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# Global Contagion of Investor Sentiment during the US Subprime Crisis: The Case of the USA and the Region of Latin America

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**ABSTRACT**

This paper contributes to a growing body of literature studying investor sentiment. Sentiment measures for USA investors are constructed from commonly cited sentiment indicators using the first principle component method. We then examine if the investor sentiment propagates among the markets and how the interdependency through the propagation changes during the course of the US subprime crisis. We adopt a bivariate conditional dynamic correlation generalized autoregressive conditional heteroscedasticity model, and use a sample of the global markets for the following area: USA and Latin America, in our investigation between "turbulent" and "tranquil" periods in the financial markets. Our results identify that: (1) A long-run equilibrium relationship existed between investor sentiment in the US and other global markets during the subprime crisis period; (2) a global contagion of investor sentiment occurred from the US market on September 15, 2008 to other developed countries; and (3) the global markets are all interrelated. (4) We find that sentiment tends to be a more important determinant of returns in the run-up to crisis than at other times.

**Keywords:** Subprime Crisis, Investor Sentiment, Contagion, Bivariate Conditional Dynamic Correlation Generalized Autoregressive Conditional Heteroscedasticity Model
**JEL Classifications:** G01, G11, G15, C53

## 1. INTRODUCTION

We study the influence of an American investor sentiment of the investor sentiment from other international countries, while studying the correlation between them, using measures of sentiment US and the other countries. The objectives of the paper are two. First we construct two new measures of investor sentiment for the USA and the other countries at a annual frequency, Second, we study the impact of investor sentiment in the US on equity returns, both in general, and more specifically distinguishing between ''tranquil'' market periods and periods of "financial crisis," when there were sharp falls in the market.

Empirical studies of financial markets have uncovered numerous anomalies and puzzles, where asset returns behave in ways that traditional finance theories struggle to explain. Examples include: Short horizon stock price momentum (Jegadeesh and Titman, 1993), long-run mean reversion (De Bondt and Thaler, 1985) and excess volatility (Shiller, 1981). To explain these and other anomalies, finance research has been extended to include the direct study of market participants, integrating psychological insights with neo-classical economic theories. Much of this literature is concerned with investor sentiment: Its formation, development and possible impact on share returns.

Seminal examples include Kahneman and Tversky (1973; 1974), De Long et al. (1990), Daniel et al. (1998), Odean (1998), and Barberis et al. (1998). These studies demonstrate that investor sentiment may divert asset prices from their "rational, fundamental" values.

Baker and Wurgler (2007) define investor sentiment as "…a belief about future cash flows or investment risks that is not justified by the facts at hand." Not surprisingly therefore, one of the most difficult empirical questions concerning investor sentiment is that of how it should be measured. Three methods are common. The first uses survey-based techniques that involve asking people about their thoughts and expectations about the stock market. These aim to produce a measure of sentiment that captures the mood of investors.

Examples include the American Association of Individual Investors and Investors Intelligence (II) surveys (Brown, 1999; Verma and Soydemir, 2006; Fong, 2013). More general indices such as the consumer confidence index have also been studied (Schmeling, 2009). The second method is to employ more "objective" financial market indicators, such as the put–call trading ratio and indices of volatility (Wang et al., 2006). Third are composed indices typically using principal components to extract a single sentiment measure from a variety of relevant economic and financial data (Brown and Cliff, 2004; Baker and Wurgler, 2006).

All three methods have their drawbacks. Surveys are expensive to conduct reliably at high frequency and "quick" questionnaires may produce answers which are less reliable. Financial market data are in theory more accurate but they involve a risk of circularity as they may simply reflect the outcome of share price movements rather than be an independent measure of sentiment. Wang et al. (2006) study the ratios of put–call trading, put–call open interest and advances-to declines; and find that these sentiment indices are Granger-caused by stock returns but do not themselves cause returns. Finally, the use of principal components to create a composed index produces a variable which may not be very robust. The composition of the principal components may change as new data become available, implying that the entire time series of sentiment may change over time. However, composed indices are probably the most popular of the three sentiment measures, particularly in studies of US data, arguably because they do largely overcome the reliability issues of surveys and the independence issues of pure financial market data.

In this paper we use principal components to construct indices of investor sentiment for US and investor sentiment of other countries. Principal components analysis extracts orthogonal time series from a dataset in such a way that each successive principal component accounts for as much as possible of the (residual) variation in the dataset. Brown and Cliff (2004) argue that the first principal component of various financial market indicators is sufficient to provide a reliable measure of unobserved sentiment. This procedure is now a generally accepted method of measuring investor sentiment, and has been used by Baker and Wurgler (2006; 2007), Chen et al. (2010), Baker et al. (2012), Chen et al. (2014) and Bai (2014) to construct sentiment indices for various countries so as to examine the effect of sentiment on stock returns. Notwithstanding the popularity of this method, few composed sentiment indices have been constructed for the US. In fact, the only two as far as we are aware is an annual market-wide index by Baker et al. (2012), and a weekly market-wide index by Bai (2014) based on the Baker and Wurgler (2006) approach. Furthermore, there are no survey-based investor sentiment indices available for the US.

In contrast, the US investor sentiment index composed in our paper includes a more comprehensive range of investor sentiment proxies, based as it is on combining the approaches of Brown and Cliff (2004) and Baker and Wurgler (2006). We also construct an index investor sentiment of other countries of each area, the first such that has been constructed for the US.

The second objective of the paper is to study the phenomena of contagion of investor sentiment and the impact of sentiment on stock returns in the US and the nine countries of the region of Latin America. There is broad agreement that, even after controlling for ''rational'' influences such as mean–variance Yu and Yuan (2011) and Fama–French factors (Xu and Green, 2013), indicators of sentiment do contribute significantly to explaining the time series and cross-sectional behavior of stock returns in a variety of settings. The preponderance of the evidence from a variety of datasets and measures of sentiment is that unusually high levels of sentiment tend to be associated with increased trading (Brown, 1999), greater volatility (Lee et al., 2002), and lower returns (Brown and Cliff, 2004; Schmeling, 2009).

We study the relation between sentiment and each proxy of the measure of the sentiment index, for each country. We distinguish between "tranquil" and "crisis" periods in the stock market and between "high" and "low" sentiment periods.

Beckmann et al. (2011), Baker et al. (2012) and Bai (2014) discuss three channels through which investor sentiment contagion may occur. First, if investors in one country are optimistic (say) about investment prospects in another country, they may bid up the shares of that particular country. Second, if investors in one country are optimistic, this may cause a general shift into risky assets, including international equities. Both these channels postulate that the effect of foreign sentiment on home country share prices occurs through market purchases by foreign residents. Third, when foreign investors are optimistic about their own economy this leads to domestic investors being optimistic about the local economy due to the linkage between the two economies, the foreign sentiment affecting domestic share prices indirectly via domestic sentiment.

We argue that there is a fourth possible mechanism: Sentiment in a foreign country may affect sentiment in the home country directly because of the herding instinct of noise traders, and through this channel affect share prices, as home country residents become more or less optimistic and trade accordingly. It is well-established that ''word-of-mouth'' social interactions can affect sentiment and investment decisions (Shiller, 1984; Brown et al., 2008). Investors in different countries are not usually as geographically close to one another as the investors that Shiller and Brown et al. investigated. However, internet message boards have a global reach and there is evidence that they influence sentiment and trading (Sabherwal et al., 2011).

In summary we make two contributions to the growing body of literature on investor sentiment by providing an empirical examination of sentiment in the US and other countries. One is that we construct new measures of US and the other countries investor sentiment using the first principle component method.

We build one index for overall investor sentiment for US and a second for other countries of the region of Latin America. The other is that we study the impact of investor sentiment on all countries asset returns.

Four key results of the paper are worth stating at the outset. First, we find that US sentiment has an impact on the indexes of investor sentiment in other countries. Second, we find that equity returns are significantly influenced by sentiment and not at all investor sentiment: Suggesting that stock returns are affected by investor sentiment that is "born in the USA." This could be due to the high proportion of foreign investors holding US shares as noted above, or to other factors, but it would certainly appear to warrant further investigation. Third, sentiment tends to be a more important determinant of stock returns outside crisis periods than in a crisis. This is consistent with previous evidence that, in a financial crisis, prices revert back to fundamentals, as they are no longer driven by sentiment. Fourth, we find pervasive evidence that changes in sentiment contribute to market volatility, ceteris paribus. The signs of lagged sentiment coefficients in stock return regressions suggest that investors invariably have "second thoughts:" If sentiment has a significant positive coefficient in the returns regression, lagged sentiment invariably has a significant negative and substantially offsetting coefficient, and vice-versa.

The rest of the paper is organized as follows: Section 2 describes the data used in the study including the new US sentiment indexes that we construct; in Section 3 we examine the relationships, particularly the dynamic conditional correlation, between US investor sentiment on the one hand and investor sentiment on the other countries; Section 4 investigates how investor sentiment affect equity returns; Section 5 contains some concluding remarks.

## 2. CONSTRUCTION OF THE SENTIMENT INDEXES AND OTHER DATA

The data making up the sentiment indexes are annual and cover the period 1st January 1985-30th December 2013.

In our empirical study, we have been interested in studying the contagion of investor sentiment over the period 1985-2013 in order to be able to present the important effect of the international financial crisis in 2008 on the irrational behavior of the investor. has already explained, and its impact on the psychology of the investor, whose the transmission of sentiment effect between the various stock markets, this has been shown by the presence of large and very high peaks, compared to other previous crises (see graphs) noting as an example, in 1985, the banking crisis in New York. In 1987, the October Krach of the bond market, then the stock markets. In 1989, Junk bonds, and Japanese speculative bubbles. In 1990, the invasion of Kuwait. In 1992 and 1993, the crisis of the European monetary system (EMS). In 1994, the Mexican economic crisis. In 1997, the Asian crisis, and the crisis of Brazil. In 1998, the crisis of Russia where there is the quasi-failure of the Hedge fund. In 2000, the bursting of the internet bubble and finally in 2001, the economic crisis in Argentina.

Previous work suggests several variables that can be used as proxies for sentiment and we use seven underlying variables to construct the sentiment measures. These are:

The volatility premium (PVOL) is the year end log of the ratio of the value-weighted average market-to-book ratio of high volatility stocks to that of low volatility stocks. High (low) volatility denotes one of the top (bottom) three deciles of the variance of the previous year's monthly returns, where decile break points are determined country by country. Total volatility is defined as the standard deviation of the trailing 12 months of monthly returns, and to control for any association with beta and a confusion with priced risks, we compute the volatility premium based only on beta-adjusted idiosyncratic volatility (for simplicity, however, we will continue to refer to this variable as the volatility premium). This variable was available for all years and all countries. On average in our sample, the market-to-book ratio of high volatility stocks has been higher than that of low volatility stocks, but in each country this relationship has been reversed within our time period.

The second and third proxies we employ are derived from initial public offering (IPO) data. They are the total volume of IPOs and their initial, 1st-day returns (some- times called under pricing). The theoretical motivation for using the volume of IPOs is simply that insiders and long-run shareholders have strong incentives to time the equity market for when valuations are greatest, which is presumably when sentiment is highest. Low long-run returns to IPOs have been noted by Stigler (1964), Ritter (1991), and Loughran et al. (1994), which is ex post evidence of successful market timing relative to a market index. But issuers need not care that much whether their firm's misvaluation is due to firm-specific or market wide factors; consistent with that notion, equity issues as a fraction of total new issues forecast low market returns as well (Baker and Wurgler, 2000). The worst future returns occur for IPOs and equity issues from "hot market" cohorts with high total issuance volume.

It has been widely noted that the initial returns on IPOs (RIPOs) increase in hot markets. In the United States in 1999, for example, there were 477 IPOs and the average raw 1st-day return was 70%. And in Japan that year, the average 1st-day return was 137%! It is implausible that these figures reflect just adverse selection premiums, for example. If anything, the anecdotal evidence suggests that the issues with the highest 1st-day returns were in the greatest demand. Ritter (1998) sums up our motivation for these two sentiment proxies: "Rational explanations for hot markets are difficult to come by."

The number of IPOs (NIPOs) is the log of the total NIPOs that year.

The initial RIPOs are the average initial (most often, 1st-day) return on that year's offerings. The returns are equal-weighted across firms. The data were obtained from a variety of sources. We were able to find both variables for the full sample. In the United States, the annual NIPOs has ranged from 64 to 953 in the sample period, and the average 1st-day return on IPOs has ranged from around 7% to a high of 70%, as noted above. Most other countries have also seen high variation in these quantities.

The fourth sentiment proxy is market turnover. Commentators on speculative episodes such as Bagehot (1873) and Kindleberger (1978) have noted that high trading volume in the overpriced asset is a pattern that goes back to the tulip bubble. Cochrane (2002) states that "the association of price and volume is a generic feature of the historical 'bubbles." Lamont and Thaler (2003) examine tech stock carve outs and find that the relatively overpriced IPO subsidiaries have an average turnover rate of 38% per day over the first 20 days of trading (not including the 1st day), which is more than 5 times that of parent turnover. There was much greater volume in Internet relative to non-Internet stocks between 1998 and 2000 (Ofek and Richardson, 2003). In a cleaner test, Mei et al. (2009) find a correlation between trading and price differentials in fundamentally identical Chinese A–B shares. Smith et al. (1988) find experimental evidence that bubbles are associated with high turnover. Subsequent research indicates that this correlation is robust to the introduction of trading fees, short-sales constraints, and the use of business professionals as test subjects.

There is also ample theory to connect sentiment and trading volume. Any greater fool theory of rational bubbles (Harrison and Kreps, 1978) or models of positive feedback trading by informed investors essentially requires that those who believe the asset is overvalued be able to trade it away before the mispricing corrects (De Long et al., 1990b). Uninformed fund managers can churn bubbles to confuse their clients into thinking they are informed (Allen and Gorton, 1993). Baker and Stein (2004) point out that when shorting is relatively costly, sentimental investors are more likely to trade when they are optimistic, and overall volume goes up. Scheinkman and Xiong (2003) provide a complementary argument based on overconfidence for using turnover as a proxy for sentiment. So, as with the other three measures, we expect a positive relationship between the observed proxy and underlying sentiment.

Market turnover (TURN) is the log of total market turnover, i.e., total dollar volume over the year divided by total capitalization at the end of the prior year. We detrend this with an up-to-5-year moving average. We could obtain market-level turnover statistics for all markets.

The fifth sentiment proxy is the dividend yield is the difference between the sum of dividends received and the sum of dividends paid.

The sixth sentiment proxy is the trading volume: Baker and Stein (2004) argue that market confidence is related to liquidity and that trading volume is a noisy measure of liquidity. In our case, the trading volume is defined as the number of shares traded or quantity of shares traded on the stock market.

The seventh and the final sentiment proxy is the performance index(ARMS): Another indicator used to estimate the investor sentiment, this indicator shows the number of shares that have experienced an increase in standardized prices by their trading volumes divided by the number of shares experienced a decrease during standardized by the trading volume of such shares, this indicator is often cited by the Wall Street Journal as an excellent market timing indicator "a lower indicator (greater than) 1 indicates that the market is overbought (oversold).

Therefore, we construct the sentiment indices using the levels of the remaining indicators (see Appendix 1, 'The correlation between the composite sentiment index and the proxy of the measure of sentiment'). We first analyze preliminary characteristics of each composite index of sentiment, we second analyze the relation between the American sentiment composite Index is the benchmark index and the other sentiment composite index.

Before embarking on the presentation of results of the estimate series of composite indices sense, it is proposed to take a glance at some descriptive statistics elements then move to stationary tests of the series.

The tables below summarize the characteristics of the sense of composite indices selected on the total period from 1985 to 2013 for the eight countries to see the United States, Canada, France, Italy, Germany, UK and Japan.

## 3. METHODOLOGY

At first, we tried to present the preliminary characteristics of each composite index sentiment.

The two above table (see Table1 'Descriptive statistics of composite indices of sentiment') presenting the descriptive statistics of the various series of eight composite sentiment indexes for Latin America and USA constructed based on the coefficients of the first principal component (CPA), these tables summarize the means and standard deviations for eight time series indexes investor sentiment in our sample that spans the period from 1/1/1985 to 31/12/2013, these statistics bring several comments. We note that for eight series that statistical skewness and kurtosis of respectively different from 0 and three. In addition to these results, it therefore rejects the assumption of a normal distribution of the series. That is to say, the non-normality of the distributions is characterized by the fact that the characteristics of eight series seem to be different from a Gaussian distribution. In our study the coefficient of skewness equal to zero; this coefficient is positive for all series this means that the thick portion of the variable distribution is asymmetrical is skewed that is to say in the positive direction. The presence of this asymmetry may be a non-linearity indicator, since the linear Gaussian models are necessarily symmetrical. These distributions are asymmetric and have a leptokurtsis. Some series have skewness tests below 1.96, while other tests show higher than normal law of value at the 5% threshold where the rejection of the assumption of normality that is to say, the skwness coefficient and kurtosis series of variables indicates a clear rejection of normality and shows a clear difference between the distributions of these variables and the normal distribution, this divergence from normality of the distribution may also be explained by the existence of shocks, if the skewness coefficient is negative is spread to the left of where the response to a shock is negative if the coefficients are positive spread right where the response to a shock is positive. Thus, we can conclude that all the variables in question sets do not follow a normal distribution, in this respect, will be analyzed the stationary distribution of sets of all variables (see Table 2, 'Stationary test yield market indexes (ADF test)'), which according to the study stationary of the various series of composite indexes of sentiment, we can conclude that all series are stationary in level, and all values calculated are below the statistical values to the three thresholds 1%, 5% and 10%. In view of all these results, the preliminary study of the statistical properties of the various series used is important since some statistical characteristics of the series must be verified to apply many econometric tests. This motivates our choice will eventually use a generalized autoregressive conditional heteroscedasticity (GARCH) model that the model of the dynamic conditional correlation varied multi DCC MGARCH.

The sentiment index coefficients for each country are estimated using the first principal component of each of the macro orthogonalized sentiment proxies. The resulting indexes are linear functions of the within country standardized values of the proxies and thus have mean zero:

The first sentiment proxy is the volatility premium (PVOL), is the log of the ratio of the value-weighted average market-to-book ratio of high volatility stocks to that of low volatility stocks. High (low) volatility denotes one of the top (bottom) three deciles of the variance of the previous year's monthly returns. The second sentiment proxy is (NIPO) is the log of the total NIPOs that year. The third sentiment proxy is the initial RIPOs are the average initial (most often, 1[st]-day) return on that year's offerings. The fourth sentiment proxy is turnover (TURN) over the year. The fifth sentiment proxy is the dividend yield (PDIV) is the difference between the sum of dividends received and the sum of dividends paid. The sixth sentiment proxy is the trading volume (VT) is defined as the number of shares traded or quantity of shares traded on the stock market. The seventh and the final sentiment proxy is the performance index (ARMS) is shows the number of shares that have experienced an increase in standardized prices by their trading volumes divided by the number of shares experienced a decrease during standardized by the trading volume of such shares; This indicator is often cited by the Wall Street Journal as an excellent market timing indicator "A lower indicator (greater than) 1 indicates that the market is overbought (oversold)." Prior to forming the first principal component, the proxies are orthogonalized with respect to consumption growth, industry production growth, employment growth, the short-term interest rate, inflation, and the term premium.

Sent USA, t=0.615 PVOL+0.829 NIPO+0.672 RIPO +0.983 TURN-0.898 PDIV+0.932 VT-0.781 ARMS.

Sent Argentina, t=0.615 PVOL+0.765 NIPO+0.879 RIPO +0.798 TURN-0.630 PDIV+0.804 VT +0.645 ARMS.

Sent Brazil, t=−0.782 PVOL+0.717 NIPO-0.738 RIPO +0.900 TURN+0.700 PDIV+0.805 VT + 0.628 ARMS

Sent Chile, t=0.615 PVOL+0.828 NIPO-0.649 RIPO + 0.775 TURN+0.572 PDIV+0.808 VT +0.645ARMS

Sent Colombia, t=0.615 PVOL+ 0.831 NIPO+0.866 RIPO + 0.883 TURN-0.747 PDIV+ 0.935 VT +0.867 ARMS

Sent Mexico, t=0.744 PVOL-0.651 NIPO+0.750 RIPO +0.822 TURN+0.842 PDIV+0.798 VT +0.536 ARMS

Sent Peru, t=0.615 PVOL+ 0.854 NIPO-0.766 RIPO+ 0.755 TURN +0.592 PDIV+0.747 VT+ 0.675 ARMS

Sent Venezuela, t=0.615 PVOL+0.738 NIPO+0.755 RIPO +0.799 TURN+0.968 PDIV+0.725VT +0.963 ARMS

Where the country subscripts on the proxies have been suppressed the fraction of variance explained by the first principal components are in order of the countries listed above, 25% for Argentina, 34% for Brazil, 25% for Chile, 30% for Colombia, 39% for Mexico, 25% for Peru, 34% for Venezuela, and in each country there is at least one eigenvalue that exceeds unity. These figures resemble the 49% reported in Baker and Wurgler (2006) for a seven-factor index of U.S. sentiment.

We standardize the total sentiment indices and plot them in Figure 1. A prominent feature is the Internet bubble of the late 1990s and its subsequent crash; this is clearly represented not only in the United States.

The United States is widely considered the world's bellwether market. Consistent with this position, the United States' total sentiment index exhibits a high degree of commonality with other countries' indexes and receives the highest loading in the index.

Qualitative interpretations of the indexes involve a large degree of conjecture as well as an understanding of historical market conditions. Proper interpretation of the local indices, in particular, requires a grasp of both global and market conditions, as well as some caution given the unavoidable noise in the estimates. With these qualifications in mind, one can speculate on some of the variation in the U.S. Index.

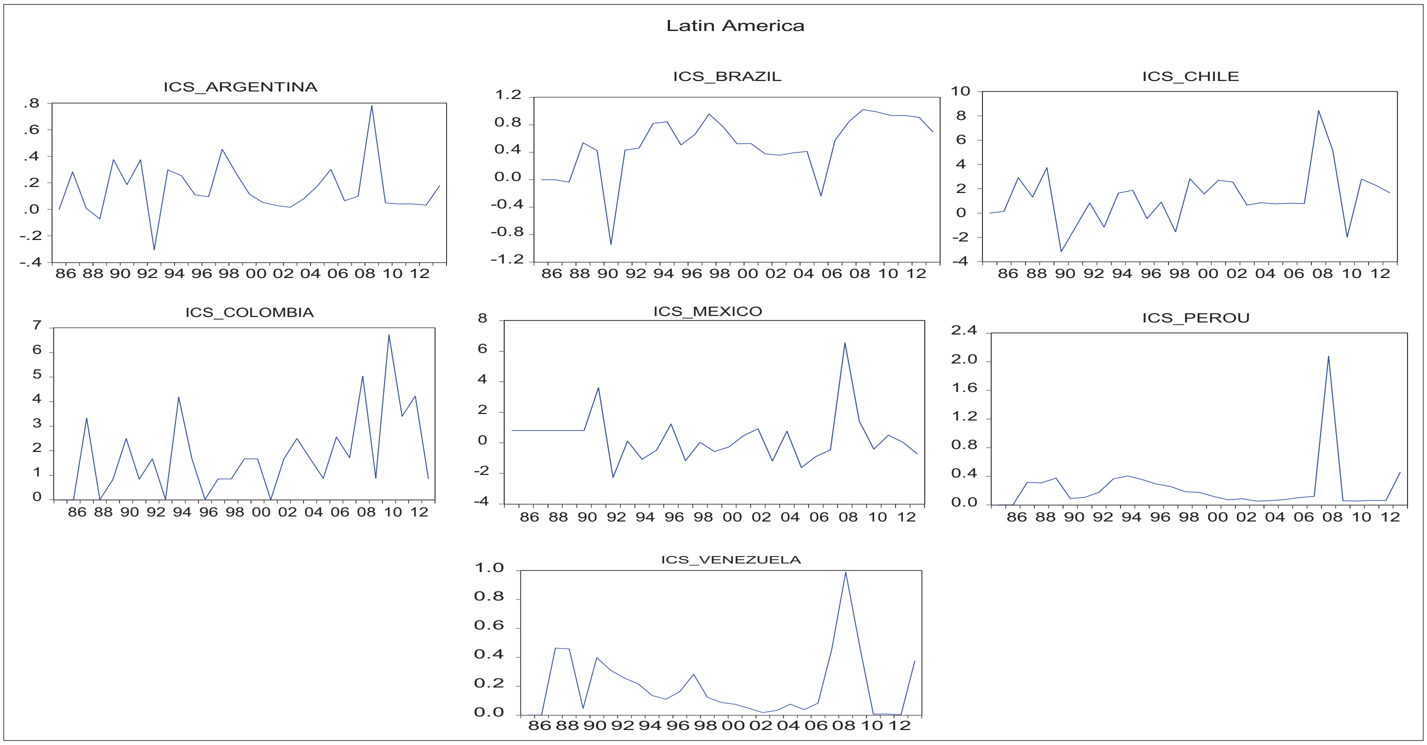
The index reaches high levels in the early 1980s, perhaps reflecting speculative activity in biotech and natural resources shares that was concentrated in the United States.

The index declines somewhat following the1987 crash, but not dramatically, reflecting the fact that the crash was a global phenomenon (Roll, 1988). Perhaps because the technological advances of the Internet were concentrated in the United States, the index suggests that the sentiment associated with the bubble. Interestingly, while the U.S. total sentiment was high at the bubble's peak, it was not uniquely high relative to other countries in the sample. However, U.S.-specific sentiment did decline to an unusual degree with the crash, most likely reflecting the combination of the crash and the terrorist attacks on September 11, 2001, same for the period of the financial crisis in 2008.

### 3.1. DCC-GARCH Model Estimation between the American ICS and the Other ICS

- Dynamic conditional correlations' asymmetric model (DCC-GARCH (1.1)) Engle (2002).

**Figure 1:** The different composites sentiment indexes. The investor sentiment on the period (1985-2013). Is the first principal component of seven time-series proxies for sentiment for the given country




We apply DCC-MGARCH model of Engle (2002) to test the existence of contagion during Global Financial Crisis. A major advantage of using this model is the detection of possible changes in conditional correlations over time, which allows us to detect dynamic investor behavior in response to news and innovations. Moreover, the dynamic conditional correlations measure is appropriate to investigate possible contagion effects due to herding behavior in emerging financial markets during crises periods (Corsetti et al., 2005, Chiang et al., 2007 and Syllignakis and Kouretas, 2011). Another advantage of DCC-MGARCH model is that DCC-GARCH model estimates correlation coefficients of the standardized residuals and so accounts for heteroscedasticity directly (Chiang et al., 2007). Since the volatility is adjusted by the procedure, the time varying correlation (DCC) does not have any bias from volatility. Unlike the volatility-adjusted cross-market correlations employed in Forbes and Rigobon (2002), DCC-GARCH continuously adjusts the correlation for the time-varying volatility. Hence, DCC provides a superiour measure for correlation (Cho and Parhizgari, 2008). The estimation of Engle's DCC-GARCH model comprises two steps: The first is the estimation of the multivariate GARCH model; the second is estimation of the conditional correlations that vary through time. The multivariate DCC-GARCH model is defined as follows;

$$X_t = \mu_t + H_t^{1/2} \varepsilon_t \tag{1}$$

$$\begin{cases} H_t = D_t R_t D_t \\ R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \\ D_t = diag(\sqrt{h_{11,t},} \sqrt{h_{22,t},} \ldots, \sqrt{h_{NN,t},} \end{cases} \tag{2}$$

Where $X_t = (X_{1t}, X_{2t}, X_{Nt})$ is the vector of the past observations, $H_t$ is the multivariate conditional variance, $\mu_t = (\mu_{1t}, \mu_{2t}, \ldots \mu_{Nt})$ is the vector of conditional returns, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots \varepsilon_{Nt})$ is the vector of the standardized residuals, $R_t$ is a N×N symmetric dynamic correlations matrix and $D_t$ is a diagonal matrix of conditional standard deviations for return series, obtained from estimating a mltivariate GARCH model with $\sqrt{h_{ii,t,}}$ on th ith diagonal, $i$=1, 2.,$N$.

The DCC specification is defined as follows;

$$R_t = Q{*}_t^{-1} Q_t Q{*}_t^{-1} \tag{3}$$

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1} \tag{4}$$

Where $Q_t$ is a positive matrix, it defines the structure and dynamic $Q{*}_t^{-1}$ resizes the items in $Q_t$ to ensure that $|q_{ij}| \leq 1$. $Q{*}_t^{-1}$ is the inverse matrix of the matrix $Q_t$. $Q_t$ is the conditional variance of standard errors.

And $\alpha$ and $\beta$ are two scalar

$\lambda_1$=α and $\lambda_1 = \beta$ are parameters that govern the dynamics of conditional quasicorrelations.

$\lambda_1$ and $\lambda_1$ are nonnegative and satisfy $0 \leq \lambda_1 + \lambda_2 < 1$.

Therefore, for a pair of markets i and j their conditional correlation at time t can be defined as:

$$\rho_{12,t} = \frac{q_{ij}}{\sqrt{q_{ij,t}\, q_{jj,t}}}, \; with\, i, j = 1, 2, \ldots n. and\, i \neq j \tag{5}$$

Where $q_{ij}$ is the element on the ith line and jth column of the matrix $Q_t$. The parameters are estimated using quasi-maximum likelihood method (QMLE) introduced by Bollerslev et al. (1992).

- Contagion effect test with dynamic conditional correlation coefficient:

We use t-statistics to test consistency of dynamic correlation coefficients between foreign Stock markets returns in the crisis periods to judge the contagion effect.

Hypothesis test:

We define null and alternative hypotheses as:

$$H_0 = \mu_\rho^{crisis} = 0\,,\; H_1 = \mu_\rho^{crisis} \neq 0$$

Where $\mu_\rho^{crisis}$ is the conditional correlation coefficient means of population in the crisis periods.

If the sample size is $n^{crisis}$ the population variance $\sigma^2$ crisis is different to zero. If the means of dynamic correlation coefficients estimated by DCC are $\bar{\rho}_{ij}^{crisis}$ and the variance is $S^{2crisis}$ the t-statistic is calculated as:

$$t = \frac{(\overline{\rho_{ij}}^{crisis}) - (\mu_\rho^{crisis})}{\sqrt{\frac{S^{2crisis}}{n^{crisis}}}} \tag{6}$$

If t-statistics is significantly greater than the critical value, $H_0$ is rejected supporting the existence of contagion effect.

We tried to use the DCC MGARCH model, to correct the weak GARCH univariate model, this model is its complication in estimating parameters when they are high, as the ARCH model, GARCH allows heteroscedasticity and excessive kurtosis. It also allows modeling the grouping of volatility. The GARCH model provides a more parsimonious parameterization the ARCH model. The GARCH model has the same weaknesses as the ARCH model, that is, it assumes that positive and negative shocks have the same magnitude and that it can predict volatility. Univariate models only allow one analysis of a financial series at a time. But in practice, analyzing one series at a time is not very useful.

The interest for such a model is to be able to examine and analyze the various relations that the different series have with each other. In order to be able to estimate several financial series to analyze their correlations and volatility transfers, it is necessary to use multivariate GARCH models (MVGARCH). This multivariate model is often used to test volatility shifts and spillover effects in contagion studies. This multivariate model not only allows us to analyze volatilities, but also the correlations of different markets. There are several specifications to the multivariate GARCH model; linear, nonlinear, asymmetric models, jump models, conditional correlation models, and many others. In our research, the model with conditional correlations will be presented and used, as we find parameters that are sensitive to short-term conditional volatility shocks, others that indicate the sensitivity to crises, the sensitivity to shocks of volatility of asset, the persistence of conditional volatility, as well as those that indicate whether the asset remains affected for a long time by shocks and that we are particularly interested because they represent the interaction between the two assets.

The advantages of the DCC-GARCH model are the direct modeling of variance and covariance and its flexibility, allowing the matrix of conditional correlations to vary over time, compared to other models that are too restrictive and unrealistic in nature. Assuming constant conditional correlations, because in practice they vary over time. This model will examine the volatility transfers between several variables, more specifically, from one market to another. We will also be able to examine whether the correlations between the two countries have increased during the financial crisis. The parameters measure the persistence of shocks in the short term, these parameters are those that represent the sensitivity of the stock market index to shocks of volatility or crisis, other parameters measure the persistence of the volatility of previous periods and the transmission of volatility from one market to another.

Searches using the BEKK-GARCH model limit the number of assets studied and impose restrictions such as assuming that the correlations are constant. This hypothesis is erroneous Several empirical studies show that correlations vary over time. So the hypothesis of constancy of correlations does not stand up to the reality of the facts. In order to model both the variances and the conditional correlations of the several series, we adopted the DCC method, this model is very flexible, the advantage of this model is to keep a reasonable number of parameters to estimate while taking into account the variation temporal correlations between variables and the possible asymmetry effect of shocks on the conditional variance. The results of previous research prove that bivariate DCC models perform very well compared to other multivariate models.

They always rank among the first in the various tests, another advantage of the DCC -GARCH model is its ability to model a large number of variables and give good forecasts of volatility regardless of the number of assets. This model provides conditional variances estimated closer to actual variances that BEKK -GARCH and VAR models.

## 4. EMPIRICAL RESULTS AND INTERPRETATIONS

In our empirical work we studied the interdependence between the composite index of US sentiment that the benchmark index and other composite indexes build on the basis of the coefficients of the first principal component while trying to answer the following question: What are the determinants of dynamic conditional correlations between the US market and other international markets? The tests based on correlation coefficients estimated DCC-MGARCH models and lend support to our argument.

The estimation results suggest that the shocks are transmitted to a persistently for most of the Latin Americas countries (see appendix2, 'Fig. 2: The conditional dynamic correlation between the different sentiment indexes.').

**Table 1: Descriptive statistics of composite indices of sentiment**

| Area/country | Mean | Median | Max. | Min. | Standard deviation | Skewnes | Kurtosis | Jarque-Bera | Proba |
|---|---|---|---|---|---|---|---|---|---|
| Latin Amercia | | | | | | | | | |
| Argentina | 0.151715 | 0.099263 | 0.782980 | −0.304595 | 0.197797 | 0.883271 | 5.360870 | 10.50571 | 0.005233 |
| Brazil | 0.507111 | 0.527919 | 1.022784 | −0.945996 | 0.432923 | −1.437642 | 5.570269 | 17.97219 | 0.000125 |
| Chile | 1.299175 | 0.903831 | 8.444088 | −3.183398 | 2.261208 | 0.831021 | 5.033937 | 8.336632 | 0.015478 |
| Colombia | 1.798676 | 1.665719 | 6.722825 | 0.000000 | 1.672913 | 1.158084 | 3.988510 | 7.662989 | 0.021677 |
| Mexico | 0.325193 | 0.118088 | 6.559555 | −2.268406 | 1.653080 | 1.942973 | 8.472273 | 54.43101 | 0.000000 |
| Peru | 0.236522 | 0.118290 | 2.079220 | 0.000000 | 0.378499 | 4.153022 | 20.81568 | 466.8867 | 0.000000 |
| Venezuela | 0.197775 | 0.109893 | 0.989947 | 0.000000 | 0.224041 | 1.692749 | 6.298119 | 26.99319 | 0.000001 |
| USA | 2.715633 | 2.451223 | 8.024976 | 0.773670 | 1.813530 | 1.114704 | 3.893925 | 6.971316 | 0.030634 |

**Table 2: Stationary test yield market indexes (ADF test)**

| AreZa/ country | Test: ADF | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | With trend and constant | | With constant | | Neither trend nor constant | | Threshold (%) | Stationary |
| | Calculated value | Critical value | Calculated value | Critical value | Calculated value | Critical value | | |
| Argentina | −6.135337 | −4.323979 | −6.259947 | −3.69987 | −3.934498 | −2.650145 | 1 | Yes |
| Brazil | −7.115405 | −3.580623 | −7.245835 | −2.976263 | −7.348882 | −1.953381 | 5 | Yes |
| Chile | −3.992288 | −3.225334 | −4.821818 | −2.627420 | −3.772963 | −1.609798 | 10 | Yes |
| Colombia | −5.290189 | | −5.396025 | | −11.46818 | | | Yes |
| Mexico | −5.145401 | | −5.245554 | | −5.164768 | | | Yes |
| Peru | −5.308759 | | −5.378841 | | −3.940648 | | | Yes |
| Venezuela | −4.205020 | | −4.292180 | | −2.106943 | | | Yes |
| USA | −4.616427 | | −4.796737 | | −4.479564 | | | Yes |

We estimate the dynamic conditional correlation coefficients between major financial variables in our study (composite indexes sentiment) through the markets. Our study uses the DCC-MGARCH (dynamic conditional correlation of heteroscedastic autoregression model generalized multivariate) to assess the nature of the correlations between major financial variables across regions. This model allows us to detect the dynamic behavior of investors in response to new innovations. We include eight international financial markets, based on the correlation between the composite index of sentiment in the US market and other international indexes. The evaluation results of DCC-MGARCH model are mixed. The results provide compelling evidence that the feeling was contagious through the financial markets and especially during periods of financial crash. The data used for the empirical analysis is the annual frequency, covering the period 1985-2013, we choose eight international markets: This choice is also useful to analyze the contagion of sentiment across different markets investor financial world. In this case, it is necessary to compare the correlation between two financial markets during this period. For financial variables, we consider the composite indexes sentiment construct based on the coefficient of the correlation matrix after rotation after following the analysis of the main component of various indirect indicators of sentiment measure namely the volatility premium, the dividend premium, the performance index, the NIPO, the average annual profitability of newly introduced companies, the turnover rate and end the transaction volume for the analysis of the contagion of investor sentiment. All data is obtained from Datastream, thomson financial and the World Bank. As shown in the various figures that present the changes in the dynamic conditional correlation, the correlation between the composite index of US sentiment and other indices is increased just after the financial crisis. In particular, it increased suddenly during this financial event.

The figures suggest that correlation between the composite indexes sentiment, if it is important, this proves that it is mainly triggered by financial instability. The contagion effect of shocks through international financial markets is a topic of particular interest because it can reflect the structural fragility of some financial markets.

Our empirical study finds that contagion is high between the United States and other countries forming the area of Latin Americas during periods of financial crash. The correlations between markets have significantly important during the subprime crisis in the United States; we can conclude that the crisis has spread across different markets, which is clear evidence of contagion.

These important correlations are presented periodically by the t-statistic that is substantially larger than the critical value (the coefficients are positive and higher than the critical value of 1.96 which is the threshold around 5%), $H_0$ is rejected supporting the existence of the contagion effect. based on the importance average values of DCC, as some countries appear to be more influenced by the contagion of the sentiment. This proves the existence of evidence of significant contagion conditional correlations between the different composite sentiment indexes.

For the American countries, which as Argentina, Brazil, Chile, Colombia, Perou, the coefficient of correlation, to all, between the composite sentiment index of these countries and the American composite sentiment index are significantly positives because it presented the t-statistic superiors to the critical value, which in order to 1.96 and they're respectively in order to 0.8406296, 0.7234649, 0.913522, 0.8367604, 0.9653702. However, for Mexico and Venezuela are presented the t-statistic significantly negatives, which in order to (−0.587584) and (−0.290277), so the two index are negatively correlated with the American composite sentiment index.

The sentiment indices include both changes or return like components, such as 1st-day RIPOs and perhaps detrended turnover, and level components, like the volatility premium. We therefore compare them to changes in and levels of relative prices. We use annual observations on the year end log price ratio, scaled such that a value of zero represents theoretical parity and examinate the changes and levels to the prevailing o U.S. sentiment.

We control for the lagged relative price level because it is empirically quite persistent; because the sentiment indexes are not measured without error; and because both sentiment indexes have been standardized, removing any differences in means or scales. The change in the deviation is not very persistent, so its inclusion in the first specification is not material.

Otherwise, according to graphics (Appendix) and based on the analysis of the evolution of the correlation between the composite indexes sentiment, one can notice that this correlation increases with the crisis, probably reflecting the impact of the crisis, which proves the existence of a significant relationship between the relative level of investor sentiment and the relative level of price changes where sentiment affects stock prices. When sentiment is high, future stock returns are low. Given the sample size and high power of this test, the magnitude of the coefficients is statistically significant and economically important. This result proves that the sentiment affecting financial markets internationally, not just in the US where it has been studied the most, but it can spread to other countries.

As according to the previous studies; there are two sources of contagion. One possibility is that investors in one country are optimistic about investment prospects in another, and have increased the actions of this country. it will be captured by the correlation between the sentiment and the various indirect indicators of sentiment far Sentiment increases with volatility premium, the NIPOs, the return of the 1st day of IPO, the turnover, the dividend premium, the trading volume, the performance index, These are measures which reflect the activity of the capital market, which in principle can encourage investors.

Another possibility is that investors in one country, for example, the United States, are simply optimistic, leading to a change in risk assets including global equities. Sentiment in the United States may then influence prices in other target countries.

In conclusion, our results show that sentiment affects stock prices, that is to say, when sentiment is high, the future stock performance is low. Thus, this effect may spread and spread to countries other than the United Etas, where this effect is contagious. It spreads to other countries by private capital flows.

Our results suggest that sentiment affect the financial market. The sentiment effects extend the evidence from the United States on sentiment suggests a more novel mechanism: Sentiment may be contagious. There are two sources of contagion. One possibility is that investors in one country are optimistic (for example) about investment prospects in another and bid up the shares of that particular country. Using our measures, this will be captured by sentiment. Sentiment rises with the volatility premium, the NIPOs, the 1st-day return on IPOs, the rate of share turnover, dividend premium, performance index, and the trading volume. These are local measures, but they reflect capital market activity, which in principle can come from foreign as well as local investors. The evidence in Klibanoff et al. (1998) and Hwang (2011), who examine the pricing of closed end funds, is suggestive of this channel. Another possibility is that investors in one country, say, e.g. the United States, are simply optimistic and this leads to a shift into risky assets more broadly, including international equities. United States sentiment will then affect prices in another target country, above and beyond sentiment, provided that our measure of sentiment is not absolutely complete, as it surely is not, and provided that there is a robust flow of private capital from the United States into the target. To be specific, what we care about is the round-trip flow of capital, both from the United States to another country in our sample and back to the United States.

In every case where the effect of sentiment of the country is statistically significant, there is also a strong and conditional effect of U.S. sentiment. Provided the capital flows between the United States and the countries forming the Area of Latin America (if Venezuela), to take an example, are high in absolute value, then U.S. sentiment has the same effect on hard to value and to arbitrage Latin American stocks as Latin American sentiment. The results are consistent with private capital flows being a mechanism that spreads sentiment across markets. There are, of course, other mechanisms to spread sentiment. One is social influence, i.e., word-of-mouth sharing of positive investment experiences. Shiller (1984) discusses this mechanism, and Hirshleifer (2009) models how the bias toward sharing positive information leads to the spread of investing, particularly in volatile, hard to value stocks. Kaustia and Knupfer show that high stock returns of local peers in Finland encourage additional stock market participation. Hong et al. (2004) find that mutual fund managers in the same city exhibit common trading patterns. Brown et al. (2008) find that stock market participation depends on that of neighbors. Strictly speaking, this evidence pertains to the spread of sentiment within a geographic area. The effects tail off with the distance between actors. Technology and mass-media can reduce the effects of distance and represent another distinct mechanism by which sentiment can spread, potentially across borders, in the absence of direct investment. Shiller (1984) discusses this as well. Tetlock (2007) shows a causal effect of business news on stock returns, for instance, and Antweiler and Frank (2004) try to connect them to the conversations of Internet chat rooms.

## 5. CONCLUSION

Our research has focused on the empirical study of financial contagion while introducing the notion of irrational investor behavior due to the deviation of prices from their fundamental values which may explain the price formation reality. This study empirically examines the relationship between the composite indexes sentiment of seven economies and those of the US. This work also examines the contagion of investor sentiment based on irrational behavior of investors in the financial market, we used the multi varied dynamically GARCH model to estimate the dynamic conditional correlations using annual data the period (1985-2013) of the various indirect indicators measuring sentiment namely the volatility premium, the dividend premium, the NIPO's, the return of the 1st day of IPO, the turnover, the trading volume, and in the end the performance index.

such that from these proxies the composite indexes were constructed based on the coefficients of the correlation matrix after rotation according to the method of the ACP (analysis by principal component).An advantage of the various multi model DCC-GARCH is based on the fact that we can get al. the possible correlation coefficients of each index in the sample and studied their behavior during periods of particular interest, such as periods of financial crash. These coefficients were statistically significant, providing evidence for the influential role of the composite index of US sentiment on other indexes.

The magnitude of the effect of the 2008 stock market crash on the correlation coefficients is indicated by the significance of predicted coefficients and the evolution of graphics correlations, which were significantly higher than those of financial crises previous. This finding provides support for evidence of herding behavior during the stock market crash of 2008.

The analysis of dynamic correlations coefficients provided substantial evidence for contagion effects due to herding behavior of investors on these markets studied.

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# APPENDICES

## Appendix 1

**Table 3: The correlation between the composite sentiment index and the proxy of the measure of sentiment**

| Correlation between indirect measures | ARMS | NIPO | PDIV | PVOL | RIPO | TRADING_VOLUME | TURN |
|---|---|---|---|---|---|---|---|
| ICS_ARGENTINA | 0.136 | 0.173 | 0.040 | 0.627 | −0.007 | 0.276 | 0.075 |
| ICS_BRAZIL | 0.228 | 0.161 | −0.337 | −0.152 | −0.401 | 0.734 | 0.830 |
| ICS_CHILE | −0.081 | 0.205 | 0.338 | 0.627 | 0.152 | 0.285 | 0.172 |
| ICS_COLOMBIA | −0.148 | 0.999 | −0.149 | 0.627 | 0.180 | 0.633 | −0.067 |
| ICS_MEXICO | −0.035 | 0.142 | 0.193 | −0.079 | −0.041 | 0.0368 | −0.034 |
| ICS_PEROU | 0.004 | 0.103 | −0.090 | 0.627 | −0.115 | 0.208 | 0.136 |
| ICS_VENEZUELA | −0.176 | −0.160 | −0.144 | 0.627 | 0.140 | −0.158 | −0.151 |
| ICS_USA | −0.270 | 0.092 | 0.023 | 0.627 | 0.310 | 0.986 | 0.980 |

**Table 4: The estimation results of DCC GARCH composite indices between composite index of the investor sentiment (entire period)**

| Correlation between country/variables | Constant | $\lambda_1$ | $\lambda_2$ | ρ (correlation) |
|---|---|---|---|---|
| USA_Argentina | 2.920886 | 0.9315144 | 0.0019152 | 0.8406296 |
| | 0.4139831 | 0.0577975 | 0.0069912 | 0.1965536 |
| | 7.06 | 16.12 | 0.27 | 4.28 |
| | (0.000) | (0.000) | (0.784) | (0.000) |
| USA_Brazil | 2.00035 | 0.2515811 | 0.5953769 | 0.7234649 |
| | 0.0001397 | 0.4149378 | 0.4073489 | 0.1503108 |
| | 1.4e+04 | 0.61 | 1.46 | 4.81 |
| | (0.000) | (0.544) | (0.144) | (0.000) |
| USA_Chile | 3.614017 | 0.5663987 | 0.2134869 | 0.913522 |
| | 0.9495343 | 0.1442228 | 0.1442668 | 0.1027949 |
| | 3.81 | 3.93 | 1.48 | 8.89 |
| | (0.000) | (0.000) | (0.139) | (0.000) |
| USA_Colombia | 2.084763 | 0.0771942 | 0.8286475 | 0.8367604 |
| | 0.3697315 | 0.2073022 | 0.1992829 | 0.2586197 |
| | 5.64 | 0.37 | 4.16 | 3.24 |
| | (0.000) | (0.710) | (0.000) | (0.001) |
| USA_Mexico | 3.89202 | 0.1773067 | 0.5373265 | −0.587584 |
| | 2.255218 | 0.182918 | 0.2518491 | 0.2339146−2.51 |
| | 1.73 | 0.97 | 2.13 | (0.012) |
| | (0.084) | (0.332) | (0.033) | |
| USA_Perou | 3.495542 | 0.9040208 | 0.0626767 | 0.9653702 |
| | 0.1730792 | 0.0472138 | 0.0386466 | 0.0478866 |
| | 20.20 | 19.15 | 1.62 | 20.16 |
| | (0.000) | (0.000) | (0.105) | (0.000) |
| USA_Venezuela | 2.018106 | 0.6786377 | 0.016613 | −0.290277 |
| | 0.0601709 | 0.7458315 | 0.0615524 | 0.2400652−1.21 |
| | 33.54 | 0.91 | 0.27 | (0.227) |
| | (0.000) | (0.363) | (0.787) | |

For each country, it has been estimated parameters, and each parameter was the coefficient, standard deviation, t−statistic and probability

## Appendix 2

**Figure 2:** The conditional dynamic correlation between the different sentiment indexes. Figure 2 indicates that our sentiment measures are highly correlated for some countries and lowly correlated for other countries