U.S. Investor Sentiment and Financial Contagion in the Americas: Lessons From the U.S. Financial Crisis

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This study investigates the influence of U.S. investor sentiment on financial contagion across the Americas during the 2008–2009 global financial crisis. Using a DCC-GARCH model, we analyze daily stock returns from Argentina, Brazil, Canada, Chile, Colombia, Mexico, Peru, and the U.S., incorporating the VIX along with individual and institutional sentiment measures. Results indicate that investor sentiment, particularly during periods of crisis, significantly increases correlations across markets, pointing to sentiment-driven spillovers. Institutional investor sentiment emerges as a strong predictor of market returns, and the findings ultimately highlight the critical role of institutional investors in amplifying financial contagion across borders.

Keywords: financial contagion, Latin America, U.S. financial crisis, market volatility, investor sentiment, behavioral finance

INTRODUCTION

The 2008-2009 U.S. financial crisis is of high importance because it represented the most extensive U.S. stock market decline since the Great Depression of the early 20th century and because of its rapid spread to other economies worldwide. The financial contagion observed during this period challenges the ability to build diversified portfolios by investing in different stock markets worldwide during times of crisis. It prompts us to investigate the sources of this contagion.

In addition to the fundamentals-based contagion theories of Kaminsky and Reinhart (2000), other authors identify that investor behavior can also accentuate financial contagion. Investors may attempt to mitigate the risk of their international holdings by withdrawing their funds from countries with high economic ties to the country in crisis, resulting in increased correlations between the country in crisis and its trade partners (Yuan, 2005; Pasquariello, 2007).

Kodres and Pritsker (2002) developed a rational expectations model to explain financial market contagion. They identify that investors transmit shocks from one market to another when they rebalance their portfolios to adjust their exposure to macroeconomic risks.

Markowitz (1952) defines investors as well-informed and rational when building efficient portfolios to maximize expected returns for any given risk. Modern Financial theory states that individual investors are rational utility maximizers who care about their investment’s risks and returns and make investment decisions based on economic fundamentals (Fama, 1970). Traditional Efficient market theory states that markets are rational and that stock values equal discounted future cash flows. It also says that any deviation from fundamental values should be eliminated in a short time by arbitragers, reducing the effects of investor sentiment (Fama and Macbeth, 1973).

De Long et al. (1990) highlight the role of rational and noise traders in stock pricing, arguing that limitations to arbitrage allow for noise traders and that stock prices consist of two elements: a fundamental value given by rational investors and a risk premium attributed to noise traders. Baker and Wurgler (2006, 2007) identify two types of investors: rational traders, arbitrageurs, and sentiment traders. Arbitrageurs make informed decisions to determine expectations about the future value of an asset. At the same time, sentiment traders (i.e., noise traders) could be optimistic or pessimistic about the market, leading them to underestimate or overestimate asset prices.

Most investor sentiment literature focuses on the U.S. markets and finds evidence that investor sentiment affects securities pricing and stock returns. The literature also finds that investor sentiment is driven by demand shocks and/or arbitrage limitations (Lee, Shleifer, &Thaler, 1991; Lee, Jiang, & Indro, 2002; Brown & Cliff, 2004; Baker & Wurgler, 2007; Verma, Baklaci, & Soydemir, 2008; Ho &Hung, 2009; Baker, Wurgler, & Yuan, 2012; Huerta, Egly & Escobari, 2016).

A growing branch of literature investigates the effects of international investor sentiment on a country’s stock valuation. Investor sentiment is: “a belief about future cash flows and investment risks that is not justified by the facts at hand” (Baker and Wurgler, 2007). Lee et al. (2002) find that changes in investor sentiment and excess stock returns are positively correlated. They also find that bullish shifts in investor sentiment are inversely correlated to market volatility. Verma and Soydemir (2006) investigate how U.S. investor sentiment propagates to other countries, finding that U.S. investor sentiment influences international stock market returns, varying significantly across countries. They also find that changes in institutional investor sentiment have a more substantial influence than individual investor sentiment. Rational and irrational factors drive both but conclude that U.S. investor sentiment can be an essential spillover factor. Investor sentiment can influence trading decisions at both the firm and market levels, especially for firms that are difficult to value or arbitrage (e.g., Baker and Wurgler, 2007). Rodriguez-Nieto & Mollick (2020) identify that increases in U.S. stock volatility contributed to the financial contagion to the major markets in the Americas during the U.S. financial crisis.

Schmeling (2009) uses consumer confidence as a proxy for individual investor sentiment and assesses its impact on stock returns for 18 industrialized countries. He finds a causal effect between investor sentiment and stock market returns from t to t_{t+1}. He observes that individual investor sentiment negatively forecasts stock market returns and suggests that this is stronger for countries that are culturally more prone to overreaction and herd-like behavior.

Hwang (2011) finds that U.S. investor sentiment can influence the demand for foreign securities, affecting their price and deviating from their fundamental value. Baker et al. (2012) find evidence that investor sentiment can influence market volatility, and that return predictability is consistent with over-reaction corrections. They also find that investor sentiment comprises two factors, namely “global” and “local,” and that global investor sentiment is spilled across markets through capital flows.

Sayim and Rahman (2015) find significant spillover from U.S. individual and institutional investor sentiment to the Turkish stock market stock returns. Perez-Liston, Huerta, and Gutierrez (2015) use a vector autoregressive model (VAR) to identify U.S. investor sentiment spillover to Mexican investor sentiment and the Mexican stock market returns. They attribute this spillover to the cross proximity, strong trade ties, ease of capital flows, and exchange rates.

We apply the multivariate DCC–GARCH model, introduced by Engle (2002), to identify the role of U.S. market volatility and U.S. investor sentiment as sources of contagion from the U.S. to the Americas during the 2008-2009 financial crisis. We first assess contagion from the U.S. to Argentina, Brazil, Canada, Chile, Colombia, Mexico, and Peru. We use the CBOE Volatility Index®, or VIX, to control for the impact of market volatility on the conditional correlations obtained from the DCC-GARCH between the U.S. and each stock market. We then assess the effects of investor sentiment on these conditional correlations by using survey-based proxies used in the literature (Brown and Cliff, 2004; Huerta, Egly, and Escobari, 2016) as direct measures of investor sentiment.

We distinguish the effects of the Individual Investor Sentiment, represented by the American Association of Individual Investors (AAII) survey, and Institutional Investor Sentiment, using the Investor Intelligence (II) Survey.

This essay contributes to the investor behavior literature by identifying the role of the perceived market volatility *VIX*, individual investor confidence *AAII*, and institutional investor confidence *II* on the stock market returns of the major markets in the Americas during the U.S. financial crisis. We find that institutional investor sentiment not only has a more significant influence than individual investor sentiment on the stock returns of the U.S. but that this more significant influence also applies to the largest markets in the Americas.

Individual and Institutional Investor Sentiment

We use two sentiment indexes widely used in the literature to capture the effect of institutional and individual investor sentiments on the stock returns of the major stock markets in the Americas. Following Brown and Cliff (2004) and Huerta et al. (2016), we first use a survey performed by the American Association of Individual Investors AAII to proxy individual investor sentiment. The American Association of Individual Investors is a nonprofit corporation that provides education, information, and research to individual investors. Since 1987, Individual investors have been pooled weekly to measure the percentage of bullish, bearish, or neutral about the stock market's short-term performance. Those who are said to be bearish are individual investors who are pessimistic about the stock market performance in the next six months; those who are bullish expect the stock prices to rise, and those who are neutral expect the stock prices to remain unchanged. Following Brown and Cliff (2004), we build the *AAII* index by calculating the difference between bullish and bearish investors; the result is the bull-bear spread, commonly used as a proxy for individual investor sentiment.

We then use the Investors Intelligence II survey to build a proxy for institutional investors' Intelligence. The Investors Intelligence Survey analyses the market views of more than 100 investment advisor newsletters and interprets them as bullish, bearish, and those that expect a correction or neutral. Since professional advisors are the authors of these letters, we follow Brown and Cliff (2004) and use this survey to build a proxy for Institutional Investor Sentiment. The Investor Intelligence Index, *II*, represents the spread between the percentage of bullish and bearish newsletters.

Since individual and institutional investor sentiments positively affect U.S. stock returns, we hypothesize that investor sentiment will also impact international markets. We define three hypotheses based on individual and institutional investor sentiments:

H1: *Increases in the Individual Investor Sentiment, AAII, will have positive and statistically significant effects on Canadian and Latin American stock market stock returns.*

H2: *Increases in the Institutional Investor Sentiment II will have positive and statistically significant effects on the stock returns of Canadian and Latin American stock markets.*

H3: *Institutional Investor Sentiment II will have a more significant influence on the stock returns of the markets in the Americas than Individual Investor Sentiment as measured by AAII.*

DATA AND DESCRIPTIVE STATISTICS

We collect country-specific data from DataStream, consisting of weekly closing prices from Argentina (BURCAP), Brazil (BOVESPA), Canada (S&P/TSX Composite Index), Chile (IPSA), Colombia (IGBC), Mexico (BOLSA), Peru (ISBL), and the United States (S&P 500). Data are in U.S. Dollars from January 1, 2002, through December 31, 2015.

We use three proxies to measure sentiment. First, we use the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) to proxy implied market volatility. The VIX is widely used as a fear gauge since it represents the market's expectation of stock market volatility for the next 30-day period.

Following Brown and Cliff (2004), we employ two survey-based weekly sentiment measures collected by the American Association of Individual Investors, *AAII*, and Investor's Intelligence *II*.

Table 1 reports the descriptive statistics for the pooled dataset, both in levels and returns for the country stock indexes, and the first differences for *VIX*, *AAII*, and *II*. We first report the data in levels and provide statistics about the mean, standard deviation, variance, skewness coefficient, kurtosis coefficient, the Shapiro-Wilk normality test, and the Ljung–Box autocorrelation test. Except for *AAII*, the Shapiro-Wilk test statistic suggests that the series are non-normally distributed. The Ljung–Box test statistics indicate that all return series are auto-correlated except for Argentina and Peru.

For the data reported in returns and differences, we observe that Colombia and Peru report the highest means at 0.24, with standard deviations of 3.91 and 4.15, respectively. They are followed by Mexico with mean returns of 0.17, Argentina at 0.16, and Chile at 0.12, respectively, with standard deviations of 3.83, 5.1, and 2.92. Brazil and Canada report identical mean returns of 0.09; however, their standard deviations differ at 4.77 and 3.20, respectively. We observe that except for *AAII*, the series are non-normally distributed, and except for the stock returns of Argentina and Peru, all series are auto-correlated.

Table 2 reports the unconditional correlation between the pooled sample's stock index returns, ΔVIX Δ, AAII, and ΔII. All pairwise correlations amongst the stock returns are positive and significant. The highest correlations are those between the U.S., Canada, Mexico, and Brazil, with pairwise correlations ranging between 0.6487 and 0.7818. Correlations between the stock index returns and changes in VIX are negative and significant. It is unsurprising to find a high correlation between the U.S. and ΔVIX of -0.7976. Still, it is interesting that the highest correlations are with Mexico, Canada, and Brazil at -0.6934, -0.6655, and -0.5594, respectively, since they represent the largest stock markets in the Americas. The relationship between investor sentiment indexes and country-specific stock indexes is positive and significant. The individual investor sentiment AAII ranges from 0.1919 for Canada, Chile with 0.1633, the U.S. at 0.1566, and 0.1038 for Colombia. The institutional investor sentiment *II* presents larger correlation coefficients with stock returns than the individual investor sentiment *AAII* in all cases, ranging from a high of 0.4090 for the U.S., 0.3154 for Mexico, and 0.3057 for Canada, with the lowest pairwise correlation being that of Peru at 0.2009. We also find a low correlation coefficient of 0.2074 between *II* and *AAII*, highlighting the importance of including both sentiment measures in the empirical model.

Table 3 includes the results of the stationary tests for the country stock indexes expressed in returns and VIX, individual investor sentiment *AAII*, and institutional investor sentiment *II* expressed in first differences. We perform the ADF, KPSS, and Philips-Perron tests, identifying that all series are stationary.

THE DCC MODEL AND ESTIMATION RESULTS

We use a DCC-GARCH model, introduced by Engle (2002), to assess the changes in the conditional pairwise correlations between the stock market returns, the difference in market volatility ΔVIX, the change in individual investor confidence ΔAAII, and the change in institutional investor confidence represented by ΔII.

The model used in this study is as follows. We model the return dynamics by using an autoregressive model in the form of:

$$r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{\Delta VIX} + \gamma_3 r_{t-1}^{\Delta AAII} + \gamma_3 r_{t-1}^{\Delta II} + \varepsilon_t , \tag{1}$$

The vector of returns is:

$$r_t = \left(r_{Argentina,t}, r_{Brazil,t}, r_{Canada,t}, r_{Chile,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t}, r_{U.S.,t}\right)'$$

and the vector of error terms is:

$$\varepsilon_t = \left(\varepsilon_{Argentina,t}, \varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{Peru,t}, \varepsilon_{U.S.,t}\right)'$$

The results for the multivariate DCC–GARCH model are reported in Table 4. The results for the mean equations indicate that the constant term γ_0 is positive and statistically significant for all markets. The AR(1) term γ_1 yields mixed results, being positive and statistically significant for Colombia and negative and statistically significant for the U.S. and Canada. The ΔVIX term is only statistically significant and positive for Brazil, Colombia, and Mexico. The Individual Investor Sentiment $\Delta AAII$ is not significant for any country. The Institutional Investor Sentiment ΔII is positive and significant for Peru and the U.S.; it is positive but not significant for Argentina.

We look at the parameter estimates of the mean and conditional variance equations to verify the appropriate use of the GARCH specification. We confirm that all coefficients are significant, thus ensuring the proper use of the specification. The volatility persistence (a + b) is near one (1) in all cases, varying from a high of 0.99 for Argentina and 0.98 for the U.S. to a low of 0.86 for Colombia, indicative of high volatility persistence. The lambda1 and lambda2 parameters are statistically significant at 1%, verifying the appropriate use of the DCC-GARCH over a CCC model.

Table 5 includes the DCC-GARCH-based correlations between ΔVIX, $\Delta AAII$, and ΔII, and the stock returns during the pooled data period. As expected, we see that correlations between the ΔVIX and stock market returns are negative and significant, indicating that the greater the volatility in the U.S., the lower the returns of these markets. We observe that the pairwise correlations between ΔVIX correlations are larger in magnitude for the U.S. at -0.838, followed by those of Mexico at -0.715, Canada at -0.697, and the lowest being Argentina at -0.512. The pairwise correlations with the individual investor sentiment *AAII* are all positive and significant, ranging from 0.292 for *II*, Canada at 0.213, and the U.S. at 0.196, with the lowest being Peru at 0.179; this indicates that positive individual investor confidence is associated with positive stock market returns. We also observe that pairwise correlations with the institutional investor confidence *II* are positive and significant; however, we observe that the magnitude of these coefficients is greater than the estimated coefficients for the individual investors. The highest pairwise correlation coefficients between *II* and the stock market returns are those associated with the U.S., Canada, and Mexico, ranging from 0.603 for the U.S., 0.499 for Mexico, and 0.468 for Canada.

Further, the correlation between ΔVIX and ΔII is negative and statistically significant at -0.507, which is greater than that observed between the ΔVIX and ΔII at -0.143, indicating a more substantial inverse relation between the fear index and institutional investor confidence when compared to individual investors. We also observe that the pairwise correlations amongst countries are all positive and significant. It becomes clear that the highest correlations are those between the most developed countries, namely the U.S., Canada, Mexico, and Brazil. We identify the highest pairwise correlations between Brazil-Canada at 0.839, followed by U.S.-Canada at 0.825, U.S.-Mexico at 0.806, Brazil-Mexico at 0.794, and U.S.-Brazil at 0.711.

Explaining the Conditional Correlation Coefficients

One advantage of the DCC-GARCH model is that we can obtain the dynamic correlations between ΔVIX, ΔII, and $\Delta AAII$ and the stock market returns and represent them graphically. Figure 1 includes the dynamic conditional correlations between ΔVIX and the various stock market returns. We observe a general downward trend during the pre-crisis period, indicating that the inverse relationship between ΔVIX and each stock market grew from approximately -0.1 to levels greater than -0.5 in all cases. We observe a slight correction in the opposite direction during the financial crisis, which sharply reverts and remains at the highest negative levels. For the post-crisis period, the dynamic conditional correlations between ΔVIX and stock returns stay at lower levels than during the pre-crisis period, with the most notorious being those of Canada and Mexico at around -0.7 and the U.S. at -0.9.

Figure 2 documents the conditional correlations for all pairs between ΔII and the stock markets. We observe that correlations are positive and with an upward trend during the pre-crisis period; these correlations remain at around the highest level reached during the financial crisis but with apparently increased volatility. We observe that correlations during the post-crisis period remain higher than in the pre-financial crisis period, with a notorious upper trend for the U.S., Canada, and Mexico. Dynamic conditional correlations reach around 0.5 for the U.S. and 0.4 for Canada and Mexico.

Figure 3 includes all pairwise dynamic conditional correlations between individual investor sentiment *ΔAAII* and the stock markets. We observe positive pairwise correlations, with upward trends in most cases, during the pre-crisis period. We then detect a slight downward trend after the beginning of the financial crisis period, followed by a sharp correction. We observe that during the post-crisis period, the correlations remain positive and, in most cases, higher than the levels observed during the pre-crisis period. However, they behave very erratically, with similar patterns for Brazil, Canada, Chile, Mexico, Peru, and the U.S.

We are interested in defining if the financial crisis affected the conditional correlation coefficients between the stock market returns, *ΔVIX*, *ΔAAII*, and *ΔII*. To capture the effect of the financial crisis on these pairwise conditional correlations, we use the following regression model:

$$\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DSCRISIS_t + \epsilon_{ij,t}, \text{ for } i \neq j \qquad (2)$$

We identify two periods in the sample: the first runs from January 1, 2002, to December 31, 2007, and we define it as the pre-crisis period. We describe the second period as the time since the crisis because it began in the wake of the financial crisis on January 01, 2008, and continues until the end of the pooled sample (December 31, 2015). We create a dummy variable (*DSCRISIS*) for the since-the-crisis period, which is set equal to one for such period and zero otherwise. We regress the predicted dynamic conditional correlation coefficients. $\hat{\rho}_{ij,t}$, Between markets and sentiment indexes i and j at time t, with dummy variable *DSCRISIS* for the since-the-crisis period (January 1, 2008, to December 31, 2015).

The estimation results in Table 6 indicate that the financial crisis has a significant impact on the conditional correlation for all the pairwise correlations. We first examine the effects on the pairwise correlations between the stock markets in the Americas and Δ*VIX*. We observe that the financial crisis has an inverse and significant impact in all cases, indicating that the relationship between Δ*VIX* and each stock index increases after the financial crisis begins. We identify that Δ*VIX* has the highest negative pairwise correlations with the U.S. at -0.8157, Mexico at -0.6963, Canada at -0.6628, Chile at -0.5662, Brazil at -0.5648, Peru at -0.5106, Colombia at -0.4954, and Argentina at -0.4876.

The pairwise correlations between these stock market indexes and the individual investor confidence *AAII* increase significantly. We identify that the correlation with the U.S. has the largest coefficient at 0.1902, followed by Canada at 0.1858, Chile at 0.1682, Argentina at 0.1635, Brazil at 0.1551, Mexico at 0.1493, Peru at 0.1330, and Colombia at 0.1202. This confirms that the contemporaneous relationship between individual investor confidence and stock market returns increased during the U.S. financial crisis.

We identify that the effect on the relationship between the institutional investor confidence *II* and the stock market returns is also significant and relatively greater in magnitude than the coefficients observed for the pairwise correlations between *AAII* and each stock index. The correlation coefficients range from a high of 0.4899 with the U.S., Mexico at 0.3780, Canada at 0.3627, Brazil at 0.3060, Chile at 0.2713, Colombia at 0.2580, Argentina at 0.2413, and Peru at 0.2306.

To capture the effects of the financial crisis period and the following post-crisis period in more detail, we break the since-the-crisis period into two. We redefine the resulting subsamples as pre-crisis, crisis, and post-crisis. The pre-crisis period runs from January 1, 2002, to December 31, 2007. The crisis period starts in the wake of the financial crisis on January 01, 2008, and ends on June 30, 2009. The post-crisis period includes data from July 1, 2009, and ends on December 31, 2015.

To differentiate the effect of the financial crisis and the post-crisis on the pairwise correlations between ΔVIX, ΔAAII, ΔII, and the country-specific stock markets, we use the following regression model:

$$\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}, \text{ for } i \neq j \qquad (3)$$

We create dummy variables for the crisis period (*DCRISIS*) and the post-crisis period (DPOSTCRISIS), which are set equal to one for each respective period and zero otherwise. We regress the predicted dynamic conditional correlation coefficients $\hat{\rho}_{ij,t}$, between markets and sentiment indexes *i* and *j* at time *t*, with dummy variable *DCRISIS* for the crisis period and DPOSTCRIS for the post-crisis period.

The estimation results for equation 5, which are crucial for understanding the impact of the U.S. financial crisis on stock market correlations in the Americas, are reported in Table 7. Panel A includes the regression results for the pairwise correlations between the stock returns of the U.S. and each of the other countries. We observe that $\lambda_0 C$during the pre-crisis period, the impact of the U.S. financial crisis is significant, with coefficients ranging from a high of 0.6354 for Canada, followed by Mexico at 0.6304, Brazil at 0.5340, Chile at 0.4694, Argentina at 0.4132, and Colombia at 0.3789. This underscores the profound influence of the financial crisis on stock market correlations. λ_1 Is also positive and significant, with coefficients ranging from a high of 0.1933 for Peru, 0.1848 for Colombia, 0.1747 for Mexico, 0.151 for Argentina, 0.1359 for Brazil, 0.1354 for Chile, and 0.1007 for Canada. The effect of the post-financial crisis, as indicated by λ_2, is positive and significant, ranging from a high of 0.1795 for Peru, 0.1562 for Canada, 0.1427 for Colombia, 0.1400 for Mexico, 0.1365 for Argentina, 0.1251 for Chile, and 0.1147 for Brazil. In this study, we interpret a strong correlation between the stock returns of the U.S. and each of the countries. Notably, all countries increase their correlations with the U.S. during the financial crisis, indicating contagion. Except for Canada, which continues to strengthen its co-movements with the U.S. after the financial crisis has ended, the other countries maintain higher correlations than those observed before the start of the financial crisis. Yet, they are smaller than those from the crisis.

In table 7, panel B, we report the effects of the financial crisis on the pairwise correlations between the stock markets in the Americas and ΔVIX. In all cases, we observe negative and statistically significant coefficients for the constant $\lambda_0$that indicates a strong inverse relationship during the pre-crisis period. The λ_0 coefficients range from -0.6818 for the U.S., -0.5532 for Mexico, -0.5301 for Canada, -0.4507 for Brazil, -0.4299 for Chile, -0.3715 for Peru, -0.3646 for Colombia, and -0.3512 for Argentina. We observe that the financial crisis λ_1 effect is also negative and significant for all pairs, indicating contagion since the inverse correlations increase during this period. The λ_1 coefficients range from Mexico at -0.1683, Argentina at -0.1592, Colombia at -0.1448, Chile at -0.1434, Peru at -0.1374, U.S. at -0.1318, Brazil at -0.1303 ad Canada at -0.877. The effect of the post-crisis period λ_2 is negative and significant in all cases, with most cases being smaller in magnitude than λ_1, such as Mexico at -0.1372, Chile at -0.1346, Argentina at -0.1312, Colombia at -0.1276, and Brazil at -0.1104. In the cases of Canada at -0.1460, Peru at -0.1394, and the U.S. at -0.1343, the post-financial crisis coefficients for $are \lambda_2$, are larger than those observed during the financial crisis. These observations indicate the long-term effects of the financial crisis on the correlations between VIX and each country in the study.

The results for the effects of the financial crisis for the individual investor confidence *AAII*, and each of the country-specific stock returns, are included in Table 7 panel C. We first observe positive and significant coefficients for λ_0, that range from 0.1651 for the U.S, followed by Canada at 0.1542, Chile at 0.1369, Brazil at 0.1312, Argentina at 0.1176, Mexico at 0.1151, Peru at 0.1083, and Colombia at 0.095. We observe mixed effects of the financial crisis on these pairs, with five countries presenting inverse and statistically significant coefficients, like Peru at -0.0324, Canada at -0.0320, the U.S. at -0.0201, Brazil at -0.0131, and Chile at -0.0059. The other pairs observe positive and significant coefficients, ranging from 0.0153 for Mexico, 0.0052 for Colombia, and 0.0041 for Argentina. The effect of the post-crisis period is positive and significant for all pairs, indicating that increases in individual investor confidence are associated with increases in stock returns. The coefficients range from 0.0555 for Argentina, 0.0462 for Canada, 0.0398 for Chile, 0.0386 for Mexico, 0.0378 for Peru, 0.0355 for the U.S., and 0.0331 for Brazil.

The last panel for Table 7 is panel D, which includes the results of the regressions for the pairs composed of the institutional investor confidence *II* and the stock returns for each country. We first observe that the constant termλ_0, which represents the pre-crisis period, is positive and significant for all the pairs. We find that higher institutional investor confidence is correlated to positive stock market returns in the Americas during the pre-crisis period. The coefficients range from a high of 0.3590 for the U.S., followed by Mexico at 0.2833, Canada at 0.2602, Colombia at 0.2333, Brazil at 0.2208, Chile at 0.2107, Argentina at 0.1490, and Peru at 0.1477. The table then reports that the effect of the U.S. financial crisis, represented by λ_1, is positive and significant for all the pairs. This suggests contagion, with coefficients ranging from a high of 0.0996 for the U.S. followed by Mexico at 0.0854, Peru at 0.0789, Brazil at 0.0684, Canada at 0.0654, Argentina at 0.0604, Colombia at 0.0413, and Chile at 0.0283. Finally, the effect of the post-crisis period on the pairs is positive and significant, with coefficients that are larger than those from the crisis period in most cases except for Colombia, which is smaller than the effect from the crisis. The λ_2 The coefficients range from a high of 0.1381 for the U.S. to Canada at 0.1111, Argentina at 0.0997, Mexico at 0.0969, Brazil at 0.0891, Peru at 0.0838, Chile at 0.0680, and Colombia at 0.0208.

We compare the coefficient of determination R^2 for each ostock market return the U.S., VIX, *AAII*, and *II*, to identify the regression with the highest explaining value for each regression model. For Argentina, we recognize that *II* has the highest R^2 value of 0.5602, followed by VIX at 0.4153, the U.S. at 0.3867, and *AAII* at 0.3751. For Brazil, we identify that the highest R^2 value is from *II* at 0.4995, VIX at 0.2918, the U.S at 0.2537, and *AAII* at 0.1579. For Canada, we observe a similar pattern, with a R^2value for *II* at 0.5685, followed by VIX at 0.4256, the U.S at 0.3784, tailed by *AAII* at 0.3613. For Chile, we identify that the highest R^2value is VIX at 0.4402, followed by the U.S. at 0.4141, *II* at 0.4019, an *AAII* at 0.115. The U.S. leads the case of Colombia with a R^2 of 0.4834, VIX at 0.4349, *AAII* at 0.1246, and *II* at 0.0786. FMexico hasthe highest R^2 value with *II* at 0.4443, followed by VIX at 0.369, the U.S. at 0.3069, and *AAII* at 0.0884. For Peru, the highest $R^2$is for *II* at 0.5531, the U.S. at 0.4767, VIX at 0.4266, and *AAII* at 0.279. The Case of the U.S. has the highest R^2 value with *II* at 0.5531, VIX at 0.2748, and *AAII* at 0.1608.

Our findings support the flight to safety theory indicating that investor confidence played a significant role in the contagion from the U.S. stock market to the major stock markets in the Americas during the U.S. financial crisis. We also identify that the institutional investor confidence II's level of influence is significantly higher than that of the individual investor confidence *AAII*. These findings align with those of Verma and Soydemir (2006), who observe that institutional investor sentiment has a more considerable impact than individual investor confidence on international markets. Our findings are related to the observations made by Huerta, Egly, and Escobari (2016) that large institutional investors influence the U.S. markets at a greater rate than individual investors do, attributing this to their greater access to capital and their tendency to trade in large blocks. We contribute to the literature by identifying that U.S. institutional investors have greater influence than individual investors on the U.S. markets and the stock returns of the largest market in the Americas. We observe that this influence increased during the U.S. financial crisis.

SUMMARY AND CONCULSIONS

This study examines the role of U.S. investor sentiment as a source of financial contagion across major stock markets in the Americas during the U.S. financial crisis. Using a DCC-GARCH model, we analyze the dynamic correlations between U.S. market volatility, individual and institutional investor sentiment, and stock returns in Argentina, Brazil, Canada, Chile, Colombia, Mexico, Peru, and the United States.

Our findings indicate that institutional investor sentiment has a stronger impact on international stock markets than individual investor sentiment. Institutional investors' behavior significantly influenced stock returns in the Americas, particularly during the financial crisis. This supports the flight-to-safety theory, where large investors react to uncertainty by shifting capital away from riskier markets.

We also observe a negative and significant correlation between changes in VIX (market volatility) and stock returns, reinforcing the role of market uncertainty in driving financial contagion. Furthermore, correlations between investor sentiment and stock returns increased during the financial crisis, highlighting sentiment-driven spillover effects.

This study contributes to the literature by demonstrating that U.S. institutional investor sentiment has a more pronounced influence on stock markets in the Americas than individual sentiment, especially during periods of financial instability. Policymakers and investors should consider the impact of institutional trading behavior in times of crisis, as large-scale capital movements can amplify market contagion.

Future research could explore how investor sentiment affects stock market contagion in more recent crises, such as the COVID-19 pandemic, and assess the role of sentiment-driven investment strategies in global markets.

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APPENDIX

TABLE 1
DESCRIPTIVE STATISTICS (WEEKLY DATA FROM JAN. 2002 TO DEC. 2015)

Levels	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	U.S.	VIX	*AAII*	*II*
Observations	730	730	730	730	730	730	730	730	730	730	730
Mean	1930.15	391.68	10198.77	1191.24	4.56	2170.68	899.30	1333.68	19.97	6.86	21.82
Standard Dev.	898.52	202.55	3071.00	483.43	2.56	937.89	483.31	340.36	9.25	18.19	14.78
Variance	807340.00	41027.22	9431054.00	233704.20	6.56	879631.90	233593.10	115841.80	85.49	331.05	218.58
Skewness	0.02	-0.03	-0.60	-0.09	-0.19	-0.43	-0.15	0.79	2.33	0.03	-0.90
Kurtosis	2.31	1.88	2.11	2.02	1.79	1.72	1.65	2.88	10.89	2.91	3.58
Shapiro-Wilk (Normality)	6.405***	7.354***	9.061***	6.847***	8.465***	9.491***	8.827***	8.718***	11.256***	-1.05	8.013***
Ljung-Box test (Auto Correlation)	20045.81***	21420.17***	20977***	24122.14***	23943.21***	23931.28***	23237.52***	22284.44***	8672.29***	1946.80***	6091.48***
Returns/Differences											
	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.	Δ_VIX	Δ_*AAII*	Δ_*II*
Observations	730	730	730	730	730	730	730	730	730	730	730
Mean	0.16	0.09	0.09	0.12	0.24	0.17	0.24	0.08	-0.01	-0.05	-0.02
Standard Dev.	5.1	4.77	3.20	2.92	3.91	3.83	4.15	2.44	3.16	14.37	4.83
Variance	26.04	22.75	10.24	8.55	15.32	14.67	17.24	5.94	9.98	206.59	23.35
Skewness	-1.92	-0.71	-1.33	-1.68	-1.18	-0.64	-0.59	-0.85	0.73	0	0.04
Kurtosis	15.21	7.93	13.53	18.49	9.23	13.13	8.46	11.2	13.73	3.46	3.94
Shapiro-Wilk (Normality)	9.796***	7.966***	9.601***	9.413***	8.501***	9.324***	7.739***	8.684***	9.793***	1	3.201***
Ljung-Box test (Auto Correlation)	33.3	64.50***	66.66***	70.24***	58.46**	64.51**	40.04	54.55*	58.03**	108.49***	102.49***

Notes: All stock indexes in levels represented in U.S. Dollars. All variables are in returns except *VIX*, *AAII*, and *II*, which differ. Sharpe Ratio = Mean/Standard-Dev.

TABLE 2
CORRELATION COEFFICIENTS OF WEEKLY STOCK INDEX RETURNS, *TED*, *AAII*, AND *II* – (WEEKLY DATA FROM JAN. 2002 TO DEC. 2015)

	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	U.S.	*VIX*	*AAII*	*II*
In Levels											
Argentina	1										
Brazil	0.6572***	1									
Canada	0.8741***	0.8809***	1								
Chile	0.7267***	0.8869***	0.8823***	1							
Colombia	0.7043***	0.865***	0.8858***	0.9648***	1						
Mexico	0.883***	0.8236***	0.9511***	0.9111***	0.9169***	1					
Peru	0.7618***	0.9022***	0.8885***	0.9644***	0.9307***	0.9244***	1				
U.S.	0.8234***	0.2533***	0.6345***	0.4132***	0.422***	0.6951***	0.4627***	1			
VIX	-0.295***	-0.0061***	-0.2842***	-0.142***	-0.152***	-0.2409***	-0.0729***	-0.5016***	1		
AAII	-0.0832***	-0.2382***	-0.1379***	-0.1332***	-0.1422***	-0.1403***	-0.162***	0.0796***	-0.3911***	1	
II	0.1752***	-0.0818***	0.129***	0.0641***	0.0679***	0.1257***	0.0344***	0.3789***	-0.7017***	0.5906***	1

Returns/Differenced

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.	*VIX*_CHG	*AAII*_CHG	*II*_CHG
RET_ARG	1										
RET_BRA	0.5741***	1									
RET_CAN	0.5844***	0.7537***	1								
RET_CHI	0.486***	0.6761***	0.6591***	1							
RET_COL	0.4015***	0.5508***	0.5539***	0.5423***	1						
RET_MEX	0.5346***	0.741***	0.7454***	0.6678***	0.5802***	1					
RET_PER	0.5059***	0.6769***	0.7568***	0.5785***	0.4932***	0.6651***	1				
RET_U.S.	0.519***	0.6487***	0.7818***	0.5966***	0.506***	0.7731***	0.562***	1			
*VIX*_CHG	-0.4453***	-0.5594***	-0.6655***	-0.5573***	-0.4913***	-0.6934***	-0.532***	-0.7976***	1		
*AAII*_CHG	0.1525***	0.1354***	0.1919***	0.1633***	0.1038***	0.1264***	0.1494***	0.1566***	-0.0798***	1	
*II*_CHG	0.2037***	0.265***	0.3057***	0.2516***	0.2381***	0.3154***	0.2009***	0.4090***	-0.3253***	0.2074***	1

TABLE 3
UNIT ROOT TESTS ON WEEKLY DATA FROM JANUARY 1, 2002, TO DECEMBER 31, 2015

Series	ADF(k)	KPSS(19)	PHILLIPS-PERRON(k)
RET_ARG	-14.833 (2)***	0.0552	-28.642***
RET_BRA	-14.497 (2)***	0.0738	-29.400***
RET_CAN	-19.193 (1)***	0.0385	-28.760***
RET_CHI	-14.262 (2)***	0.0593	-28.560***
RET_COL	-12.769 (2)***	0.0599	-26.996***
RET_MEX	-15.498 (2)***	0.0519	-29.485***
RET_PER	-26.325 (0)***	0.0359	-26.328***
RET_U.S.	-27.962 (0)***	0.0578	-27.976***
VIX_CHG	-20.078 (1)***	0.0253	-32.042***
AAII_CHG	-20.806 (2)***	0.0188	-44.237***
II_CHG	-17.761 (1)***	0.0296	-23.538***

Notes: The lag length (k) is selected as follows: the null hypothesis is the unit root for the ADF test. We use the Campbell and Perron (1991) data-dependent procedure starting with an upper bound $k_{max} = 2$, on k. if the last lag is significant, choose $k = k_{max}$; if not, we reduce k by one and continue this process until this is satisfied, or else k = 0. The KPSS assumes a null that the series is stationary. We use the Bartlett-Kernel criteria to select k = 19 as truncating parameter. The critical values for the KPSS test are 0.119 (10%), 0.146 (5%), and 0.216 (1%) . The Phillips-Perron test has a null hypothesis of unit root and uses the equation $k = 4(T/100)^{2/9}$ to select the maximum lag, in this case k = 7. *, **, and *** significant at 10%, 5% and 1%, respectively.

TABLE 4
DCC ESTIMATIONS FOR STOCK RETURNS, VIX, AAII, AND II (WEEKLY DATA FROM JAN. 2002 TO DEC. 2015)

	RET_U.S.	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER
Mean Equations								
ϒ0	0.33738***	0.42810***	0.49117***	0.38381***	0.30679***	0.52815***	0.50810***	0.45549***
	(0.0575)	(0.1390)	(0.1299)	(0.0799)	(0.0826)	(0.1213)	(0.0977)	(0.1223)
ϒ1	-0.10692***	-0.04435	-0.04263	-0.09703***	0.03277	0.07279**	-0.03726	0.01583
	(0.0321)	(0.0364)	(0.0271)	(0.0257)	(0.03164)	(0.0368)	(0.0294)	(0.0299)
ϒ2 (Δ*VIX*)	0.04792	-0.02693	0.10258**	0.01466	0.05366	0.16285***	0.10037**	-0.00924
	(0.0293)	(0.0515)	(0.05176)	(0.0347)	(0.0336)	(0.0476)	(0.0427)	(0.0089)
ϒ3 (Δ*AAII)*	-0.00296	0.00595	0.00941	-0.00403	0.00683	-0.00720	-0.00244	0.01623
	(0.0043)	(0.0096)	(0.0097)	(0.0059)	(0.0059)	(0.0087)	(0.0071)	(0.0286)
ϒ3 (Δ*II*)	0.02714*	-0.00849	0.03564	0.03094	0.01281	0.02623	0.01213	0.09922**
	(0.0152)	(0.0299)	(0.0310)	(0.0197)	(0.0192)	(0.0285)	(0.0238)	(0.0496)
Variance Equations								
Cons	0.18749***	0.76925***	1.48375***	0.41229***	0.74120***	2.8151***	0.74069***	0.76746***
	(0.0427)	(0.2682)	(0.3519)	(0.0886)	(0.2158)	(0.9571)	(0.1633)	(0.2371)
Arch	0.13326***	0.13804***	0.07856***	0.08243***	0.12714***	0.18973***	0.11673***	0.06522***
	(0.0167)	(0.0232)	(0.0128)	(0.0124)	(0.0265)	(0.0517)	(0.0168)	(0.0135)
Garch	0.85070***	0.85274***	0.85933***	0.88087***	0.79129***	0.67330***	0.84416***	0.89298***
	(0.0167)	(0.0231)	(0.0224)	(0.0164)	(0.0437)	(0.0871)	(0.0204)	(0.0220)
Persistence								
	0.98396	0.99078	0.93790	0.96330	0.91843	0.86302	0.96089	0.95820
Multivariate DCC Equation								
Lambda1	0.01079***							
	(0.0014)							
Lambda2	0.97745***							
	(0.0026)							
Observations	729							
χ2	364.19							
χ2 (p-value)	0.000							

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01. The mean equation is $r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{\Delta VIX} + \gamma_3 r_{t-1}^{\Delta AAII} + \gamma_3 r_{t-1}^{\Delta II} + \varepsilon_t$ Where $r_t = (r_{Argentina,t}, r_{Brazil,t}, r_{Canada,t}, r_{Chile,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t}, r_{U.S.,t})'$; and $\varepsilon_t \mid I\Omega_{(t-1)} \sim N(O, H_t.)$. The variance equations are $h_{ii,t} = c_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}\, for\ i = 1,2, \dots, n.$ for i=1,2,…,n. The null for the x^2test is $H_0 : \alpha = \beta = 0$. Persistence is calculated as the sum of the coefficients in the variance equation (Arch and Garch).

TABLE 5
MGARCH-DCC BASED CORRELATIONS BETWEEN VIX, AAII, II, AND STOCK RETURNS

	ΔVIX	$\Delta AAII$	ΔII	RET_U.S.	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER
ΔVIX	1										
$\Delta AAII$	-0.143* (0.082)	1									
ΔII	-0.507*** (0.06)	0.292*** (0.08)	1								
RET_U.S.	-0.838*** (0.024)	0.196** (0.087)	0.603*** (0.058)	1							
RET_ARG	-0.512*** (0.057)	0.182** (0.084)	0.339*** (0.072)	0.603*** (0.05)	1						
RET_BRA	-0.597*** (0.05)	0.186** (0.089)	0.419*** (0.071)	0.711*** (0.039)	0.672*** (0.047)	1					
RET_CAN	-0.697*** (0.04)	0.213** (0.087)	0.468*** (0.068)	0.825*** (0.026)	0.647*** (0.048)	0.839*** (0.024)	1				
RET_CHI	-0.575*** (0.051)	0.188** (0.087)	0.379*** (0.073)	0.635*** (0.048)	0.541*** (0.057)	0.724*** (0.04)	0.73*** (0.041)	1			
RET_COL	-0.553*** (0.054)	0.157* (0.089)	0.305*** (0.077)	0.614*** (0.052)	0.557*** (0.055)	0.751*** (0.041)	0.743*** (0.044)	0.694*** (0.046)	1		
RET_MEX	-0.715*** (0.038)	0.18** (0.089)	0.499*** (0.066)	0.806*** (0.028)	0.628*** (0.051)	0.794*** (0.029)	0.793*** (0.03)	0.73*** (0.039)	0.674*** (0.047)	1	
RET_PER	-0.52*** (0.056)	0.179** (0.088)	0.324*** (0.077)	0.617*** (0.05)	0.572*** (0.055)	0.733*** (0.038)	0.782*** (0.031)	0.646*** (0.049)	0.648*** (0.052)	0.677*** (0.043)	1

Notes: Robust standard errors are in parentheses. *, **, and *** significant at 10%, 5% and 1%, respectively.

TABLE 6
REGRESSION COEFFICIENTS (SINCE-THE-CRISIS)

	ΔVIX	Δ*AAII*	Δ*II*
RET_ARG	-0.4876***	0.1635***	0.2413***
	(0.0119)	(0.0042)	(0.0052)
RET_BRA	-0.5648***	0.1551***	0.3060***
	(0.0151)	(0.0048)	(0.0074)
RET_CAN	-0.6628***	0.1858***	0.3627***
	(0.0174)	(0.0054)	(0.0086)
RET_CHI	-0.5662***	0.1682***	0.2713***
	(0.0143)	(0.0052)	(0.0071)
RET_COL	-0.4954***	0.1202***	0.2580***
	(0.0122)	(0.0035)	(0.0078)
RET_MEX	-0.6963***	0.1493***	0.3780***
	(0.0183)	(0.0047)	(0.0094)
RET_PER	-0.5106***	0.1330***	0.2306***
	(0.0125)	(0.0041)	(0.0052)
RET_U.S.	-0.8157***	0.1902***	0.4899***
	(0.0225)	(0.0058)	(0.0119)

Notes: Numbers in parentheses denote standard errors. *pb.10, **pb.05, ***pb.01

TABLE 7.1
REGRESSION ANALYSIS OF CONDITIONAL CORRELATIONS COEFFICIENTS AND THE U.S. FINANCIAL CRISIS (WEEKLY DATA FROM JAN. 2002 TO DEC. 2015)

Country/Index i: Country j:	RET_U.S RET_ARG	RET_U.S. RET_BRA	RET_U.S. RET_CAN	RET_U.S. RET_CHI	RET_U.S. RET_COL	RET_U.S. RET_MEX	RET_U.S. RET_PER
λ_0	0.4132***	0.5340***	0.6354***	0.4694***	0.3789***	0.6304***	0.3835***
	(0.0049)	(0.0057)	(0.0054)	(0.0042)	(0.0077)	(0.0062)	(0.0053)
λ1	0.1517***	0.1359***	0.1007***	0.1354***	0.1848***	0.1747***	0.1933***
	(0.0110)	(0.0128)	(0.0120)	(0.0095)	(0.0099)	(0.1389)	(0.0119)
λ2	0.1365***	0.1147***	0.1562***	0.1251***	0.1427***	0.1400***	0.1795***
	(0.0068)	(0.0079)	(0.0074)	(0.0059)	(0.0061)	(0.0086)	(0.0074)
Observations	730	730	730	730	730	730	730
F	230.78	124.94	222.91	258.67	342.04	162.41	333.07
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.3867	0.2537	0.3784	0.4141	0.4834	0.3069	0.4767

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01.
The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$, for $i \neq j$

TABLE 7.2
REGRESSION ANALYSIS OF CONDITIONAL CORRELATIONS COEFFICIENTS AND THE U.S. FINANCIAL CRISIS
(WEEKLY DATA FROM JAN. 2002 TO DEC. 2015)

Country/Index i: Country j:	ΔVIX RET_ARG	ΔVIX RET_BRA	ΔVIX RET_CAN	ΔVIX RET_CHI	ΔVIX RET_COL	ΔVIX RET_MEX	ΔVIX RET_PER	ΔVIX RET_U.S.
λ_0	-0.3512***	-0.4507***	-0.5301***	-0.4299***	-0.3646***	-0.5532***	-0.3715***	-0.6818***
	(0.0046)	(0.0050)	(0.0044)	(0.0043)	(0.0042)	(0.0053)	(0.0045)	(0.0061)
λ1	-0.1592***	-0.1303***	-0.0877***	-0.1434***	-0.1448***	-0.1683***	-0.1374***	-0.1318***
	(0.0102)	(0.0112)	(0.0099)	(0.0096)	(0.0094)	(0.1179)	(0.0101)	(0.0136)
λ2	-0.1312***	-0.1104***	-0.1430***	-0.1346***	-0.1276***	-0.1372***	-0.1394***	-0.1343***
	(0.0063)	(0.0069)	(0.0062)	(0.0060)	(0.0058)	(0.0073)	(0.0062)	(0.0084)
Observations	730	730	730	730	730	730	730	730
F	259.9	151.15	271.07	287.67	281.54	214.18	272.17	139.09
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.4153	0.2918	0.4256	0.4402	0.4349	0.369	0.4266	0.2748

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01.
The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$, for $i \neq j$

TABLE 7.3
REGRESSION ANALYSIS OF CONDITIONAL CORRELATIONS COEFFICIENTS AND THE U.S. FINANCIAL CRISIS (WEEKLY DATA FROM JAN. 2002 TO DEC. 2015)

Country/Index i: Country j:	ΔAAII RET_ARG	ΔAAII RET_BRA	ΔAAII RET_CAN	ΔAAII RET_CHI	ΔAAII RET_COL	ΔAAII RET_MEX	ΔAAII RET_PER	ΔAAII RET_U.S.
λ_0	0.1176***	0.1312***	0.1542***	0.1369***	0.0950***	0.1151***	0.1083***	0.1651***
	(0.0020)	(0.0024)	(0.0021)	(0.0032)	(0.0021)	(0.0033)	(0.0022)	(0.0026)
λ1	0.0041***	-0.0161***	-0.0320***	-0.0059***	0.0052***	0.0153***	-0.0324***	-0.0201***
	(0.0044)	(0.0054)	(0.0047)	(0.0071)	(0.0048)	(0.0073)	(0.0049)	(0.0059)
λ2	0.0555***	0.0331***	0.0462***	0.0398***	0.0298***	0.0386***	0.0378***	0.0355***
	(0.00276)	(0.0034)	(0.0029)	(0.0044)	(0.0030)	(0.0045)	(0.0030)	(0.0037)
Observations	730	730	730	730	730	730	730	730
F	219.81	69.36	205.64	48.36	52.87	36.36	142.03	70.86
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.3751	0.1579	0.3613	0.115	0.1246	0.0884	0.279	0.1608

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01.
The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$, for $i \neq j$

TABLE 7.4
REGRESSION ANALYSIS OF CONDITIONAL CORRELATIONS COEFFICIENTS AND THE U.S. FINANCIAL CRISIS (WEEKLY DATA FROM JAN. 2002 TO DEC. 2015)

Country/Index i: Country j:	ΔII RET_ARG	ΔII RET_BRA	ΔII RET_CAN	ΔII RET_CHI	ΔII RET_COL	ΔII RET_MEX	ΔII RET_PER	ΔII RET_U.S.
λ_0	0.1490***	0.2208***	0.2602***	0.2107***	0.2333***	0.2833***	0.1477***	0.3590***
	(0.0024)	(0.0024)	(0.0026)	(0.0022)	(0.0026)	(0.0030)	(0.0024)	(0.0033)
λ1	0.0604***	0.0684***	0.0654***	0.0283***	0.0413***	0.0854***	0.0789***	0.0996***
	(0.0053)	(0.0054)	(0.0058)	(0.0050)	(0.0058)	(0.0066)	(0.0053)	(0.0075)
λ2	0.0997***	0.0891***	0.1111***	0.0680***	0.0208***	0.0969***	0.0838***	0.1381***
	(0.0033)	(0.0033)	(0.0035)	(0.0031)	(0.0036)	(0.0041)	(0.0033)	(0.0046)
Observations	730	730	730	730	730	730	730	730
F	465.2	364.77	481.17	245.91	32.09	292.46	352.79	452.11
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.5602	0.4995	0.5685	0.4019	0.0786	0.4443	0.4911	0.5531

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01.
The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$, for $i \neq j$

FIGURE 1
DYNAMIC CONDITIONAL CORRELATIONS – ΔVIX TO STOCK MARKET RETURNS

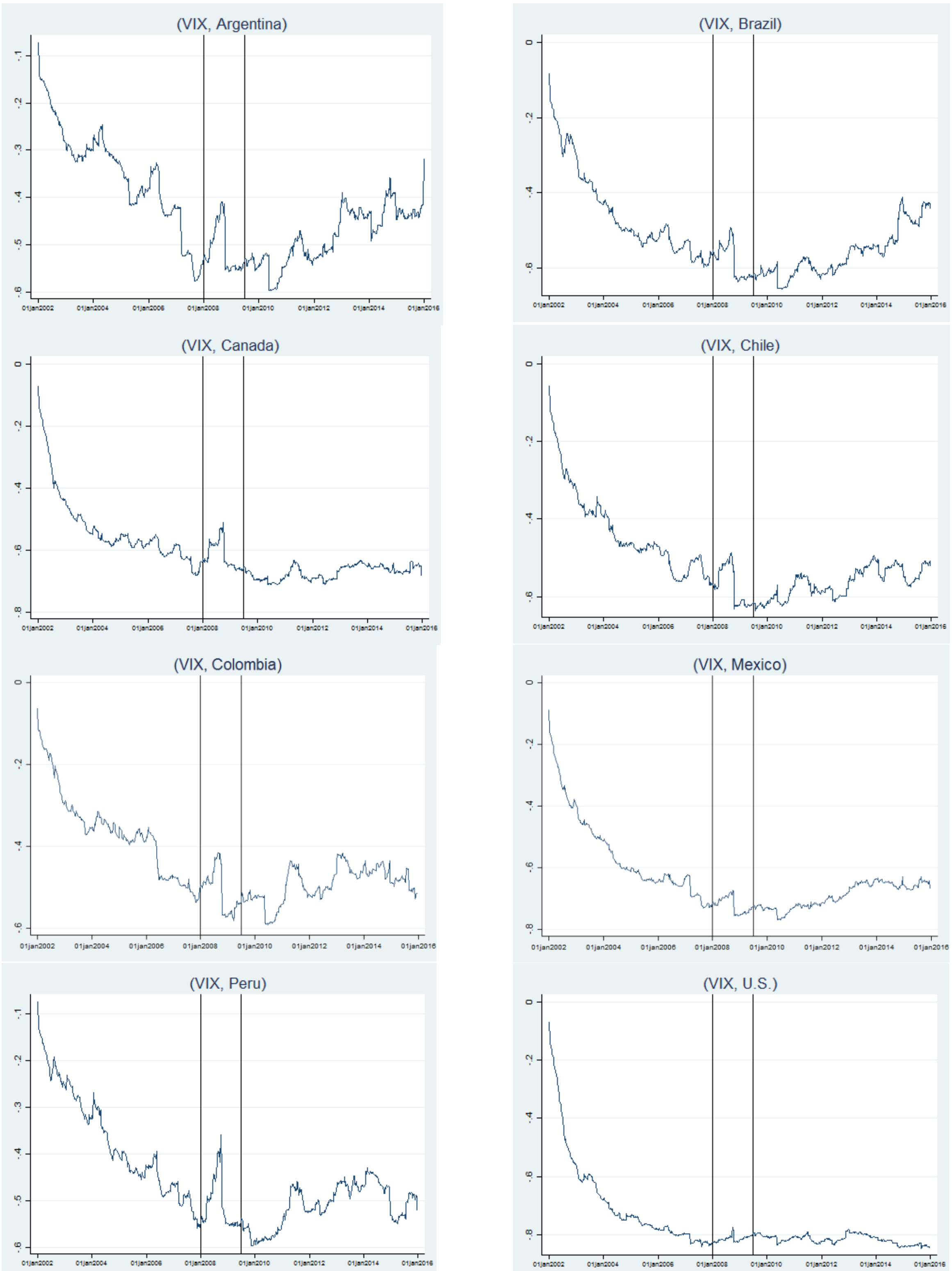

FIGURE 2
DYNAMIC CONDITIONAL CORRELATIONS – Δ*II* TO STOCK MARKET RETURNS

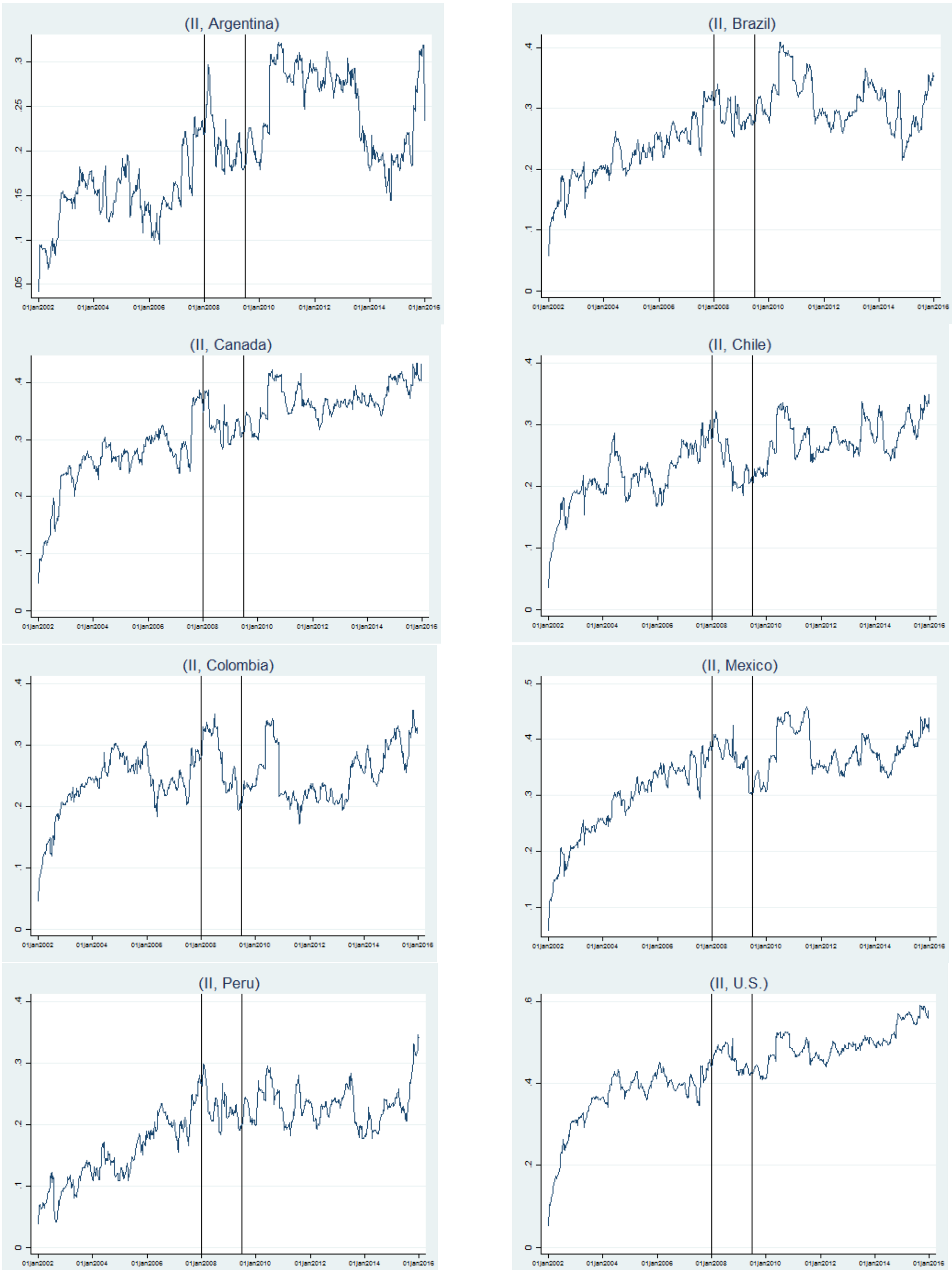

FIGURE 3
DYNAMIC CONDITIONAL CORRELATIONS – ΔAAII TO STOCK MARKET RETURNS