by the state (hereinafter referred to as "retail sales"). Combining emotion attention data from Weibo with retail sales data constitutes balanced panel data for panel data analysis.

3.2 Descriptive Statistics

Using the expanded seven-category emotion lexicon from Study 1, we calculated word frequencies across emotion dimensions for 31 provincial-level administrative units from 2010-2020 based on Weibo data. Specific results are shown in Table 4 Word Frequency Statistics by Emotion Dimension.

Table 5 shows the correlation matrix for each emotion dimension:

```
0.338*** 好
-0.191*** -0.118** 0.096* 0.316***
哀 -0.424*** -0.550*** 0.389*** -0.247*** 0.183*** -0.093* -0.243***
惊 -0.214*** -0.380*** 0.155*** -0.371*** 0.697*** -0.294***
```

恶 -0.346*** -0.486*** 0.411*** -0.303*** 0.929*** -0.316*** 0.785***
注： * <0.05,** <0.01,*** <0.001

Table 6a presents collinearity analysis for 7 emotion dimensions, while Table 6b shows collinearity analysis for 6 emotion dimensions. The collinearity results indicate that the VIF value for the disgust (zee x7) dimension is 11.38, indicating excessively high collinearity. Table 6b, after excluding the disgust dimension, shows VIF values for other dimensions all below 3. Therefore, subsequent analysis excludes the disgust dimension data and focuses only on the six emotion dimension data.

3.3 Model Construction and Comparison

We constructed OLS, fixed effects, and random effects models using the above data. Specific results are shown in Table 7 :

1312.615*** 784.421*** 822.500***
(499.903) (446.271) (222.845)
419.290** (178.905) 464.022***
(446.991) -3567.639***
(684.120) (422.827) (177.026)
(278.790) (223.950) 387.101**
(180.207) 448.441**
(178.529) (280.611)
(149.194) (150.718) 1126.673*
-1984.980*** -1878.949***
(608.109) (293.604) (294.288)
9389.284*** 9389.284*** 9389.284***
(399.304) (134.014) (1248.646)
注： 路径系数均为非标准化系数。*p < .05, **p < .01, ***p < .001

Hausman test results (Table 8) indicate significant differences between fixed effects and random effects models, with the fixed effects model being optimal. The model's effect is significantly superior to both OLS and random effects models. The random effects model is significantly superior to the ordinary least squares regression model.

Table 8 shows Hausman test results:

Constant Observations
784.4*** (222.8) 419.3** (178.9) 464.0*** (177.0)
(278.8) (149.2) -1,985.0*** (293.6)
9,389.0*** (134.0)
Number of province R-squared
Hausman p-value <0.001
注： 路径系数均为非标准化系数。*p < .05, **p < .01, ***p < .001

3.4 Two-way Fixed Effects Model

After testing, the two-way fixed effects model controlling for both year and province showed the best fit, with $R^2 = 0.635$, adjusted $R^2 = 0.578$, $F(16, 294) = 32.01$ ($p < .001$), corr(u_i, Xb) = -0.168. The model explains 63.5% of the variance, and certain provincial-level characteristics exhibit some degree of covariation with emotions. Specific results are shown in Table 9 Two-way Fixed Effects Model P>|t| 95% Confidence Interval _{cons}.

3.5 Results Analysis

Through two-way fixed effects model analysis, we found that different emotions have varying effects on total retail sales of consumer goods. Specifically, the positive emotions of joy and good significantly promote retail sales growth, indicating that positive emotions drive consumption. The positive effect of anger suggests that angry emotions may lead to increased impulsive or cathartic consumption, prompting people to purchase more goods to release stress. The positive effect of sadness indicates that sad emotions may drive retail sales through compensatory consumption. The negative effect of surprise suggests that sudden emotions may lead to significant reductions in consumption levels. Fear did not significantly affect consumption.

In consumer behavior research, emotion is considered an important factor influencing people's consumption decisions. According to the research results, positive emotions such as joy and good can significantly promote consumption, while some negative emotions may either reduce consumption levels or drive consumption.

The positive emotions of joy and good have particularly significant effects in driving consumption. Optimistic, pleasant, and happy emotions can stimulate people's consumption desires and make consumers more inclined to make positive purchase decisions when shopping. Optimistic emotions may make individuals more willing to invest in consumption behaviors that satisfy their needs and desires. This emotion-driven consumption is not limited to purchasing goods but may also extend to service consumption and experiential consumption. Through these consumption activities, consumers can obtain immediate psychological satisfaction and emotional release, further strengthening the positive cycle between positive emotions and consumer behavior.

Meanwhile, good emotional states are typically associated with higher self-efficacy and well-being. Consumers in these emotional states exhibit higher consumption willingness and stronger purchase motivation. This emotional 激励 effect makes consumers more likely to make quick decisions when shopping, reducing hesitation and uncertainty in product selection. More importantly, joy and good emotions can also reduce consumers' risk perception, making them still inclined to make purchases even when facing high-priced or non-essential items. Therefore, if merchants can enhance consumers' emotional states through promotional activities, emotional advertising, and other means, they can effectively promote sales growth.

Similarly, angry emotions also have a significant positive impact on consumption. Anger typically leads to increased impulsive or cathartic consumption. When individuals feel angry, they often seek quick emotional release, and consumption becomes a way for them to process negative emotions. Anger not only stimulates individuals' aggressiveness and leads to decreased self-control but may also produce stress responses to conflict and pressure. Therefore, anger may prompt consumers to shop without careful consideration, especially when emotions are running high, making them prone to impulsive purchases.

The positive impact of anger on consumption can also be interpreted as cathartic consumption behavior, where consumers use shopping to shift attention or compensate for psychological dissatisfaction and anger through purchased items. For example, when people encounter setbacks or conflicts at work or in life, shopping becomes a way for them to release pressure and regain a sense of control. This behavior not only promotes merchant sales but also alleviates consumers' emotions, providing them with short-term satisfaction.

Additionally, sadness also positively affects consumption, but unlike anger's cathartic consumption, sadness tends to promote consumption through compensatory mechanisms. Sadness is a complex emotion typically associated with negative psychological states such as loss, loneliness, and powerlessness. When consumers feel sad, they seek ways to fill inner emptiness or restore emotional balance, and consumption provides a potential avenue. Compensatory consumption is behavior that compensates for emotional deficiencies or disappointments through purchasing goods, bringing psychological comfort to consumers.

This compensatory consumption phenomenon is particularly common in modern society, especially when facing emotional issues, social pressure, or major life changes. Consumers may obtain short-term comfort and psychological compensation by purchasing luxury goods, enjoying high-end services, or selecting emotionally resonant consumer products. During this process, merchants can effectively attract consumers and promote retail sales growth by launching emotionally valuable products targeted at emotionally low consumers.

Unlike the positive effects of anger and sadness, surprise shows a negative impact. As a sudden and transient emotion, surprise typically places consumers in a state of uncertainty and anxiety. Under this emotion, consumers tend to reduce their consumption willingness. Especially when encountering unexpected information or events, they may feel insecurity or instability about consumption. This unpredictability caused by surprise makes consumers' consumption decisions more cautious and hesitant, leading them to postpone consumption decisions and reduce unnecessary expenditures.

Fear is a strong negative emotion typically accompanied by perception of unknown risks or threats. However, this study's results indicate that fear did not significantly affect consumption. The reason may be that fear's influence on consumption is relatively indirect and moderated by other factors, making its overall impact on consumption trends relatively weak.

The role of emotion in consumption decisions is complex and diverse, with different emotions producing different effects on consumer purchasing behavior. Positive emotions such as joy and good can promote consumption growth, while anger and sadness drive total consumption through impulsive and compensatory consumption. In contrast, surprise and fear emotions suppress consumer behavior to some extent, with surprise's negative effect being particularly significant. Understanding these emotional effects on consumer behavior not only helps merchants develop more precise marketing strategies but also assists consumers in better managing their own consumption.

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Note: Figure translations are in progress. See original paper for figures.