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Volatility Spillovers across Major Equity Markets of Americas

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ABSTRACT

This paper investigates the daily volatility spillovers between Standard and Poor's 500, and equity indices of Brazil, Argentina, and Mexico for the period of August 2007 through August 2012. We find that equity indices under study exhibit nonlinear dependencies, inconsistent with chaotic structure. Bivariate GARCH estimations indicate bi-directional spillovers. Findings show evidence of asymmetric market responses to shocks in all markets. Therefore, we estimate asymmetric bivariate EGARCH models. We find evidence of leverage effect as positive and negative shocks to each market impart unequal impact on the volatility of the other market. Furthermore, effects of negative shocks are much more pronounced than positive shocks. Finally, the non-linear Granger causality test results confirm that markets of Americas cause one another, i.e., there is shock feedback.

JEL Classifications: *G00, G15, G14*

Keywords: *international volatility spillover; causality; shocks*

I. INTRODUCTION

The world financial markets have experienced increasing integration, resulting in transmission of financial shocks across connected markets. Equity markets have felt the effects positive as well as negative shocks to economies and equity markets of all sizes around the world. While this is not a surprising outcome of economic and financial integration, the dynamics, the mode, and channels of contagion and shock transmission continue to be subjects of interest and investigation. Studying the spread of shocks, and financial crises throughout global economies, pique the interest of academicians, financial professionals, domestic and international regulators, and central bank policy makers. The consensus among researchers is that the globalization and expanding regional integration, through banking systems, international trade, and other cross investments have been instrumental in spreading economic and financial turmoil.

Events of the decades of 1990s and 2000, as well as financial turmoil of Ireland, Greece, Portugal, and Spain in 2012-2013, demonstrate how economies of even small size can play a significant role in transmitting banking and equity market crises across world economies. Furthermore, these events have reignited interest in this line of research for all involved.

Researchers have gone to great lengths to investigate the channels of contagion, shock transmission, and volatility spillovers among world major markets, in emerging markets, and between them. There are some obvious ramifications of the findings of such research. For instance, evidence of volatility spillovers and dynamics would offer an understanding on the degree of openness and economic co-dependence of global economies. Many emerging markets have implemented policies that have led to financial liberalization which has contributed to capital inflows. Increased capital flows into emerging market securities by portfolio managers and hedge funds have fueled renewed attention to these equity markets. Given that rates of economic growth in emerging markets dwarf those of developed economies, the attention given to them is understandable. Given that equity market returns and GDP growth rates are correlated, emerging market equities will only enter more fund portfolios.

On the down side, concerns about the spread of financial crises from emerging markets have raised the risk of exposure to these economies. Portfolio managers want to understand the dynamic interactions between all equity markets, including emerging, in order to be able to evaluate market risk and hedging strategies. National and international regulators and central bankers need information and insight into these issues in order to be able to cope with spillovers of volatility, especially during the periods of financial crises. In particular, world’s central bankers and other financial policy makers would benefit from this line of research findings may become better equipped to cope with contagious effects of shocks among markets. Academic researchers are interested in contagion and dynamic relationships among equity markets for intellectual curiosity, policy ramification, and empirical evidence in support of theoretical paradigms such as market efficiency, information arrival, price discovery, and shock transmission mechanisms across markets.

The empirical research in the last few decades has recorded the following findings. First, generally equity returns do not follow a Gaussian distribution and their third and fourth moments confirm skewed and leptokurtic distributions. Second, returns exhibit long memory and nonlinearity, i.e., auto correlation of returns and squared returns are statistically significant for high lag orders. This also leads to volatility clustering, where high and low returns cluster for a period of time. Third, conditional volatility reaction to positive and negative innovations emanating from their own and other markets are asymmetric. This creates the leverage effect because as equity values drop sharply in response to negative news, debt to equity ratios rise.

In this paper we examine the behavior of the major equity markets of the Americas. Our paper analyzes nonlinearities, volatility spillovers, and causalities in these markets. We examine the daily values of the Standard and Poor's 500 (S&P 500), Bolsa, Bovespa, and Merval indices over the period 2000 to 2012. The assessment of the feedback between the four markets will provide an opportunity for a comparative analysis of spillovers between the major markets of the Americas. An incidental though important contribution of the paper is the examination of the possibly nonlinear, chaotic, and asymmetric nature of the price dynamics following information arrival within each of the three markets. We deploy tests of nonlinearity, chaos, GARCH models, and Granger causality to investigate the behavior, dynamics and bilateral causality between equity index pairs.

Three specific issues motivate the paper. Foremost, investigating the role of the US market and its relationship to the markets of Americas will be of obvious interest to the academics and policy makers. Given the ongoing liberalization of the financial sector in the transition economies such as Brazil, Mexico and Argentina, the integration of financial markets of Americas is bound to increase. While the comprehensive Free Trade Agreement of Americas has met serious headwinds, the US and its Latin neighbors continue to be significant trading partners. For instance, Mexico is the third largest trading partner of the US, while Brazil ranks as the eighth. Furthermore, findings of this research may be helpful in better understanding of the spread of financial crises in general, and among markets under study, in particular. Given the importance of the Latin American Equity markets and country funds of Brazil, Mexico, and Argentina in portfolio diversification, this study is quite timely. However, the diversification benefits of LA markets may be limited by their dynamic interdependence with the US equity markets. Furthermore, given the wealth effect of equity markets, the dynamic interdependence between the US and LA markets may have broader implications for economic recessions and recoveries in their economies.

Second, contagion and dynamics of relationships among equity markets in the globalized economic climate remain critical subjects of research. Exploring the underlying linear and nonlinear complexities of equity prices and indices and possible chaotic behavior may shed some light on appropriate modeling of the dynamic relationship among equity index series. Financial econometrics of time series and modeling nonlinearity in the last few decades has gone through innovations that offer researchers econometric capabilities conducive to non-linear structures. A study of the price dynamics of the US equity prices with Latin American equities in the context of nonlinearity would offer further insights into possible nuances of market behavior and price discovery.

Third, investigating volatility spillovers, information arrival, asymmetric reactions to positive and negative news or economic shocks, and approaches to proper modeling of these behaviors, are useful to academicians, capital market managers, and policy makers.

Our paper complements the existing literature on the markets of Americas, and furthers their methodologies by explicitly examining more recent data for the sources of non-linear behavior of equity series and deploying the proper methodologies based on the dynamics of the equity series under question. The US policy makers and portfolio managers are specifically interested in these bilateral relationships.

We find evidence that stock index price series exhibit nonlinear dependencies that are inconsistent with chaotic structure. Applying nonlinear Granger causality tests, we find that the returns in US market Granger cause the returns in Latin American (LA) markets, but there is feedback. We identify GARCH (1,1) process as a model that satisfactorily explains the nonlinearities in prices. We propose and estimate a set of VAR-bivariate GARCH (1,1) models to ascertain the flow of information between prices. The estimates indicate that the volatility spills in both directions, i.e., there is feedback between markets. We also find evidence of asymmetric market responses to negative and positive shocks. We propose and estimate asymmetric bivariate VAR-EGARCH models for the index pairs. These findings suggest the shock transmissions are asymmetric and there is leverage effect. Specifically, volatility responses to negative innovations are larger than to positive ones, no matter where they occur. Our paper contributes to the existing work by emphasizing and explicitly testing for the underlying nonlinearities and deploying the nonlinear Granger causality tests.

The remainder of the paper is organized as follows. Section II summarizes the related research. Section III discusses the methodology. Data and summary statistics are contained in Section IV. Section V describes our main empirical findings. Summary and conclusions are presented in Section VI.

II. RELATED RESEARCH

There is a significant body of research on international spillover effects across financial markets dating back to Morgenstern (1959). Scholars have examined various aspects of intertwining of financial markets under the categories of interdependence, contagion, comovement, and volatility spillover.

We limit our review of the literature to the international interrelationships among equity markets to three main categories. The first comprises of papers that address contagion, spillovers, comovement and causality among the world's mature economies and their equity markets. The second category covers papers that also include equity markets of the developing world. The last group of papers consists of studies that involve Latin American markets.

Notable among papers in the first subset that investigate the behavior of first and second moments of equity returns and their spillovers across major equity markets are those by King and Wadhwani (1990), Hamao, Masulis and Ng (1990), Lin et al. (1994), Ito and Lin (1993), Koutmos and Booth (1995), Koutmos (1996), Longin and Solnik (1995), Kaminsky and Reinhart (2000), Ledoit et al. (2003), Connolly and Wang (2003), Baele (2005), Hakim and McAleer (2010), among others. These studies mainly employ variation of GARCH models or equity markets time-varying correlations, among others as their methodology.

These papers employ VARs and variations GARCH Models, to investigate the topic. Taken together, the results from these studies suggest increasing cross market correlations. Moreover, there appears to be an important role for the interdependence of banking in international financial market contagion.

Papers that examine contagion among markets of developing countries, and between developed and developing markets comprise the second category. Notable among these are Baig and Goldfajn (1999), Chan-Lau et al. (2004), Bekaert, et al. (2005), Talla and Imad (2006), Caporale et al. (2006), Kim et al. (2001), Christiansen (2007), Worthington and Higgs (2004), Dungey et al. (2006), Lucey and Voronkova (2008), Beirene et al. (2009), Diebold and Yilmaz (2009) Harrison and Moore (2009), and Sok-Gee et al. (2010), among others. While summarizing each of their findings in detail may not be appropriate in this paper, it can be noted that these papers generally point out to spillover and contagion effects in various degrees in the markets under study. They deploy variations of GARCH modeling, VAR, Kalman filters, and variance decomposition to investigate contagion and spillovers. The findings from all of these studies suggest that there is a uni-directional spillover of equity market volatility from major economies to others.

The third group of papers summarized in this section is devoted to the emerging markets of Latin America. Some notable papers in this subset are, Choudhry (1997), Christofi and Pericli (1999), Pagan and Soydemir (2000), Chen et al. (2002), Johnson and Soenen (2003), Barari (2004), Fujii (2005), Verma et al. (2008), Rivas et al. (2008), El Hedi et al. (2010), Aloui (2011), among others. Following in the path of the previous two categories, these researchers deploy the well-known methodologies of previous papers to investigate the volatility contagion among markets of Americas.

Methodologies applied run the gamut. They include cross-correlation function analysis, vector autoregression models, constant and time –varying correlation coefficients, cointegration, regime switching models, stochastic volatility models, Kalman filters, univariate and multivariate GARCH models (MGARCH), among others.

These researchers establish co-movement, cointegration, and asymmetric volatility spillover among the markets of Latin America. Their salient findings can be summarized as follows.

There is a notable trend toward increased regional integration relative to global integration until the mid-1990s. However, the second half of the 1990s, the global integration proceeds faster than regional integration. Volatility in these markets shows asymmetry and long memory. Furthermore, conditional correlations in these markets increased in the face of the global as well as regional financial turmoil.

The cointegration tests show that there is a long-term comovement among these neighboring economics. The conditional correlations are largely affected by their own volatility shocks. However, regional and international crises affect the interaction among these markets. The cross-market comovements and integration are time-varying, and have increased in the last two decades.

Latin American equity market volatility is more responsive to negative news than positive news. Furthermore, due to globalization and integration with the world economy, Latin American equity markets have become more susceptible to contagion from the world financial crises. There are asymmetric volatility spillovers and feedback among the Latin equity markets.

The significance of findings of the past research may be that the diversification benefits of investing in various Latin American equity markets may be limited.

III. METHODOLOGY

To begin our analysis, we first examine the equity indices of the markets under study for stationarity and non-linearities. Augmented Dickey Fuller (ADF), Phillips-Peron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests of stationarity are employed for this purpose. To examine nonlinearities in the series under study, we compute the Q and Q^2 statistics, and perform Wald test for ARCH effects. To test for chaotic behavior, we apply the Brock, Dechert, and Scheinkman (1987) test (BDS) and Correlation Dimension (CD) tests of chaos. If nonlinearities are present, but we find no chaos, we estimate appropriate variations of autoregressive GARCH (1,1) models to capture the dynamic behavior of equity indices. We complete the analysis with Granger causality test or its adaptation for nonlinear processes. Of the various tests used in this research, a brief description of tests of Chaos may be appropriate. We present more detail on the methodologies used as we apply them.

We deploy two tests of chaos: (i) the Correlation Dimension of Grassberger and Procaccia (1983) and Takens (1984), (ii) and the BDS statistic of Brock, Dechert, and Scheinkman (1987) which are discussed in detail in Adrangi et al. (2001a,b). The correlation dimension is based on the following statistic:

$$SC^M = \frac{\{ \ln C^M(\varepsilon_i) - \ln C^M(\varepsilon_{i-1})\}}{\{ \ln(\varepsilon_i) - \ln(\varepsilon_{i-1})\}} \tag{1}$$

for various levels of M (e.g., Brock and Sayers, 1988). The SC^M statistic is a local estimate of the slope of the C^M versus e function. Following Frank and Stengos (1989), we take the average of the three highest values of SC^M for each embedding dimension.

The BDS statistic is proposed by Brock, Dechert and Scheinkman (1987), which is based on the correlation integral that has been quite robust in discerning various types of nonlinearity as well as deterministic chaos. BDS show that if x_t is (i.i.d) with a nondegenerate distribution,

$$C^M(\varepsilon) \to C^1(\varepsilon)^M \quad ,\text{as} \quad T \to \text{infinity} \tag{2}$$

for fixed M and ε. Based on this property, BDS show that the statistic

$$W^M(\varepsilon) = \sqrt{T}\{[C^M(\varepsilon) - C^1(\varepsilon)^M]/\sigma^M(\varepsilon)\} \tag{3}$$

where σ^M, the standard deviation of [·], has a limiting standard normal distribution under the null hypothesis of IID. W^M is termed the BDS statistic. Nonlinearity is indicated by a significant W^M for a stationary series with no linear dependence. Chaos is rejected if there is evidence that the nonlinear structure arises from a known non-deterministic system.

IV. DATA AND SUMMARY STATISTICS

We employ daily index values of Bolsa (Mexico), Bovespa (Brazil), Merval (Argentina) and Standard & Poor's 500 (S&P500) spanning the period of 2007 through October 2012. All series are retrieved from the Bloomberg data base. Percentage changes (index returns) are given by $R_t = (\ln(P_t/P_{t-1}))\cdot 100$, where P_t represents the daily closing values.

The graphs of indices exhibit mean and covariance nonstationarity, as well as volatility clustering. Percentage change, i.e., returns (R_t) series for the four indices are mean-stationary, but may be covariance non-stationary. These graphs are not presented here for the purpose of brevity, however, justify formal statistical tests of stationarities and possible nonlinearities in return series. We provide the statistical evidence of behavior of these series in Table 1.

Table 1

Diagnostics

Returns are given by $R_t=\ln(P_t/P_{t-1})\cdot 100$, where P_t represents closing index values on day t. ADF represents the Augmented Dickey Fuller tests (Dickey and Fuller (1981)). The Q(12) and $Q^2(12)$ statistics represent the Ljung-Box (Q) statistics for autocorrelation of the R_t and R_t^2 series respectively. The ARCH(6) statistic is the Engle (1982) test for ARCH (of order 6) and is χ^2 distributed with 6 degrees of freedom.

Panel A: Price Levels

	S&P 500	MERVAL	BOVESPA	BOLSA
Interval: 7/2007-7/2012 (N=127)				
ADF_trend	-1.900	-1.266	-2.015	-2.075
PP_trend	-1.851	-1.337	-1.872	-2.011
KPPS_trend	0.797	0.531	0.282	0.560
Q(24)	23177.00	23858.00	22283.00	24001.00
$Q^2(24)$	23020.00	23703.00	22011.00	23985.00
LM_ARCH (6)	255.975	98.945	180.985	104.720

Panel B: Percentage Changes

	S&P 500	MERVAL	BOVESPA	BOLSA
Interval: 7/2007-7/2012 (N=1271)				
ADF_trend	-28.735[a]	-33.725[a]	-36.190[a]	-33.338[a]
PP_trend	-40.564[a]	-33.836[a]	-36.345[a]	-33.279[a]
KPPS_trend	0.315	0.164	0.084	0.153
Q(24)	69.766[a]	32.162[a]	44.134[a]	48.046[a]
$Q^2(24)$	1655.010[a]	867.480[a]	1801.400[a]	1249.700[a]
LM_ARCH (6)	333.589[a]	223.859[a]	339.309[a]	201.050[a]

Notes: S&P500, MERVAL, BOVESPA, and BOLSA, represent equity indices of the US, Argentina, Brazil and Mexico. Q(12) and $Q^2(12)$ are the Ljung Box statistics for AR(1) residuals and their squared values.
a, b, and c , represent significance at .01, .05, and .10, respectively.

Panel C: Summary descriptive statistics for model variables. All variables are in level.

	S&P 500	MERVAL	BOVESPA	BOLSA
Interval: 7/2007-7/2012 (N=1271)				
Mean	1199.577	2279.117	59190.331	31050.240
Stand Dev	191.634	658.409	9219.429	5306.679
Skewness	-0.439	0.025	-0.975	-0.669
Kurtosis	2.520	2.730	3.341	2.811
J-B	52.33789[a]	3.917	204.302[a]	97.135[a]

Notes: S&P500, MERVAL, BOVESPA, and BOLSA, represent equity indices of the US, Argentina, Brazil and Mexico.
a represents significance level of .01.

Panel A shows that index levels are nonstationary and there is evidence of nonlinear behavior as evidenced by significant Q^2 statistics. The R_t series are found to be stationary employing the Augmented Dickey Fuller (ADF), PP and KPSS statistics. There remain linear and nonlinear dependencies as indicated by the Q and Q^2 statistics, and Autoregressive Conditional Heteroskedasticity (ARCH) effects are suggested by the ARCH (6) chi-square statistic. Whether these dynamics are chaotic in origin is the question we turn to next.

To capture the linear structure, we estimate autoregressive models,

$$R_t = \sum_{i=1}^{p} \pi_i R_{t-i} + \varepsilon_t . \tag{4}$$

The lag length for each series is selected based on the Akaike (1974) criterion. The residual (ε_t) represents the index movements after filtering the linear relationships. The mean equation of the GARCH model is the same as given in Equation (7), while the conditional variance equation of the model is given by

$$\sigma^2_{i,t} = \beta_i + \gamma_i u^2_{i,t-1} + \phi_i \sigma^2_{i,t-1} \quad \text{i=1, 4} \tag{5}$$

where $\sigma^2_{i,t}$ is the conditional variance, $u_{i,t-1}$ is the lagged innovations, and $\sigma^2_{i,t-1}$ is the lagged conditional volatility.

V. EMPIRICAL FINDINGS

A. Tests for Chaos

1. Correlation dimension estimates

Table 2 reports the Correlation Dimension (SC^M) estimates for the returns and logistic series. The values of the correlation dimension for chaotic series and its filtered version shown in the first two rows of the Table do not show an explosive trend. For instance, SC^M estimates for the logistic map stay around one as the embedding dimension rises. Furthermore, the estimates for the logistic series are insensitive to AR transformations, consistent with chaotic behavior. For the return series, SC^M estimates show inconsistent behavior with chaotic structures. For instance, the SC^M does not settle. The estimates for the AR or GARCH transformation do not change results much, but are mostly larger and do not settle with increasing of the embedding dimension. These initial indicators suggest that the series under consideration are not chaotic.

2. BDS test results

Tables 3 and 4 report the BDS statistics (Brock, Dechert, and Scheinkman, 1987) for [AR(p)] series, and standardized residuals ($\varepsilon/\sqrt{h}$) from the GARCH (1,1) models, respectively. The critical values for the BDS statistics are reported in Adrangi et al. (2001a, b). The BDS statistics strongly reject the null of no nonlinearity in the [AR(1)] errors for all of the return series. However, BDS statistics for the standardized residuals from the GARCH-type models are mostly insignificant at the 1 and 5 percent levels. On the whole, the results provide compelling evidence that the nonlinear dependencies in the series arise from GARCH-type effects, rather than from a complex, chaotic structure. From the BDS statistics presented in Table 4, it is apparent that the variations of the GARCH model may explain the nonlinearities.

B. Bivariate GARCH Models

To model the relationship between the returns while accounting for the GARCH effects, we estimate three VAR models in a bivariate GARCH context. We summarize the findings of this model but do not report it in the interest of brevity. Most model coefficients are statistically significant at five or ten percent levels of significance, indicating that a variation of GARCH model maybe well-suited for modeling the interaction between markets under study. Examining sign bias tests show that size bias and joint sign and size bias tests are statistically significant pointing toward asymmetric volatility effects of positive and negative shocks or news. This may also indicate that EGARCH model may be better suited for modeling the volatility spillovers for Latin American markets.

To account for asymmetric shock responses, we estimate bivariate EGARCH models that are better suited to account for the asymmetric volatility response within and across markets. This model is an extension of the univariate EGARCH model of Nelson (1991). Koutmos (1999), Cheung and Ng (1992), Hakim and McAleer (2010), Rivas et al. (2008), among others, have documented this pattern of asymmetric volatility transmission in financial markets. The following equations represent the proposed VAR-EGARCH model:

$$R_{it} = \alpha_{i,0} + \sum_{j=1}^{2} \alpha_{ij} R_{i,t-1} + u_{i,t} \tag{6}$$

$$\mathrm{Ln}(\sigma_{i,t}^2) = \beta_{i,0} + \sum_{j=1}^{2} \beta_{ij}\phi_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2) \quad i,j=1,2 \tag{7}$$

$$\phi_j(z_{j,t-1}) = (\left|z_{j,t-1}\right| - E(\left|z_{j,t-1}\right|) + \delta_j z_{j,t-1}) \quad i,j=1,2 \tag{8}$$

$$z_{j,t} = (\left|u_{j,t} / \sigma_{j,t}\right| - \sqrt{2/\pi}) + \delta_j u_{jt} / \sigma_{j,t}$$
$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t} \quad \text{i,j=1,2,..} \tag{9}$$

where $z_{j,t} = (\left|u_{j,t} / \sigma_{j,t}\right| - \sqrt{2/\pi}) + \delta_j u_{jt} / \sigma_{j,t}$ and $z_{i,t}= \varepsilon_{it}/ \sigma^2_{i,t}$ is the standardized innovations of market i at time t. Volatility persistence is measure by γ. Nelson (1991) notes that unconditional volatility is finite and measurable if $\gamma_i <1$ while $\gamma_i = 1$ signals a non-stationary and unconditional volatility is not well-defined. We deploy a combination of the simplex method with the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm to maximize the likelihood function, $L(\Omega)$.

Table 2

Correlation dimension estimates

The Table reports SCM statistics for the Logistic series (w=3.750, n=2000), daily percentage changes in index values over four embedding dimensions: 5, 10, 15, 20. AR(1) represents autoregressive order one residuals. GAR(1,1) represents standardized residuals from a AR1- GARCH(1,1) model.

M=	5	10	15	20
Logistic	1.02	1.00	1.03	1.06
Logistic AR	0.96	1.06	1.09	1.07
BOLSA AR(1)	2.198	3.601	4.458	5.549
BOVESPA AR(1)	2.472	4.218	5.706	7.153
MERVAL AR(1)	2.384	4.576	6.451	8.519
S&P AR(1)	2.145	3.440	4.340	5.107
BOLSA _ GAR(1,1)	3.591	7.000	1.0225	15.149
BOVESPA _ GAR(1,1)	3.697	7.312	10.602	11.460
MERVAL _ GAR(1,1)	3.142	6.909	10.767	Infinity
S&P _ GAR(1,1)	3.515	6.701	9.070	11.258

Notes: S&P500, MERVAL, BOVESPA, and BOLSA, represent equity indices of the US, Argentina, Brazil and Mexico. AR(1) indicates AR(1) model residuals fitted to each index, and GAR(1,1) represents standardized residuals of GARCH(1,1) model fitted to the indices under study.

Table 3
BDS statistics for AR(1) residuals

The figures are BDS statistics for the AR(p). [a], [b], and [c] represent the significance levels of .01, .05, and .10, respectively.

	M			
ε/σ	2	3	4	5
BOLSA AR(1)				
0.50	6.905	9.941	13.174	16.597
1	6.324	9.281	11.884	14.276
1.5	6.538	9.228	11.105	11.266
2	7.605	9.976	11.152	12.083
BOVEPA AR(1)				
0.50	2.877	5.218	7.380	9.109
1	53.244	7.771	9.514	11.198
1.5	7.415	10.093	11.375	12.471
2	8.678	12.075	13.219	14.006
MERVAL AR(1)				
0.50	3.225	6.309	8.205	9.481
1	4.609	8.119	10.023	11.400
1.5	5.946	9.601	11.314	12.523
2	6.340	10.153	11.592	12.615
S&P500 AR(1)				
0.50	4.292	8.644	123.711	17.225
1	5.501	9.262	11.790	14.319
1.5	7.441	10.532	12.363	13.957
2	8.480	11.764	13.403	14.742

Notes: S&P500, MERVAL, BOVESPA, and BOLSA, represent equity indices of the US, Argentina, Brazil and Mexico. AR(1) indicates AR(1) model residuals fitted to each index. All BDS statistics are significant at 1 and 5 percent levels.

Table 4
BDS statistics for GARCH (1.1) standardized residuals

The figures are BDS statistics for the standardized residuals from GARCH(1,1) models. The BDS statistics are evaluated against critical values obtained from Monte Carlo simulations (Appendix 1). [a], [b], and [c] represent the significance levels of .01, .05, and .10, respectively.

	M			
ε/σ	2	3	4	5
BOLSA_gar11				
0.50	-1.355	-0.914	-0.896	-1.225
1	-1.432	-1.220	-1.207	-1.159
1.5	-1.592	-1.404	-1.444	-1.416
2	-1.078	-0.693	-0.765	-0.889
BOVESPA_gar11				
0.50	-2.166	-1.209	-0.559	-0.0004
1	-2.318	-1.624	-1.286	-1.027
1.5	-2.289	-1.314	-1.066	-0.859
2	-1.814	-0.572	-0.409	-0.370

MERVAL_gar11				
0.50	-1.880	-0.342	0.142	0.068
1	-2.103	-0.539	-0.079	0.199
1.5	-1.805	-0.310	-0.021	0.244
2	-1.499	0.115	0.233	0.435
S&P500_gar11				
0.50	-3.931[a]	-1.973	-9.580[a]	-0.308
1	-4.260[a]	-2.561[a]	-1.760	-1.084
1.5	-4.438[a]	-3.141[a]	-2.534[a]	-2.090[a]
2	-4.082[a]	-2.785[a]	-2.442[a]	-2.125[a]

Notes: S&P500, MERVAL, BOVESPA, and BOLSA, represent equity indices of the US, Argentina, Brazil and Mexico. GAR(1,1) represents standardized residuals of GARCH(1,1) model fitted to the indices under study.

Table 5
Bivariate asymmetric VAR- EGARCH model with volatility spillovers
Americas and S&P 500 Index

Mean Equation	S&P500	BOLSA	S&P500	BOVESPA	S&P500	MERVAL
Intercept α10, α20	0.028	0.005	-0.142	-0.122	-0.150	-0.173
	(0.022)	(0.012)	(0.028)	(0.036)	(0.0214)	(0.037)
Lagged Return SP α11 α21	-0.108[a]	-0.039	-0.127[a]	-0.096[a]	-0.167[a]	-0.289[a]
	(0.025)	(0.0257)	(0.037)	(0.048)	(0.015)	(0.035)
Lagged Return other α12, α22	0.026	0.309[a]	0.069[a]	0.040	0.094[a]	0.167[a]
	(0.023)	(0.019)	(0.029)	(0.038)	(0.021)	(0.034)
Variance Equation	**S&P500**	**BOLSA**	**S&P500**	**BOVESPA**	**S&P500**	**MERVAL**
Intercept β10, β20	0.017[a]	0.010	0.159[a]	0.019[a]	0.018[a]	0.036[a]
	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)	(0.011)
Asymmetric Effect β11, β21	0.113[a]	0.047[a]	0.071	0.005	0.125[a]	0.023
	(0.024)	(0.014)	(0.026)	(0.015)	(0.023)	(0.022)
Asymmetric Effect β12, β22	0.198[a]	0.075[a]	0.054[a]	0.110[a]	0.026	0.173[a]
	(0.020)	(0.019)	(0.019)	(0.025)	(0.020)	(0.037)
Lagged stand. Shock δ1 δ2	-1.093[a]	-0.660[a]	-1.321[a]	-0.769[a]	-0.787[a]	-0.409[a]
	(0.246)	(0.195)	(0.359)	(0.159)	(0.175)	(0.080)
Lagged Conditional Variance γ^1 γ^2	0.969[a]	0.977[a]	0.992[a]	0.989[a]	0.990[a]	0.980[a]
	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.008)
|-1+δj|/(1+ δj) Correlation	0.785		0.741		0.659	

Table 5 (continued)

Diagnostics on Standardized Residuals						
Q (12), εt/σ	9.452	6.698	13.706	14.547	12.192	16.241
Q (24), εt/σ	13.620	13.876	19.417	22.634	27.757	24.336
Q2 (12), εt2/σ	37.342 [a]	17.020	40.640 [a]	28.682	60.723 [a]	13.690
Q2 (24), εt2/σ	49.359 [a]	30.432 [a]	59.885 [a]	43.655 [a]	65.579 [a]	19.384
Q(12), εit εit /σi σj	42.117 [a]		42.130 [a]		34.158 [a]	
Q(24), εit εit /σi σj	60.841 [a]		58.149 [a]		43.784 [a]	
Sign Bias t-Statistic						
Sign bias	0.919	1.598	0.128	1.198	0.275	0.131
Size bias	1.394	-0.374	1.343	0.273	0.901	0.242
Joint sign and size bias (χ2)	18.399 [a]	5.514	6.129 [a]	3.279	8.213 [a]	0.424
System Log Likelihood	-2402.079		-2372.984		-4109.342	

Notes: Returns and conditional variance equations are estimated in a system assuming variance correlations are constant. Q and Q2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it} / \sqrt{\sigma_{it}}$) and their squared values. The sign bias test shows whether positive and negative innovations affect future volatility differently from the model prediction (see Engle and Ng (1993)).
a, b, and c , represent significance at .01, .05, and .10, respectively.

Table 5, reports the estimation results of the bivariate- EGARCH models of equations (6)-(9) for the S&P500 and three LA indices. In all equations δ_1 and $\delta_2<0$ combined with positive β_{12} and β_{21}, confirm that volatility transmission across markets is asymmetric. Negative shocks in each market results in elevated conditional volatility in the other and there is feedback in a similar manner. Statistically significant $\delta_j<0$ shows the presence of asymmetric volatility effects in each market. Thus, negative shocks in each market lead to higher volatility than positive innovations. The size effect (the degree of asymmetry) as measured by $|-1+\delta_j|/(1+\delta_j)$, are and have become known as "leverage effect." The leverage effect occurs as the negative shocks reduce the market capitalization and raise the debt to equity ratio. The unconditional volatility in both cases is finite as indicated by γ_1 and $\gamma_2<1$. Insignificant sign and size bias tests reinforce the statistical validity of the Asymmetric model even in the presence of significant joint test of size and sign bias.

Table 6
Impact of cross market shocks on the percentage change in volatility and leverage effects

Shock Origin (t-1)	S&P	Bolsa	Bovelsa	Merval
S&P (-)	0.113	0.125	0.195	0.244
S&P (+)	0.005	0.026	0.025	0.102
Bolsa (-)	0.078			
Bolsa (+)	0.004			
Bovlesa (-)	0.011			
Bovlesa (+)	0.002			
Merval (-)	0.041			
Merval (+)	0.005			
Leverage Effects	12.715	4.882	7.658	2.384

Notes: The responses of S&P and the leverage effect are the average for the three markets.

To summarize the impact of negative and positive shock transmission among markets, we use the estimated δ_j and β_{ij} coefficients. For instance, a one unit negative shock to market j affects the conditional volatility in market i by $|(-1+ \delta_j)|*$ (β_{ij}) for negative shocks and $|(1+ \delta_j)|*$ (β_{ij}) for positive shocks. Table 6 reports these effects for a percentage positive and negative shock from market i on the percentage change in volatility of market j. The notable conclusions are as follows. First, the shock transmission is asymmetric. For instance, in all cases positive shocks to the S&P500 futures have smaller percentage impact on S&P500 and other indices relative to negative shocks of the same size. Volatility reaction in all markets to own negative innovations and cross market negative innovations is much larger in all markets. Second, negative shocks to LA markets also show a significant impact on the volatility of S&P500 relative to the same size positive shocks. Finally, the largest impact of shocks to S&P500 is felt in equity market of Argentina. This may be due to the size of equity market there which is the smallest in dollar value relative to Mexico and Brazil. The leverage effects reported in Table 6 confirm that the largest leverage effect of the S&P500 is on the S&P500 and the magnitude is smaller on the LA equity markets.

C. Spillovers and Granger Causality

Having established volatility spillover, and low conditional correlations between equities markets of Americas, we proceed to investigate the possibility of nonsynchronous relationship-dynamics that may be unobservable from returns' correlations. To this end, we examine the causality deploying the nonlinear extension of the standard Granger causality test between two variables (Granger, 1969; Geweke, 1984). In the standard Granger autoregressive and linear test, the null hypothesis that an observed series x_t does not Granger cause another series, y_t, is to test the null hypothesis that γ_1 through γ_n =0.

$$y_t = \alpha + \beta_1 y_{t-1} + ...\beta_k y_{t-k} + \gamma_1 x_{t-1} + ...\gamma_n x_{t-n} + \varepsilon_t \quad (10)$$

where ε_t is normally and identically distributed with mean of zero and constant variance under H0. Our variables exhibit nonlinearities and therefore the linear framework may not be suitable. Thus, we employ a nonlinear version of the test as suggested by Skalin and Svirta (1999), based on smooth transition regression (STR). Motivated by the linear causality regression, when y_t (under the null hypothesis of non-causality) is generated by the STAR model, this test is based on the non-existent predictive power of lagged values of another variable, x_t, where the sequence $\{x_t\}$ is assumed to be stationary. The non-linear causality from x to y is modeled by an additive smooth transition component. Consider the following additive smooth transition regression model

$$y_t = \pi_{10} + \pi_1^{'} w_1 + (\pi_{20} + \pi_2 w_t) F(y_{t-d}) + \delta_1^{'} v_t + (\delta_{20} + \delta_2' u_1) G(x_{t-e}) + u_t \quad (11)$$

where δj= (δj1… δjq)', j=1, 2, ν t= (xt-1….xt-q)' and G (.) is a transition function. Non-causality is tested as H0: $G \equiv 0$ & δ1i=0, i=1,…q. It can be shown that the relevant approximation to the above equation is

$$y_t = \bar{\pi}_{10} + \bar{\pi}_1' w_1 + (\pi_{20} + \pi_2 w_t)F(y_{t-d}) + k' v_t + \sum_{i=1}^{q} \sum_{j=1}^{q} \varphi_{ij} x_{t-1} x_{t-j} + \sum_{i=1}^{q} \psi_i x^3_{t-1} + u_t \quad (12)$$

where K'= (k1…..kq), and non-causality is supported by k_i=0, φ_{ij}=0 and ψ_i=0 i=1…q, j=1…q. Under H0 the resulting test statistic has an asymptotic χ^2 distribution with (q*(q+1)/2) +2q degrees of freedom. Alternatively, as in this paper, one may perform the test based on F distribution.

Table (7) presents the results of the nonlinear Granger Causality tests for q =5….10. The reported F statistics in Table 7 test the joint null hypotheses of no causality, i.e. that k_i=0, φ_{ij}=0 and ψ_i=0. Therefore, at some lag levels of variable x the null may not be rejected. Following previous research (Skalin and Svirta, 1999), we estimate Equation (12) for a range of lag order to ensure that causality test results are robust at longer lags. For all cases and all lag levels the P-values of F statistics are virtually equal to zero, showing that the H0 is rejected and there is evidence of causality from the S&P 500 to equity markets of Latin America. However, there is also feedback,

Table 7

Nonlinear Granger causality test: F statistics for the H_o of no nonlinear Granger causality

The reported F values in Table 6 test the joint null hypotheses of no causality, i.e. that k_i=0, φ_{ij}=0 and ψ_i=0. Therefore, at some lag levels of variable x the null may not be rejected. For instance, the computed F values for bilateral nonlinear Granger causality tests show that the former causes the latter for lags of 5, 6,7,8, 9 and 10 days, but not consistently for all lags. The degrees of freedom in the numerator and the denominator of the F- test of causality are q*(q + 1)/2+2q and T - n - q*(q + 1)/2-2q, respectively, where q is the number of lags, n is the dimension of the gradient vector and T is the number of observations.

Panel A				
	Causing Variable	Caused Variables		
Lags	S&P500	MERVAL	BOVESPA	BOLSA
5		2.842	3.674	1.773
6		2.658	3.010	2.458
7		3.179	3.190	2.920
8		3.688	4.168	3.145
9		3.444	4.429	3.594
10		3.717	4.072	3.593
Panel B				
	Causing Variable	Caused Variables		
Lags	S&P500	MERVAL	BOVESPA	BOLSA
5		2.801	3.830	2.656
6		3.174	3.371	3.480
7		3.834	4.220	3.484
8		2.591	4.411	4.104
9		2.756	4.402	4.030
10		3.704	4.675	4.007

Notes:All F statistics are significant at less than 1 percent significance level, with P-values virtually equal to 0. Degrees of freedom in the numerator of the F statistics are 25, 32, 42, 52, 63, and 75 for q=5 through 10 respectively.

i.e., LA equity market volatilities also cause volatility in S&P500. This finding emphasizes that the globalization of financial markets has enhanced the role of "small" economies in the world financial markets. For instance, volatility and shocks to a Latin American equity markets, would send volatility waves to the US equity markets. These strong causality results confirm and support the findings of bivariate VAR-EGARCH models. They go beyond establishing shock spillovers from one equity market to another in Americas, and point to a concrete causality and feedback among equity markets of Americas. Indirectly, our findings confirm that financial turmoil in smaller markets could trigger headwinds for major economies of the world. As events of the year 2012 in Greece showed, US Federal Reserve Open Market Committee and equity and bond fund managers were duly and seriously concerned with the potential deleterious effects of banking and financial markets of Greece on the US economic recovery. The Fed bond buying thus continued robustly through 2012 and 2013 to partially countervail those events.

The known channels of volatility spillovers across markets are trade and banking system. Trade among major economies of Americas is expected to grow. However, there have been no serious attempts toward coordinating banking regulation, monetary policy, or interest rate targets. Unlike the Euro zone and the European Central Bank (ECB), there is no such coordinating financial body in Americas. Furthermore, the establishment of a Central Bank of Americas is far from reality, and is not even discussed at the time of this research. Thus, it is incumbent upon Central banks of Latin American economies and the Fed to coordinate policies that foster trade and economic growth without promoting instability in financial markets. For instance, tapering the quantitative easing by the Fed in the late 2013 throughout 2014, affected returns in various asset classes in the US, across the world, and Americas. Latin American equity markets suffered losses due to capital flight. Continued downturn in these markets and its effects on economic growth and trade among Americas could potentially have ripple effects on the economies of all partners, including the US.

The findings of this research also suggest that for the US money managers, Latin American equity markets may not be the best vehicles of portfolio diversification. Negative shocks to the LA markets studied in this paper result in volatility in the US of more than 4 percent in two out of three cases. The effects of positive shocks to these markets, on the other hand, are negligible. Therefore, US investors will not be able to reduce their portfolio risk by investing in LA equities. Events of the late 2012 and 2013 in European economies such as Greece shed light on the potential effects of negative shocks to the Brazilian economy, for instance. Negative shocks to LA equity markets are certain to trigger volatility in the US equity markets and potentially create economic growth obstacles at least in the short-run.

On the other hand, negative shocks to LA markets may also create temporary opportunities to purchase equities inexpensively. For instance, if negative shocks are seen as transitory, then the effects of these shocks on the US equities maybe short-lived. In these cases, the deep market drops due to LA negative shocks, may provide profitable buying opportunities given the significant negative effects of these shocks on equity markets. It is well known that negative news impart temporary shocks to equity markets caused by investor jitters. Equity returns are mean-reverting and in the medium and long-run revert back to long-run trends.

VI. SUMMARY AND CONCLUSIONS

This paper investigates the volatility spillovers in a dynamic framework between the Standard and Poor's 500 (S&P500), and the indices of markets of Argentina (Merval), Brazil (Bovespa) and Mexico (Bolsa). Several issues motivated the paper. Foremost, investigating the intermarket dynamics among the US equities and major emerging markets of Americas is important given the ongoing financial liberalization and integration with the US market. Investigating volatility spillovers and potentially asymmetric reactions to positive and negative shocks emanating in each of these connected markets are informative to capital market players and political policy makers in Americas.

We deploy tests of nonlinearity and chaos to determine the behavior of the indices under question and appropriate models to test the dynamic bilateral interaction between the S&P500 and each of the indices. Our statistical tests establish that every index exhibits nonlinear patterns that are not consistent with chaotic behavior. We propose and estimate two variations of bivariate VAR-GARCH models. The estimated bivariate VAR-EGARCH models capture nonlinearities in both index series. Furthermore, this model is well positioned to reflect the asymmetric reaction in each market to negative and positive shocks to the other equity market in the model. Bivariate EGARCH models also show that the volatility spills in both directions, i.e, there is bivariate feedback between equity indices of Americas.

To further investigate the nonlinear interaction the S&P500 with each market under study, we employ the nonlinear version of Granger causality test. The findings of Granger causality test strongly support the bivariate VAR-EGARCH model findings and show the causality runs in both directions, i.e., there is feedback. These findings taken together are notable for policy makers and central banks, as well as hedge funders and money managers. They provide evidence that equity market downturns (negative shocks) in the US may have serious effects on equity markets and economies of Latin America. Therefore, diversification benefits from major equity markets of Americas may be limited for all investors across Americas. More importantly for US Fed, the US economy may face headwinds that may emanate from negative shocks to Latin American equity markets.

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