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Editor-in-Chief Jinquan LIU

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The Frontiers in Economic and Management Research attempts to provide a platform for the Chinese scholars in mainland China to communicate with their peers overseas in economic and management research. The journal aims to publish articles that have conducted quality as well as innovative research, and that investigate major issues in economic and management research, and that address major economic and management issues in the Chinese market. The journal encourages cross-fertilization of ideas among the fields of thinking and application of advanced analytical techniques in the research. It is also the journal's intention to suggest directions for future research, through the articles, to the Chinese scholars and to provide insights and readings for classroom use. The journal will make efforts to contribute to the development of economic and management research in mainland China.

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Remarks from the Editor-in-Chief

The Frontiers in Economic and Management Research is published by the Business School of Jilin University in association with the Research Center for Quantitative Economics, Jilin University. The journal attempts to provide a platform for the Chinese scholars in Mainland China to communicate with their peers overseas in economic and management research. Quantitative analysis and methods are given priority by the editors. Independent and innovative thinking is highly encouraged. The journal will make efforts to contribute to the development of economic and management research in China.

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Authors from home and abroad are all welcome to submit your manuscripts to the journal.

Prof. Jinquan LIU
Editor-in-Chief

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Transmission Mechanism of Stock Market Volatility between China and the U.S.: Empirical Evidence during Subprime Crisis from EDCC-GARCH Model

Jinquan Liu Yueling Luo Guanglin Ji

(Center for Quantitative Economics, Jilin University)

Abstract: This paper studies the dynamic correlation between Chinese and the U.S. stock market prior and posterior to the 2007 *Subprime Crisis*. By incorporating time-difference in our empirical study, we analyze the possible existing transmission mechanism between these two markets by using EDCC-GARCH model and conclude that EDCC-GARCH model could well depict the relationship between Chinese and U.S. stock market. Furthermore, the performance of the U.S. market 1-day ago would lead Chinese market move to the same direction. The dynamic correlation coefficients from 2005 to 2010 suggest that the relationship between Chinese and the U.S. stock markets becomes more stable with the developing of Chinese financial market.

Key Words: financial markets; volatility; correlation analysis; EDCC-GARCH model

Introduction

Measuring the temporal and intertemporal relationships between different financial markets is a long-lasting research topic of risk management and portfolio construction. Since 2008, the *Subprime Crisis* has swept the whole world, and seriously affected the economic growth in China. As the negative impact of the crisis has gradually retreated from the financial markets around the world after 2010, lots of research have been conducted by both policy makers and researchers. However, there are lots of questions still need to be answered, such as, "How well can we depict the relationship between Chinese and the U.S. financial markets?" "How could the volatility of the U.S. financial market transmit to Chinese market?"

In order to analyze and measure the relationships between different financial markets, correlation analysis is one of the most important tools. Mostly, practitioners would use two methods-constant and dynamic conditional correlation coefficient. Most researchers view the latter as the better way for analyzing the real-time relationship between the two different series. However, in a large number of economic and financial literatures, ARCH model has become the standard research tool for volatility modeling, particularly on correlation of volatilities. In the past several years, both the univariate and the multivariate GARCH model (MGARCH model①) have been thoroughly studied for relevant researches in financial econometrics.

Since Bollerslev (1990) developed the constant conditional correlation GARCH model (henceforth, the CCC-GARCH model), multivariate analysis has become an essential framework for understanding the relationship between the (co) volatilities of several economies and markets. Besides, this model well contained the tools mentioned previously. Engle (2002) extended the CCC-GARCH model to the dynamic conditional correlation, after which proposed the DCC-GARCH model. Furthermore, He and Teräsvirta (2004) raised the extension of constant conditional correlation GARCH model (henceforth, the ECCC-GARCH), and argued that this model would better exhibit the correlation structures of different financial series.

Most studies analyze and measure the correlation between Chinese financial markets by using ARCH-type model, especially DCC-GARCH model proposed by Engle (2002). For Example, Fan and Zhang (2003) analyzed the volatility of Shanghai and Shenzhen stock markets by using genetic algorithm and MGARCH model. Li and Zhang (2007) studied the spurious persistence in the correlation of Shanghai and Shenzhen stock markets by using multivariable structural change TGARCH model. Qin and Zheng (2008) employed ADCC model to predict the correlation of Chinese main stock indices.

However, the DCC-GARCH model is built on the assumption that non-diagonal matrix elements are zero, which excludes the "spillover effects" from the model. Until now, a large number of literature have found that the lag of conditional variance tend to affect the volatility of another variable in financial market. Thus, some biases would arise if we apply this model to the analysis in which spillover effect exists.

On the contrary, the EDCC-GARCH model considered in this paper circumvents the problems mentioned above. The reason why we extend the DCC-GARCH model is that this generalization allows us including the volatility spillover effect between Chinese and the U.S. stock markets. Based on this specification, EDCC-GARCH model can solve the problem on correlation and depict the volatility spillover effect between different financial markets by assuming nonzero of all the elements in the coefficient matrix. Statistically speaking, the diagonal elements in the parameter matrix of

① Bauwens et al. (2006), gave a detailed description of MGARCH model.

MGARCH model reflect the (auto) correlation of every specific variance-covariance series, and non-diagonal elements reflect the correlations between different series. So this specification for the correlation coefficients not only conduct a more comprehensive exploration about the economic implications, but also can better reflect the true mutual influences between two financial time series than DCC-GARCH model.

In addition, geographical factors may have potential influence on the correlation of these two stock markets. For example, in actual investment, Chinese investors may pay attention to the performances of foreign stock market, especially the New York Securities Exchange (NYSE), which opens 13 hours later than both the Shanghai and Shenzhen Securities Exchanges (The difference is computed by Eastern Time in the U.S. minus Beijing Time). Therefore, the market trend and volatility of the U.S. stock market one day ago tends to affect Chinese stock market fluctuations the next day. Thus, the factor of time differences should be and have to be considered in the analysis.

This paper attempts to make use of EDCC-GARCH model with incorporating the factor of time difference to analyze the correlation of the U. S. and Chinese stock markets prior and posterior to the 2007 *Subprime Crisis*. Another task in this paper is to present empirical evidence to verify that whether there is a transmission mechanism (or the contagion mechanism at the background of financial crisis) between Chinese and the U.S. stock markets.

The rest of the paper is organized as follows. Section Ⅱ reviews relevant econometrics theory in testing the correlation of Chinese and the U.S. stock markets; section Ⅲ presents and discusses the results. Section Ⅳ concludes.

1. Overview of Econometric Methodology

In this section, we use EDCC-GARCH model to analyze and measure the financial market volatility correlation. Theoretically, EDCC-GARCH model can be divided into two parts: the time-varying correlation coefficient and vector GARCH, which is the relationship of vector residuals.

According to the definition given by He and Teräsvirta (2004), we assume that y_t is a $N \times 1$ random vector, which follows the following random process:

$$\boldsymbol{Y}_t = \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t \tag{1}$$

$$\boldsymbol{\varepsilon}_t = \boldsymbol{D}_t \boldsymbol{z}_t, \boldsymbol{h}_t = [h_{1,t}, \cdots, h_{N,t}]' = \boldsymbol{W} + \sum_{i=1}^{q} \boldsymbol{A}_i \boldsymbol{\varepsilon}_{t-i}^{(2)} + \sum_{j=1}^{p} \boldsymbol{B}_j \boldsymbol{h}_{t-j} \tag{2}$$

where $\boldsymbol{\mu}$ is an $N \times 1$ conditional mean vector, $\boldsymbol{D}_t = \mathrm{diag}(\sqrt{h_{1,t}}, \rightleftharpoons, \sqrt{h_{N,t}})$ is a diagonal matrix. The elements $h_{it}(i = 1, \cdots, N)$ are the diagonals of the conditional standard deviation matrix of ε_{it}, z_t is a sequence of IID random variables with zero-means. $\blacklozenge_t^{(2)}=(\varepsilon_{1,t}^2,\cdots,\varepsilon_{N,t}^2)'$, $W=(w_1,\cdots,w_N)'$. A_i and B_j *is* $(N\times N)$ matrix. All the elements in the parameter matrices are non-negative.

According to the study of Engle (2002) on the topic of correlation coefficient for multivariate time series model, the dynamic correlation coefficient model (DCC) is defined as:

$$E[\boldsymbol{\varepsilon}_t \mid \boldsymbol{I}_{t-1}]=0, E[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t' \mid \boldsymbol{I}_{t-1}]=\boldsymbol{H}_t=\begin{cases} h_{i,t}, & i=j \\ h_{i,t}^{1/2}h_{j,t}^{1/2}r_{ij,t}, & i\neq j\end{cases} \tag{3}$$

$$q_{i,j,t}=\bar{\rho}_{i,j}+\alpha(\varepsilon_{i,t-1}\varepsilon_{j,t-1}-\bar{\rho}_{i,j})+\beta(q_{i,j,t-1}-\bar{\rho}_{i,j}) \tag{4}$$

$\boldsymbol{I}_t$ is information set. And matrix $\boldsymbol{H}_t$ can be defined as:

$$\boldsymbol{H}_t=\boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t \tag{5}$$

Besides that, elements in matrix $\boldsymbol{R}_t$:

$$\rho_{i,j,t}=\frac{q_{i,j,t}}{\sqrt{q_{ii,t}q_{jj,t}}}=[R_t]_{i,j}, \bar{\rho}_{i,j}=E(\boldsymbol{\varepsilon}_i\boldsymbol{\varepsilon}_j), \bar{\rho}_{i,i}=1 \tag{6}$$

where $\boldsymbol{Q}_t=(q_{i,j,t})$ is a $N\times N$ symmetric positive definite matrix. The DCC model can be written in the matrix form:

$$\begin{cases} \boldsymbol{Q}_t=\overline{\boldsymbol{Q}}(1-\alpha-\beta)+\alpha\,\boldsymbol{u}_{t-1}^{(2)}+\beta\boldsymbol{Q}_{t-1} \\ \boldsymbol{R}_t=(\boldsymbol{Q}_t^*)^{-1}-\boldsymbol{Q}_t(\boldsymbol{Q}_t^*)^{-1}\end{cases} \tag{7}$$

where $u_{it}=\varepsilon_{it}/\sqrt{h_{i,t}}$, $\overline{\boldsymbol{Q}}$ is the unconditional covariance matrix for standardized residual u_{it}. $\boldsymbol{Q}^*$ is formed by diagonal elements of matrix $\boldsymbol{Q}_t$.

By equation (1)～(7), we define the N-dimensional EDCC-GARCH (p,q) model. Note that EDCC-GARCH (p,q) is a highly nested specification, if both $\boldsymbol{A}$ and $\boldsymbol{B}$ are diagonal for any i and j, the ECCC-GARCH (p,q) model degrades into the CCC-GARCH (p,q) model of Bollerslev (1990). Furthermore, if we set $B_j=0$, $j=1,\cdots,p$, this model can also be reduced into the CCC-ARCH (q) model raised by Cecchetti, Cumby, and Figlewski (1988).

2. Empirical Analysis

2.1 Preliminary Analysis of the Data

In this paper, we use daily closing prices of Hushen 300 and Standard & Pool 500 as protocol of Chinese and the U.S. stock markets, respectively. The sample is obtained from Yahoo! Finance (http://finance.yahoo.com), which starts from April 8th, 2005 to April 16th, 2010 and covers the period before and after the *Subprime Crisis*, 2007. We obtain 1164 observations by eliminating common closing days as well as deducting different holidays in China and the U.S. In our study, we investigate the log return of different markets, which can be calculated as follows:

$$r_t = 100[\ln(P_t) - \ln(P_{t-1})]$$

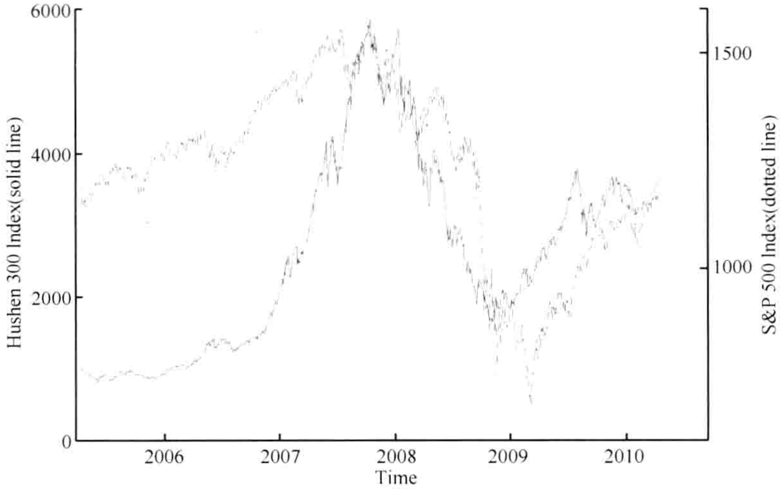

Figure 1 The Time Path of Hushen 300 (solid line) and S&P 500 (dotted line)

Figure 1 depicts the time path from April 8th, 2006 for Hushen 300 and S&P 500, respectively. From the closing prices of these two indices, we can see that both of these stock markets stayed relatively stable before 2007. But after the successful *reform of non-tradable shares* in China, a new round of "bull market" occurred, and it reached its peak at 6127, at November 2007. However, due to the regulation policy initialed at the end of 2007, Chinese stock market is on the way down since the first quarter of 2008 and lasted for nearly 4 quarters. During this period, the U. S. stock market suffered a tremendous fall in the stock market with the bankrupt of the investment bank Bear Stearns in April 2008, which followed the Lehman Brothers. The turmoil of the 2007 *Subprime Crisis* not only terminated the good performance of the U.S. stock market, but also spread across the whole world and finally formed a worldwide financial crisis. Undoubtedly, Chinese market also affected by this crisis and the situation of the stock market had become even tougher. At this critical time, the U.S. government passed the ARRA to bailout financial sectors. Meanwhile, Chinese government also realized the transmission channel from virtual economy to real economy and stimulated Chinese financial market. Under this circumstance, not only U.S. stock market, but also Chinese stock market began to stabilize. Since Chinese economy was not seriously affected by the financial crisis, our stock market recovered faster than the U. S. 's. Overall, the performances for these two markets are quite similar, which means a transmission mechanism or some kind of relationship exists between these two stock markets.

Table 1 Statistical Characteristics of Return Series

Index	Mean	Median	Max	Min	Std.Dev	Skewness	Kurtosis
Hushen 300	0.104	0.276	8.931	−13.012	2.249	−0.623	6.370
S&P 500	0.002	0.090	10.957	−13.800	1.591	−0.601	15.496

We report the log returns of these two markets in Table 1. From table 1, we can see that both the log return of Hushen 300 and S&P 500 are negative skewed, with the corresponding skewnesses equal −0.623 and −0.601, respectively. Furthermore, the standard deviations for both two return series are relatively small, which are 2.249 and 1.591. On the contrary, the values for kurtosis statistics are relatively large (6.370 and 15.496, respectively), which means that the log return series are leptokurtic distributed.

Based on the basic knowledge of these two time series mentioned above, we could deal with the main theme of this paper—analyzing the transmission mechanism between these two markets. In order to realize this goal, we will employ EDCC-GARCH model to explore the dynamic correlation between these two stock markets before and after the Subprime Crisis-whether Hushen 300 is negative related to S&P 500 or not.

2.2 The Transmission Mechanism between Chinese and the U.S. stock markets

As mentioned previously, MGARCH model has been widely used in analyzing the correlation of volatile series. For we want to implore the dynamic correlation of volatilities in the stock markets of China and the U.S., we used bivariate EDCC-GARCH (1,1) to model the log return series. The fitted estimation of the EDCC-GARCH(1,1) are showed in Table 2.

Table 2 Estimation Results of Bivariate EDCC-GARCH(1,1)

Index	W	A_1		B_1		α	β
Hushen300	0.050	0.076	0.005	0.916	0.001	0.026	0.872
	(0.020)	(0.030)	(0.032)	(0.003)	(0.006)	(0.016)	(0.115)
S&P 500	0.007	0.000	0.090	0.004	0.894		
	(0.020)	(0.023)	(0.011)	(0.022)	(0.020)		

* Values in the parentheses are p-values for the estimates.

Among all the 4 coefficients (A_{12}, B_{12}, A_{21}, B_{22}) indicating the factor of time difference, only A_{21} is zero but still statistical significant, which means that the factor of time difference does have influence on Chinese stock market and the U.S. stock market. The results can also be written with the following equations:

$$\begin{cases} h_{1,t}^2 = 0.050 + 0.076\varepsilon_{1,t-1}^2 + 0.005\varepsilon_{2,t-1}^2 + 0.916h_{1,t-1}^2 + 0.001h_{2,t-1}^2 \\ \qquad\quad (0.002) \quad (0.030) \quad (0.032) \quad (0.003) \quad (0.006) \\ h_{2,t}^2 = 0.007 + 0.000\varepsilon_{1,t-1}^2 + 0.090\varepsilon_{2,t-1}^2 + 0.004h_{1,t-1}^2 + 0.894h_{2,t-1}^2 \\ \qquad\quad (0.020) \quad (0.023) \quad (0.011) \quad (0.022) \quad (0.020) \end{cases} \tag{8}$$

Equations 8 depicts the statement for Chinese and the U.S. stock market, where ε_1 and h_1 denote the rate of return and the volatility for HS300, and *vice versa*. The first question measures the influences, induced by the performance of domestic stock market and the foreign stock market one day before, on Chinese stock market. In Table 2, the estimates of coefficients of $\varepsilon_{2,t-1}^2$ and $h_{2,t-1}^2$ are 0.005 and 0.001, which indicates that the performance of S&P 500 a day before may have positive influence on the volatility of Hushen 300.

But for the U.S. stock market, the situation is different. In the second equation, estimation results indicate that the return of HS300 and its volatility nearly have no impact on the volatility of the return of SP500 index. But the rate and fluctuation for the return of SP500 itself are the most important factor for the volatility of the U.S. stock market in the day.

The reason for this phenomenon can probably be summarized as follows: firstly, owning to the scale of the U.S. scale market, short-term changes happened in regional markets cannot lead to significant response in the U.S. market. Secondly, owning to the time difference considered in this article, if Chinese stock market does have influence on American stock market, the impact would come from the same day, not the day before. Given these factors, we conclude that the factor of time difference does influence the transmission mechanism exists between Chinese and the U.S. stock markets, and the effect does influence the dynamic correlations between these two markets.

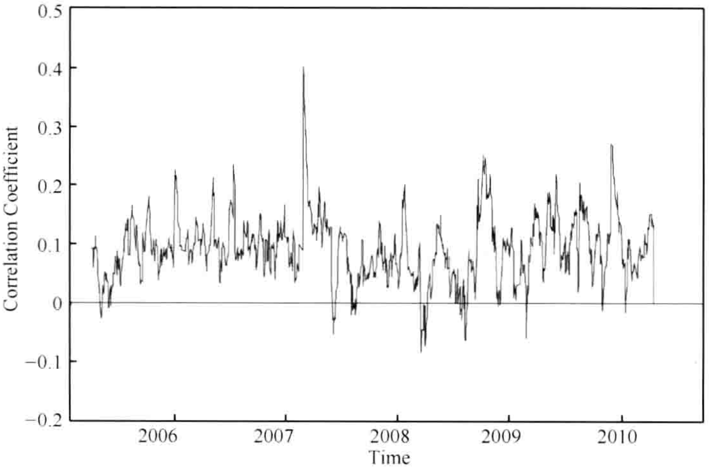

Figure 2 Time-Varying Correlation Coefficient Between Chinese and the U.S. Stock Markets

Figure 2 plots the time-varying correlation coefficient between China and U. S. stock markets in the sample period. The mean value for the correlation coefficient is approximate 0.1, and the values do not fluctuate dramatically around this value. This shows that the relationship between the U.S. stock market and Chinese stock market is relatively stable these years. This consequence can be attributed to the fact that Chinese financial market has started to become more open and more mature, and this trend still goes on. The integration of different regional markets unites financial sectors at every corner of the world, and the linkage between different markets has become even stronger than ever before, without doubt including the U.S. and Chinese markets.

3.Conclusions

Through studying the transmission mechanism between Chinese and the U.S. stock markets, we find that, owing to different opening times of stock markets derived by the geographical factor, the performance of the U.S. stock market one day before tends to have influence on Chinese market. However, traditional tools such as DCC-GARCH model, does not take this time differences induced problems into consideration. In order to solve this problem, we employ the EDCC-GARCH model to implore this problem and obtain the following results:

First, compared to DCC or CCC specification in MGARCH model, EDCC-GARCH model can better reflect the true internal relationships between different series by incorporating non-diagonal elements into the specification scheme. Second, by applying EDCC-GARCH into the analysis of the transmission mechanism between the stock markets of the U.S. and China, this article indicates that the volatility of stock return in the U. S. stock market one day before has a high correlation with that in Chinese market, and this can be validated by empirical results in our paper.

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Dimensions of Consumer-Brand Bonds

Jing Huang　Yang Tang　Qinglan Lin
(Economics and Management School, Wuhan University)

Abstract: This empirical study investigates two different types of emotional bonds consumers hold with brands: individual and social. Individual bonds result from interactions with the brand and comprise two sub-dimensions, love and subjective experience. Social bonds result from consumers' cultural identification with the brand and involve moral and obligatory concepts, pertaining to the sub-dimensions of familial unity and sense of glory and humiliation.

Key Words: Consumer-Brand　Individual bond　Social bond

Introduction

Emotionally powerful brands can exert a strong mental influence over consumers (Holt, 2004). That is, when consumers develop emotional bonds with a brand, that brand has achieved a strong brand relationship (Fournier, 1998). The processes by which consumers form emotional bonds with specific brands, and ways to measure such emotional bonds, remain uncertain though. Research has explored individual emotional bonds developed during consumer-brand interactions (Thomson et al., 2005; Carroll and Ahuvia 2006), and several useful constructs and measures emerge from recent branding literature, such as brand attachment (Thomson et al., 2005) and brand love (Carroll and Ahuvia 2006). However, the research on providing a full conceptualization and measuring the consumer-brand emotional bond(CEBD) is still remain limited.

Specifically, consumers' brand emotions may be more complicated than a simple individual bond. They may also experience social emotional bonds for specific brands. For example, expatriate Chinese people living in Southeast Asia "seek infatuatedly for the accustomed home goods... which become a tight tie to [their] Chinese home lifestyle" (Yu, 2003). Brands from their home country can trigger the consumer's social identity (Forehand and Deshpande, 2001; Forehand et al., 2002; Stayman and Deshpande, 1989) and provoke a sense of comfort or the familiar . Furthermore, by maintaining an emotional bond with a brand, a consumer can build a group identity through his or her consumption behavior (e.g., family identity; Epp and Price, 2009). Unlike an individual bond, social bonds often reflect a specific cultural background.

Under the homogeneous culture background, consumers share the bond with the particular social group which may imply some moral obligations.

Existing brand literature offers little insight into defining or measuring the proposed consumer-brand social bond, though cross-cultural marketing literature may offer some directions. For example, Diamond et al. (2009) suggest brands are complicated and the Gestalt systems reflect a particular culture. Brand components interact dynamically to produce the overall effect. Using indigenous culture as a basis, this article develops the emotional bond construct as a more completed notion that includes both individual and social bonds. In so doing, it not only extends existing research but also provides useful suggestions for marketing practice.

1. Literature Review

1.1 Human Emotion

Emotion reflects a person's attitude in certain circumstances (Strongman, 2003). Because of its subjective nature, psychologists tend to investigate human emotion from a single individual's perspective. That is, emotion is a subjective feeling that involves individual expression (Arnold, 1972). Each emotion has a relational meaning (Lazarus, 1999; 2001; 2006) that reveals the emotional meaning in an interaction. Emotions often have something to do with needs and motivations; when satisfied, people feel happy or pleased, whereas when they are unsatisfied, they might feel angry or sad. Typical individual emotions, such as love and attachment, mainly originate from a person's psychological resonance or experience, not from a sense of obligation.

However, some scholars suggest that research should go beyond the individual level; Rimé (2009) therefore proposes the construct of social sharing of emotion. As members of society, human beings construct their emotions based on their social structure and cognition, which means emotions are relatively stable, rational, and inseparable from morality. Patriotism and nationalism are typical social emotional bonds that derive from the person's identification with a culture (or society) (Philips, 2002). Culture therefore provides the root of this form of identification (Anderson, 1983).

Thus research implies that human emotion consists of both individual and social emotional bonds. The former represents a true feeling, focused on the person's subjective experience; the latter results from an identification with a culture, which involves morality, compulsion, and group norms.

1.2 Consumer-brand Bonds

In the branding domain, vast research indicates that the consumer-brand