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Virtual Integration of Financial Markets: A Dynamic Correlation Analysis of the Creation of the Latin American Integrated Market

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Abstract

This paper investigates the role of virtual integration of financial markets on stock market return co-movements. In May of 2011 the Chilean, Colombian, and Peruvian stock markets virtually integrated their stock exchanges and central securities depositories to form the Latin American Integrated Market (MILA). We utilize the dynamic conditional correlation model propose by Engle (2002) to identify a statistically significant positive correlation between these markets. Moreover, we find strong evidence that the creation of the MILA increased the levels of dynamic correlation between stock returns. A higher correlation was also found during the dot-com bubble and the 2007 financial crises. Our results imply a decline in gains from international diversification by holding portfolios consisting of diverse stocks of these countries.

Keywords: Latin American Integrated Market, Dynamic conditional correlation, Integration.

JEL: C10, F36, G11, G15

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1. Introduction.

The Latin American Integrated Market (MILA) is the first cross-border initiative that integrates equity markets without a corporate integration. It is the virtual integration of the Santiago Exchange (Chile), the Colombia Exchange, and the Lima Exchange (Peru), and uses only technological tools along with the adaptation and standardization of regulations on trading in capital markets and the custody of securities. This integration provides a unique opportunity for the study of virtual integration of financial markets. As of January 2013, MILA is the first financial market in the region based on the number of issuers (601) followed by Brazil (362), and Mexico (136), and it is second based on market capitalization ($706,098 millions) only behind Brazil ($1,257,888 million).[1]

The main goal in this study is to evaluate the dynamic co-movement –represented by the time-varying conditional correlation among of the stock markets– between markets that integrate MILA and assess the impact of the creation of the virtually integrated MILA on the conditional correlation. The creation of MILA was expected to diversify, expand and improve the attractiveness of trading in equity markets. MILA gives investors a greater supply of securities, increased number of issuers and also augmented sources of funding. However, a potential downside in the virtual integration of markets is the loss of independent investment opportunities. As markets become more closely linked, the existence of volatility spillovers means that opportunities for diversification might be restricted. Our study focuses on testing whether the creation of MILA increased the dynamic conditional correlation among its markets. This can have important implications due to the reduced diversification opportunities.

[1] Federación Iberoamericana de Bolsas, FIAB, http://www.fiabnet.org

Our empirical strategy uses the Dynamic Conditional Correlation (DCC) from the multivariate GARCH model proposed by Engle (2002). The advantage of this method is that the dynamics of the correlations are modeled along with the volatility of the returns. Furthermore, it allows us to identify the evolution of financial market co-movements. After the estimation of our DCC-GARCH model we turn to a second step in which we assess the existence of possible changes in the conditional correlations, in particular from the virtual integration of our markets. The results show that the DCC-GARCH model identifies statistically significant correlations for all the country-specific markets. Moreover, we find a statistically significant increase in the correlations after the virtual integration of the markets and during external financial crises.

Our results have important implications for investors that participate in the virtually integrated markets. A higher dynamic conditional correlation among stock returns from countries in virtually integrated markets implies that the gain from international diversification is lower. The benefit of holding diversified portfolios consisting of stocks from various countries declines because these stock markets are exposed to a higher systematic risk. Furthermore, because the dynamic correlation also increases during financial crises, this can also be associated to reduced gains from international diversification because it is during domestic markets drops when investors desire most the benefits of international diversification. While the positive benefits of a virtual integration are easy to understand, the downside to a higher dynamic conditional correlation after the virtual integration of markets is difficult to predict ex-ante. Our results and methods can be useful to assess future virtual integrations of financial markets.

Our results are also relevant for its implications for the financial integration of other emerging markets. Most of the literature on financial integration has focused on developed economies. For Latin America previous work has either excluded the countries in MILA, studied long-run dynamics or has focused on the degree of integration with the United States (see e.g., Choudhry, 1997; Chen et al., 2002; Verma and Ozuna, 2005; Hunter, 2006; Panchenko and Wu, 2009; and El Hedi Arouri et al., 2010). Choudhry (1997) looks at six Latin American stock indices and the United States to find a long-run relationship, while Chen et al. (2002) find a cointegrating relationship that explains the dependencies in prices. Moreover, Verma and Ozuna (2005) examine the response of selected Latin American stock markets to movements in macroeconomic variables. On the market integration literature side, Hunter (2006) uses American Depository Receipts (ADRs) to examine the level of integration in a sample of emerging markets in the post-liberation period, while Panchenko and Wu (2009) use a semi-parametric approach to assess the integration of emerging markets and find that integration increased the demand for stocks and reduced the demand for bonds. Hedi Arouri et al. (2010) is similar to our study in the sense that they also estimate a dynamic correlation model for Latin American stock markets, but they do not assess the role of market integration.

Another reason why the results in this paper are important is the substantial growth of capital markets in recent decades. This development of capital markets in rich countries has been accompanied by increasing financial integration. Poitras (2012) explains that financial market capitalization has increased substantially for the G-7 countries. Financial markets in developing countries have been growing in a similar fashion, usually fueled by financial liberalization and privatizations processes, policies to pursue macroeconomic stability, better business environments, and stronger economic fundamentals. Carrieri et al. (2007) point out that foreign direct investment has been a key factor behind the growth in capital markets and increased financially integration. While Latin American financial markets have also been growing relatively fast, De La Torre and Schmukler (2006) showed that capital market in Latin America could be performing better.

Additional closely related literature includes Wang and Moore (2008) who discuss the different methodologies that have been used to empirically evaluate stock market integration. Furthermore, Kim et al. (2006) and Wang and Moore (2008) focus on the nature and extent of co-movements across daily asset returns. Bekaert and Harvey (2003) and Lence and Falk (2005) find that markets are more integrated when assets of identical risk command the same expected return irrespective of their domicile. Finally, Ayuso and Blanco (2001) find more integration when there is less barriers to trade across markets, and Federico (2007) when there are no arbitrage opportunities.

The rest of the paper is organized as a follows. Section 2 describes some key characteristics of the MILA, while Section 3 presents the estimation methods. Section 4 reports and discusses the results. Section 5 concludes.

2. About the Latin American Integrated Market

The MILA is the virtual integration of the Santiago Exchange (Chile), the Colombia Exchange and the Lima Exchange (Peru) markets along with their respective Central Securities Depository (CSD). Among its goals when created, the MILA was expected to diversify, expand and improve the attractiveness of trading of the equity markets in the three countries for both local and foreign investors. The integration process started on September 8, 2009, when the Lima Stock Exchange, the Peruvian CSD (CAVALI), the Santiago Stock Exchange, the Chilean CSD, the Colombia Stock Exchange, and the Colombian CSD (DECEVAL) agreed to define a model of integration of equity markets managed by each of the participating stock market exchanges. Each of the participating institutions was also in charge of the management of the clearing and settlement systems. In November 2010 the stock exchanges and securities deposits signed the implementation agreement for the first phase of the market integration and by May 2011 they fully started the operations of the virtually integrated stock market.

What is unique about MILA is that it is the first transnational market integration initiative without fusion or corporate integration. MILA uses technological tools along with the harmonization of regulation on capital markets and the trading and custody of securities. Hence, it enables free trade of shares across countries allowing investors in any country to work with registered brokers and access the complete supply of equities. The most relevant features of MILA is the fact that none of the three initial markets loses its regulatory independence. The creation of MILA integrates the exchanges to allow brokers to purchase securities in any of the markets. In MILA all negotiations are made in local currency with entries through local intermediaries.

Under its main goal of developing the capital market through the integration of the capital markets of the three countries, investors have a larger set of securities to choose from. On the supply side, issuers also face a larger source of funding. With 601 issuers as of January 2013, MILA is the largest in the region followed by Brazil with 362, and by Mexico with 136. It is also the second largest in market capitalization ($706,098) with Brazil ($1,257,888) being the first. In terms of trading volume for the period of January through August 2012, it ranks third ($64,781) after Brazil and Mexico who have $605,712 and $75,909 respectively.[2]

Under MILA investors are expected to have a larger set of financial instruments, extended possibilities of diversification and can potentially obtain a better risk-return balance. MILA was also expected to create new portfolios for distribution to local customers. For issuers the idea is that it should offer access to new markets, expands the demand while attracting more

[2] Federación Iberoamericana de Bolsas, FIAB, http://www.fiabnet.org

investors and can potentially reduce the capital costs for businesses. For brokerage firms MILA is aimed at promoting a more attractive and competitive equity market, increasing the range of products for distribution to consumers, enabling the creation of new investment vehicles, and strengthening technology and to ease the adoption of international standards. While these factors should most likely help increase the conditional correlations between the stock returns in the three countries, it is not immediately clear whether structural differences across countries (e.g., tax considerations, cultural differences, county-specific risk, law enforcement, differences in property right) might still be strong enough to prevent a higher conditional correlation after the MILA creation. The results in this paper are additionally important in light of structural differences across countries.

3. Data and Methodology

3.1 Data and Descriptive Statistics

The data used in this study contains 3,175 observations of daily stock indices from July 7, 2001 through September 4, 2013. The stock indices we have are from of Chile (IGPA), Colombia (IGBC), and Peru (IGBL), in addition to the United States' S&P500 Composite Index, all obtained from Datastream International. All the indices are in U.S. dollars, dividend-unadjusted, based on daily closing prices. Following Pukthuanthong and Roll (2009) we use of a common currency to alleviate exchange rate noise, because such conversions represent a ubiquitous practice in studies of international financial markets. We include data from the S&P500 because the U.S. market serves as a global factor in the region (see, e.g., Dungey et al., 2003; Chian et al., 2007; and Syllignakis and Kouretas, 2011). Following the conventional approach, stock returns are calculated as the first difference of the natural logarithm of each stock-price index, and the returns are expressed as percentages.[3] When data are unavailable (e.g., because of national holidays, bank holidays), the closing price is assumed to stay the same as the previous trading day.

The summary statistics of the stock index returns of the three MILA markets and the S&P500 is presented in Table 1. The table reports the mean, standard deviation, kurtosis, skewness, and the Ljung-Box statistic before MILA, after MILA and for the pooled sample. As expected with emerging equity markets, the index return series are negatively skewed and leptokurtic. Furthermore, all the stock return series before MILA and for the pooled sample are found to exhibit significant autocorrelation as suggested by the Ljung-Box test statistic. While the average daily return is negative for all the MILA markets after its creation, the negative sign is not statistically significant at conventional levels.

[Table 1, about here]

The correlation coefficients between the MILA markets and the S&P500 are presented in Table 2. Different panels consider different samples. For the pooled sample in Panel A all pair-wise correlations across markets are positive and statistically significant. The highest coefficient is between Chile and Peru (0.5010), while the lowest is between and Colombia and the S&P500 (0.2864). By dividing our sample between the periods before (Panel B) and after MILA (Panel C), we can observe that after the creation of MILA there is evidence of stronger pair-wise unconditional correlations across markets.

[Table 2, about here]

[3] $r_{i,t} = [\ln(p_{i,t}) - \ln(p_{i,t-1})] \times 100.$

The dynamic conditional correlation methods that we employ in the modeling section required the variables to be stationary. To test for stationarity we use three popular unit root tests, the standard augmented Dickey-Fuller (ADF), the GLS augmented Dickey Fuller (GLS-DF), and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The statistics, as reported in Table 3, show strong evidence supporting that all the original series in levels have a unit root. Moreover, the daily returns ($r_{i,t}$) are stationary as required.

[Table 3, about here]

To visualize the dynamics of the returns for each of the markets, Figure 1 provides the time series graphs for the indices in natural logarithms (left-hand side) and as daily returns (right-hand side). The benefit of presenting the natural logarithm of the indices is that the slope is the rate of growth. In the three Latin-American markets stocks prices have been experiencing a sharp increase, especially during the first half of the last decade. Time series graphs of the returns show a clustering of larger volatility around 2008 for all indices and at the beginning of our sample only for the S&P500. The first one is explained by the recent financial crisis, while the second by the dot-com bubble. These market phenomena has been widely recognized and successfully captured by simpler GARCH types of models in the literature (e.g., Bollerslev et al., 1992).

[Figure 1, about here]

3.2 The Dynamic Conditional Correlation Model

We use a multivariate GARCH dynamic conditional correlations (DCC) model proposed by Engle (2002) to assess the co-movements among stock markets. The DCC-GARCH has three advantages over other estimations methods (Chiang et al., 2007). First, the DCC-GARCH model accounts for heteroscedasticity directly by estimating the correlation coefficients of the standardized residual. Cho and Parhizgari (2008) argue that the DCC-GARCH provides a superior measure of correlation because the estimates of the time varying volatility are unbiased. Second, we can include exogenous controls in the mean equation to account for common factors that affect the dynamics of the MILA. Thus, following Chiang et al. (2007) and Syllignakis and Kouretas (2011), we include the S&P500 as an exogenous global factor. Finally, compared with alternative methods that model time-varying correlations, the DCC-GARCH is relatively parsimonious. The results from the estimation will provide us with the series of time-varying conditional correlation coefficients. We can later on break down the series into different episodes, which allows us to test for the existence of regime shifts, for example, due to the creation of the MILA.

We use the following AR model to capture the dynamics of the returns:

$$r_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i r_{t-i} + \sum_{i=1}^{s} \delta_i r_{r-i}^{US} + \varepsilon_t \, , \qquad (2)$$

where the vector of error terms is assumed to follow a multivariate normal distribution, $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$, in which we model the dynamics of the variance-covariance matrix H_t. The vector of returns is given by $r_t = \left(r_{Chile,t}, r_{Colombia,t}, r_{Peru,t}\right)'$ while the vector of error terms can be written as $\varepsilon_t = \left(\varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Peru,t}\right)'$.[4] This specification includes an autoregressive term of order p and following Dungey et al. (2003) we use s lags of the S&P500 stock returns as

[4] Panel GARCH models, as in Escobari and Lee (2014), represent an alternative GARCH specification that models multiple mean equations along with a structured time-varying variance-covariance matrix.

a global factor that can affect the dynamics of r_t. The AR is used to capture the stock returns dynamics, which we find in all the markets under investigation, as reporter in Table 1. The inclusion of the lags of the U.S. stock returns is also based on the empirical finding that U.S. stock returns play an important role in determining stock returns in emerging markets. Moreover, Latin American stock returns have no significant dynamic effect on U.S. stock returns.

To model the dynamics of the conditional variance-covariance matrix we specify it as:

$$H_t = D_t R_t D_t \tag{3}$$

The $(n \times n)$ diagonal matrix D_t contains the time-varying standard deviations from univariate GARCH models with $\sqrt{h_{ii,t}}$ on the ith diagonal, for $i=1,2,..,n$. The main elements of interest are the off-diagonal elements of the $(n \times n)$ time-varying R_t correlation matrix. Following Engle (2002) we employ a two-step procedure to estimate the elements of H_t. In the first step we employ simple univariate GARCH models to obtain the standard deviations in D_t. In the second step we adjust the first stage residuals with $u_{it} = \varepsilon_{it}/\sqrt{h_{ii,t}}$, and then use the adjusted residuals to estimate the coefficients in the conditional correlation. The $(n \times n)$ matrix that captures the time-varying variance-covariance matrix of u_t is given by:

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

where α and β are nonnegative scalars that we estimate under the restriction $(\alpha + \beta) < 1$. We denote each of the elements in the Q_t matrix with $q_{ij,t}$. The $(n \times n)$ unconditional variance-covariance matrix of u_t is simply $\bar{Q} = E(u_t u'_t)$. Because correlation matrices have ones in their main diagonal we have to rescale R_t to ensure this is true here:

$$R_t = \text{diag}\left(1/\sqrt{q_{11,t}}, \dots, 1/\sqrt{q_{nn,t}}\right) Q_t \ \text{diag}(1/\sqrt{q_{11,t}}, \dots, 1/\sqrt{q_{nn,t}}). \tag{5}$$

If Q_t is positive definite then the diagonal elements in R_t will be equal to one. Moreover, the absolute value of the off-diagonal elements will be less than one. Following Equation (5), the ij element in R_t is given by $q_{ij,t}/\sqrt{q_{ii,t} \times q_{jj,t}}$ for all i and j when $i \neq j$.

With the following log likely function:

$$l_t(\theta, \phi) = -\sum_{t=1}^{T}(nlog(2\pi) + log|D_t|^2 + \varepsilon_t' D_t^{-2}\varepsilon_t) - \sum_{t=1}^{T}(log|R_t| \; + u_t' R_t^{-1} u_t - u_t u'_t) \tag{6}$$

we can estimate θ and ϕ in the matrices D_t and R_t following the two-stage approach in Engle (2002). In the first step we focus on the first component of the right-hand side of Equation (6) to estimate θ. Given the estimates of θ, the second step involves the estimation of ϕ focusing on the second component on the right-hand side of Equation (6).

4. Results

4.1 Estimates of the Model

Before we estimate the multivariate GARCH specifications we need to test for the existence of ARCH errors. The ARCH-LM statistics for Chile, Colombia and Peru using an ARCH(5) are 745.29, 694.77 and 702.73, respectively.[5] These relatively large values provide strong evidence to reject the null hypotheses of homoscedasticity in all cases. Hence, we can move to estimate the multivariate GARCH models. Table 4 presents the estimation results for the DCC-GARCH. The orders p and s in Equation (2) are selected using the Bayesian Information Criterion (see Table A1 on the Appendix for the details). While the estimated *b* coefficients in the variance equations are all statistically significant, Ma et al. (2007) indicate that large t-

[5] The lag order of the ARCH-LM test is selected using the Bayesian Information Criterion (BIC).

statistic values do not always indicate a strong GARCH effect, so we follow the strategy proposed in Ma et al. (2007) to deal with potential spurious inference in GARCH models and estimate both ARCH and GARCH models and see if the results differ substantially.[6] Table 5 present the results for the DCC-ARCH model.

The first order autoregressive coefficients on the mean equations are positive and statistically significant for all the six GARCH and ARCH specifications in Tables 4 and 5. This finding is consistent with existing evidence that explains that in emerging markets there are price frictions and partial adjustments (see e.g., Antoniou et al., 2005). The marginal effects of U.S stock returns on the MILA stock markets (δ_1 and δ_2) are statistically significant and consistently large across countries and specifications confirming the influential role of the US stock market on the MILA stock markets. Tables 4 and 5 show that the estimates in the lagged shock-squared terms in the variance equations are all statistically significant. This is consistent with time-varying volatility. Moreover, in Table 4, the highly significant lagged conditional volatility is evidence favoring the GARCH specification. The volatility persistence measures on the same table $(a + b)$ are all close to one indicating that for all the markets examined the volatility displays a high persistence. Finally, the multivariate DCC equation reports the estimates of the parameters α and β from the second step in Engle (2002). Both parameters are statistically significant at conventional levels for both ARCH and GARCH models, revealing a substantial time varying co-movement. Wald test rejects the null hypothesis that $\alpha = \beta = 0$ at all conventional levels.

[Table 4, about here]

[6] See Ma et al. (2007) for potential spurious inference of the GARCH effect when the model is weakly identified.

[Table 5, about here]

Using the estimates reported in Table 4, we plot the dynamics of the pair-wise correlations and test for particular patterns, e.g., the integration of the MILA markets.[7] Figure 2 presents the evolution of the estimated conditional correlation coefficients between the stock returns of Chile-Colombia, Chile-Peru, and Colombia-Peru. A common characteristic of the pair-wise correlations is that they reach relatively large positive values during the most recent U.S. financial crisis. Moreover, they all appear to have relatively small but positive trends. In particular, the trend in the pair-wise correlation between Chile-Colombia appears to have been positive throughout the period of study. The trend for the conditional correlation between Chile-Peru appears to have been negative or close to zero prior to 2006, then it was positive until the beginning of the most recent U.S. financial crisis. During the crises the correlation declined, a phenomenon that can be explained by the fact that Chile only suffered relatively minor effects from the crises. The dynamic correlation between Peru and Colombia showed to be relatively stable around 0.2 prior to the financial crises, and then jumped to fluctuate around 0.4.

[Figure 2, about here]

The key part of our analysis is to model the dynamics before and after the creation of the MILA. Casual observation of Figures 2 and 3 indicate that after MILA began its operations on May 30, 2011 –the vertical line on Figures 2 and 3– all the pair-wise conditional correlations

[7] The results here and in the rest of the paper are qualitatively the same when using the DCC-ARCH estimates in Table 5. Hence we focus on explaining only one of the specification.

appear to have increased. The dynamic correlation for Chile-Colombia has an average of 0.5 after MILA, but of only 0.33 before MILA. For the Chile-Peru dynamic correlation the average is calculated at 0.56 after MILA and at 0.39 before MILA. Finally, Colombia-Peru has an average of 0.45 after MILA and 0.32 before MILA. All three differences across pair-wise correlations are statically significant at a 1% level.

[Figure 3, about here]

4.2 Explaining the Conditional Correlation

A higher correlation between markets has an important implication from the investor's perspective (Chiang et al., 2007). The diversification benefits from a portfolio which includes equities from the three countries in MILA may have decreased after the creation of MILA. This is because each of these stock markets became more sensitive to the movement of the other two markets, the level of foreign investment produce by MILA, and the systematic risk. We now turn to further investigate the behavior of the conditional correlation coefficients and sort out the impact of the MILA creation on their dynamics.

We have the following regression model to analyze the dynamics of the conditional correlations:

$$\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DMILA_t + \sum_{k=1}^{2} \eta_k \, DC_{k,t} + \theta_i \hat{\rho}_{iUS,t} + \theta_j \hat{\rho}_{jUS,t} + \epsilon_t, \text{ for } i \neq j. \tag{8}$$

The dependent variable $\hat{\rho}_{ij,t}$ denotes the conditional correlation predicted by the DCC-GARCH between markets i and j at time t. The conditional correlations between the MILA markets i and j and the U.S. are $\hat{\rho}_{iUS,t}$ and $\hat{\rho}_{jUS,t}$. $DMILA_t$ is a dummy variable that is equal to one after the creation of MILA, zero otherwise. $DC_{k,t}$ is a set of dummy variables to control for the financial contagion produced by crises that can potentially affect the dynamic conditional correlation (see e.g., Chiang et al. 2007; Syllignakis and Kouretas, 2011; and Horvath and Petrovski, 2013). These dummies should help control for two known contagion mechanisms: objective contagion (that arises based on market performance) and subjective contagion (a bandwagon effect in which investors just follow other investors) because both mechanisms spread crises while they are active and our dummies allow for a differentiated level effect in the correlations during the crises periods.

We identified two crises in the time period of our analysis. The first one is part of the dot-com bubble that occurred between March 10, 2000 and September 27, 2002. The second is the most recent financial crisis in US markets, dated between December 1, 2007 and December 30, 2011. Given that $DC_{1,t}$ is set to be equal to one between March 10, 2000 and September 27, 2002 and zero otherwise, η_1 should capture the dot-com effect. Likewise $DC_{2,t}$ is equal to one between December 1, 2007 and December 30, 2011, zero otherwise. Hence, η_2 captures the recent US financial crises effect. The dates for the most recent financial crises are consistent with the dates defined by the National Bureau of Economic Research (NBER). While the NBER defines the beginning of the recession as December of 2007, we have daily data so we assume that is it at the beginning of the month (see e.g., Mollick and Abebe, 2013).

The estimation results presented in Table 6 show different specifications of Equation (8). Columns 1 through 3 include only the MILA dummy along with a constant, columns 4 through 6 include controls for the contagion effect produced by financial crises, while columns 7 through 9 additionally control for the conditional correlations of each stock market returns and the US. Consistent across the first three specifications we find that the unconditional mean of the correlations and the constant term are all positive and statistically significant at the 1% level. The latter reflects that the innovations in each stock market are positively correlated. The estimates of λ_1 reveal that after MILA co-movements of stock markets across countries increased. The strong connection between correlations is regarded as negative news for portfolio managers and investors. It is precisely when domestic market drops markedly that the domestic investors most desire the benefits of international diversification, but as the international correlation gets larger it reduced the opportunities for diversification.

[Table 6, about here]

While our study is the first to analyze the integration of virtual markets, some work has been done in the analysis of emerging markets. Our findings in this regard are consistent with Syllignakis and Kouretas (2011), who find that the dot-com crisis has a negative effect on the dynamic correlation. Table 6 shows that our estimate of η_1 is negative and statistically significant at at least 1% for the Chile-Colombia (Column 4) and the Colombia-Peru (Column 6) specifications. When we additionally control for the US market this result holds. On the other hand, during the 2007-2009 financial crises the estimates of η_2 are positive and highly statistically significant. Thus, it is consistent with previous literature that has shown that the US financial turmoil had a contagion effect in Latin America (see, e.g., Yiu et al., 2010; Verma and Verma, 2005). Finally, the correlations of each of the MILA markets with the US show a positive and statistically significant effect in five of six estimates. This is additional empirical support that Latin American markets have an important degree of integration with the US market, which in our analysis serves as a global factor control.

4.3 Controlling for Unobservables

While the formulation of the DCC-GARCH model and the specification that captures the effect of MILA on the dynamic correlations are consistent with previous literature on volatility spillovers, we might still be concerned that other common (unobserved) macroeconomic factors or cross-country corporate relationships could be driving the results. Recall that we control for the S&P500, the dot-com bubble and the most recent financial crisis. However, our three national markets might have been affected by other observed or unobserved factors. For example, the housing bubble in the US fueled by subprime mortgages lead to an increase in Collateralized Debt Obligations, which in turn moved large amounts of money in international financial markets. The burst of the bubble and the following financial crisis increased uncertainty potentially beyond what our dummy $DC_{2,t}$ might be capturing. It is not clear if including additional controls in Equation (2) or Equation (8) would solve our concerns as we might still have unobserved factors that affect the joint dynamics of the returns.

In this section we implement robustness checks that are parsimonious and do not rely on including additional controls in Equations (2) and (8). We use three Latin American stock markets that will serve as control groups: Argentina, Brazil, and Mexico.[8] We refer to this group as the No-MILA countries. The idea is that without having to include a large set of controls, we assume that any potential omitted variable that affects the dynamics of $r_t = \left(r_{Chile,t}, r_{Colombia,t}, r_{Peru,t}\right)'$ is also affecting the dynamics of $r_{Argentina,t}$, $r_{Brazil,t}$, and $r_{Mexico,t}$. Hence, if our previous results are driven by any potentially omitted variable, we should be observing that after the date of the creation of the MILA, the dynamic correlations within the control group should also be larger.

[8] These countries work as a "placebo" group. We are grateful to an anonymous referee who suggested this robustness strategy.

To implement this empirical approach we start by estimating Equation (2) but with the returns of all six countries as part of the vector r_t. Once we obtain all the estimated dynamic correlations $\hat{\rho}_{ij,t}$ we move to estimate a modified version of Equation (8). Because we are no longer interested in within-MILA cross county differences in the effect of MILA creation we estimate specifications that pools across MILA countries and pools across No-MILA countries. The estimation results are reported in Table 7. All specifications include county-pair ij dummies to control for any unobserved country-pair time-invariant characteristics that can affect $\hat{\rho}_{ij,t}$. The first three columns present the estimates for the pooled MILA countries and as in Table 6 we progressively include additional covariates: The second column controls for the dot-com bubble and the recent financial crisis, while the third column additionally controls for the dynamic correlations with the S&P500.[9] Consistent with the results in Table 6 we find that across all columns the creation of the MILA increased the conditional correlation between stock returns.

[Table 7, about here]

The key result in Table 7 is presented in columns 4 through 6. The positive and statistically significant estimates of λ_1^{NoMILA} in columns 4 and 5 indicate that without controlling for the correlations with the S&P500 the dynamic correlation in No-MILA countries also increased after the date the MILA was created. While this effect is statistically significant, the magnitude is much smaller than for MILA countries. When controlling for the S&P500, the effect is negative. This is evidence that omitted variables are not driving our results that MILA increase the conditional correlations among MILA countries. Columns 7 through 9 pool across

[9] Because we pool across all combinations of $\hat{\rho}_{ij,t}$ for $i \neq j$, by construction $\theta_i = \theta_j$. The results are exactly the same if we do not include $\hat{\rho}_{ji,t}$ once $\hat{\rho}_{ij,t}$ is already included.

all countries to test if the effect is greater in MILA countries than in No-MILA countries. The results are consistent with the previous six columns. Furthermore as reported in the lower part of the table, we fail to reject the null hypothesis that $\lambda_1^{MILA} > \lambda_1^{NoMILA}$ across all specifications.

Under the assumption that any potentially omitted (unobserved) variable has the same effect on the treatment and control groups the results in Table 7 present additional support to our main hypothesis that the MILA creation increased the conditional correlations across MILA countries. A potential explanation for the positive and statistically significant λ_1^{NoMILA} estimates is that during the high period of uncertainty after the subprime financial crisis investors moved funds to Latin America following higher performance and Fed's quantitative easing. This would have potentially increased the correlations between Latin American financial markets. Notice that once we control for the S&P500 the estimates of λ_1^{NoMILA} become negative.

This robustness check approach has some limitations. The assignment of countries into the treatment and control groups is not random. That is, there is potential for self-selection of the countries that decide to participate in the virtually integrated market. Moreover, groups are not independent over time as there is potential spillover effects of the MILA creation to countries that are not part of MILA. However, we believe that this is an important robustness check that finds additional support to our previous results while allowing parsimonious specifications to assess for the existence of any omitted variable.

5. Conclusion

This paper sets to investigate the role of virtual integration of financial markets on stock market return co-movements. In May of 2011, the Chilean, the Colombian and the Peruvian stock markets were virtually integrated to form the Latin American Integrated Market (MILA).

While virtual integration is simpler than other forms of financial integration, it can potentially achieve the same benefits. One downside from the virtual integration of financial markets is the reduced investment opportunities if the positive correlation between stock returns is higher after the integration takes place. This paper tests whether this is true for virtual integration of markets by focusing on the creation of MILA.

The first step in the analysis involves estimating a Dynamic Conditional Correlation GARCH model that includes a system of three mean equations to capture the joint dynamics of the stock returns for our three markets. Our approach allows us to model a time-varying variance-covariance matrix of our system of mean equations to capture the dynamics of the conditional correlations. In the second step we model the conditional correlations and assess the effect of the creation of the MILA. We control for the mean fluctuations, the conditional volatility, and the spillover effects of the US stock market as well as for financial crises. We also perform additional robustness checks to control for unobservables using data from three comparable Latin American stock markets that are not part of MILA.

Our results indicate that the creation of the virtual market MILA has a statistically significant positive effect on the pair-wise dynamic conditional correlations of the markets that participate in the MILA. Moreover, financial crises also increase the dynamic correlation. These findings are important because the connection between conditional volatility and correlation has implications for investors that participate in this new market. It is precisely when domestic market drops markedly that the domestic investors seek more actively for the benefits of international diversification. However, increased correlation among the stock returns of the countries that participate in the MILA implies that the gain from international diversification by holding portfolios consisting of diverse stocks declines. This is because these stock markets are commonly exposed to systematic risk.

Appendix

Table A1 presents the Bayesian Information Criterion (BIC) statistics to find the optimal values of p and s in the mean equation, Equation (2), for the DCC-GARCH specification. The minimum BIC is found for values $p = 1$ and $s = 2$. Following Lo and Piger (2005) we use these selected lags for the rest of the specifications in the paper.

[Table A1, about here]

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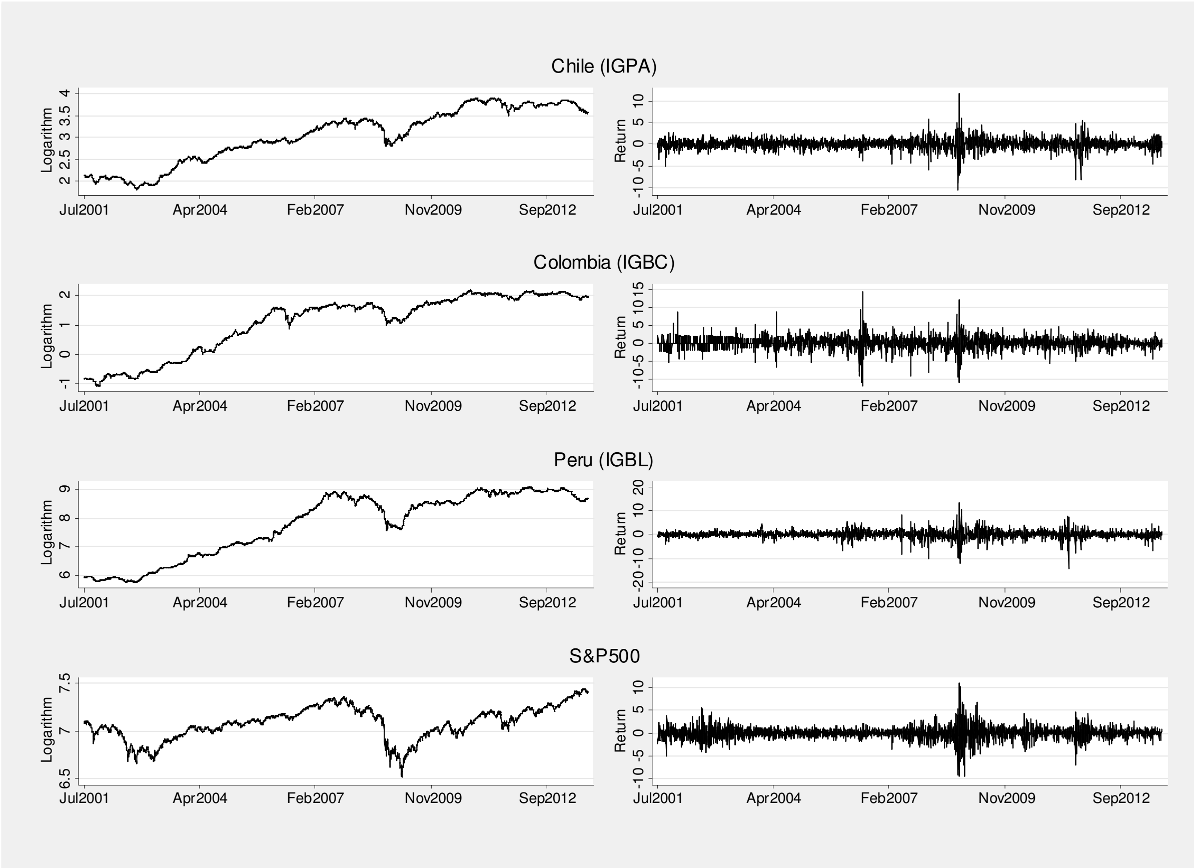
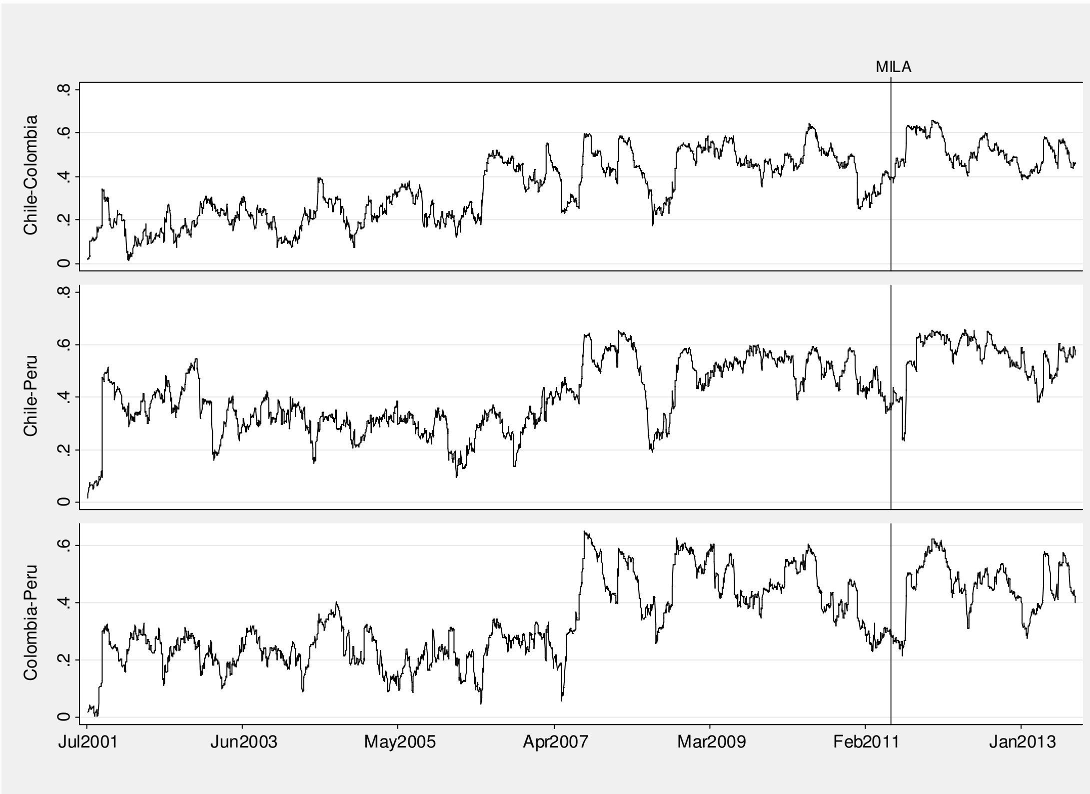
Figure 1: Stock Market Developments (2001-2013), Logarithms and Returns



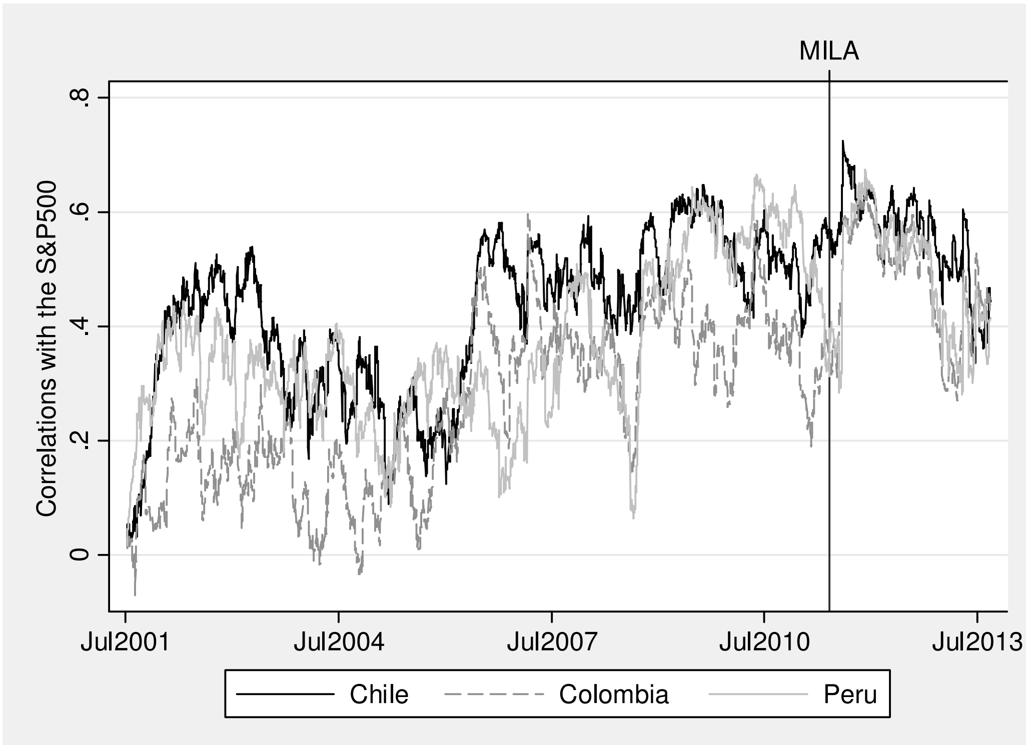
Notes. MILA stock markets and U.S. stock indices in logarithms (on the left-hand side) and as daily return $r_{i,t}$ (on the right-hand side). Daily data from July 4, 2001 to September 4, 2013.

Figure 2. Dynamic Correlations within MILA



Notes. The different panels show the estimated conditional correlation coefficients between stock market return in the countries that are part of the MILA. 2001-2013.

Figure 3. Conditional Correlation MILA – S&P500



Notes. This graph shows the estimated conditional correlation coefficients between the S&P500 and the MILA countries, 2001-2013.

Table 1: Descriptive Statistic of the Stock Index Returns

	Mean	Standard Deviation	Skewness	Kurtosis	Ljung-Box	Lags[a]
Panel A: Pooled sample (N=3,175)						
Chile	0.0450	1.166	-0.607***	13.838***	132.73***	20
Colombia	0.0884	1.672	-0.426***	11.674***	92.691***	20
Peru	0.0867	1.591	-0.576***	13.867***	147.47***	20
US	0.0092	1.292	-0.209***	11.979***	89.516***	20
Panel B: Before MILA (N=2,583)						
Chile	0.0677	1.153	-0.522***	14.489***	71.804***	20
Colombia	0.1117	1.763	-0.446***	11.394***	65.549***	20
Peru	0.1184	1.606	-0.368***	12.485***	103.87***	20
US	0.0029	1.329	-0.156**	12.238***	57.09***	20
Panel C: After MILA (N=593)						
Chile	-0.0554	1.216	-0.089***	11.420***	29.406*	19
Colombia	-0.0169	1.193	-0.301**	4.664***	0.302	1
Peru	-0.0514	1.516	-1.719***	21.118***	2.091	1
US	0.0365	1.116	-0.559***	8.079***	51.982***	20

Notes. Stock returns are calculated as first differences of the natural logarithm of the corresponding stock index times 100. Panel A includes the whole sample (07/04/2001 - 09/04/2013). Panel B is for the period before MILA (07/04/2001-29/05/2011). Panel C is for the period after the creation of MILA (05/30/2011- 09/04/2013). [a] lags of the Ljung-Box statistics (with up to 20-day lags). *, **, and *** significant at 10%, 5% and 1%, respectively.

Table 2: Correlation Coefficients

	Chile	Colombia	Peru	US
Panel A: Pooled sample				
Chile	1			
Colombia	0.4371***	1		
Peru	0.5010***	0.3983***	1	
US	0.4628***	0.2864***	0.3991***	1
Panel B: Before MILA				
Chile	1			
Colombia	0.4134****	1		
Peru	0.4918***	0.3916***	1	
US	0.4460***	0.2476***	0.3807***	1
Panel C: After MILA				
Chile	1			
Colombia	0.6157***	1		
Peru	0.5391***	0.4572***	1	
US	0.5603***	0.5937***	0.5080***	1

Notes. Figures are correlation coefficients between stock returns. Panels A, B, and C follow Table 1. *** significant level at 1%.

Table 3: Unit Root Tests

	ADF[a]	DF-GLS[b]	Lags[c]	KPSS[d]
Levels				
Chile	-1.789	-1.847	25	0.349***
Colombia	-2.316	-2.615	27	0.363***
Peru	-1.700	-2.100	27	0.325***
US	-1.762	-1.426	18	0.693***
Returns				
Chile	-26.076***	-5.942 ***	28	0.0943
Colombia	-27.711***	-10.298***	19	0.0627
Peru	-24.458***	-6.422***	28	0.111
US	-29.525***	-3.356***	28	0.0771

Notes. The results are for the pooled sample [a] Standard Augmented Dickey-Fuller (ADF). [b] Dickey-Fuller-GLS. [c] Lags associated with the DF-GLS. [d] Kwiatkowski–Phillips–Schmidt–Shin (KPSS). Null hypothesis in the ADF and DF-GLS is unit root. Null hypothesis in the KPSS is trend stationary. The critical values for the KPSS test are 0.119 (10%), 0.146 (5%), and 0.216 (1%). *** significant at 1%.

Table 4: Estimation Result from the DCC-GARCH Model

	Chile	Colombia	Peru	US
Mean equations				
γ_0	0.0948***	0.124***	0.122***	0.0732***
	(0.0152)	(0.0222)	(0.0172)	(0.0145)
γ_1	0.0615***	0.0553***	0.132***	
	(0.0172)	(0.0183)	(0.0176)	
δ_1	0.119***	0.158***	0.0919***	-0.0719***
	(0.0165)	(0.0215)	(0.0172)	(0.0181)
δ_2	0.0161	0.0463**	0.0363**	-0.0308*
	(0.0154)	(0.0209)	(0.0163)	(0.0176)
Variance equations				
c	0.0279***	0.205***	0.0496***	0.0166***
	(0.00602)	(0.0311)	(0.00867)	(0.00296)
a	0.0838***	0.153***	0.148***	0.0805***
	(0.00964)	(0.0157)	(0.0147)	(0.00768)
b	0.892***	0.762***	0.832***	0.906***
	(0.0129)	(0.0243)	(0.0158)	(0.00841)
Persistence [a]	0.976***	0.915***	0.980***	0.987***
Multivariate DCC equation				
α		0.0167***		
		(0.00236)		
β		0.976***		
		(0.00407)		
Observations		3,173		
χ^2		332.4		
χ^2 (p-value)		0.000		

Notes. [a] calculated as the sum of the coefficients in the variance equation, $a + b$. Figures in parentheses are t-statistics based on robust standard errors. ** and *** significant at 5% and 1%, respectively. The mean equation is $r_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i r_{t-i} + \sum_{i=1}^{s} \delta_i r_{r-i}^{US} + \varepsilon_t$ where $r_t = (r_{Chile,t}, r_{Colombia,t}, r_{Peru,t})'$; $\varepsilon_t = (\varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Peru,t})'$ and $\varepsilon_t | \Omega_{t-1} \sim N(0, H_t)$. The variance equations are $h_{ii,t} = c_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}$ for $i = 1, 2, \ldots, n$. The null for the χ^2 test is $H_0: \alpha = \beta = 0$.

Table 5: Estimation Result from the DCC-ARCH Model

	Chile	Colombia	Peru	US
Mean equations				
γ_0	0.0596***	0.0785***	0.0758***	0.0211
	(0.0190)	(0.0244)	(0.0215)	(0.0200)
γ_1	0.0459*	0.135***	0.192***	
	(0.0272)	(0.0192)	(0.0169)	
δ_1	0.141***	0.198***	0.0875***	-0.186***
	(0.0168)	(0.0211)	(0.0196)	(0.0183)
δ_2	0.0319**	0.0840***	0.0758***	-0.0221
	(0.0158)	(0.0206)	(0.0185)	(0.0185)
Variance equations				
c	1.030***	1.758***	1.377***	1.131***
	(0.0327)	(0.0582)	(0.0473)	(0.0369)
a	0.201***	0.321***	0.451***	0.334***
	(0.0248)	(0.0292)	(0.0358)	(0.0299)
Multivariate DCC equation				
α		0.0126***		
		(0.00306)		
β		0.536***		
		(0.06504)		
Observations		3,173		
χ^2		823.4		
χ^2 (p-value)		0.000		

Notes. Figures in parentheses are t-statistics based on robust standard errors. ** and *** significance at 5% and 1%, respectively. The mean equation is $r_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i r_{t-i} + \sum_{i=1}^{s} \delta_i r_{r-i}^{US} + \varepsilon_t$ where $r_t = (r_{Chile,t}, r_{Colombia,t}, r_{Peru,t})'$; $\varepsilon_t = (\varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Peru,t})'$ and $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$. The variance equations are $h_{ii,t} = c_i + a_i \varepsilon_{i,t-1}^2$ for $i = 1, 2, \ldots, n$. The null for the χ^2 test is $H_0: \alpha = \beta = 0$.

Table 6: Dynamic Correlation Coefficients and the MILA

Country i:	Chile	Chile	Colombia	Chile	Chile	Colombia	Chile	Chile	Colombia
Country j:	Colombia	Peru	Peru	Colombia	Peru	Peru	Colombia	Peru	Peru
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
λ_1	0.184***	0.160***	0.139***	0.179***	0.171***	0.146***	0.0303***	0.0596***	0.0203***
	(0.00617)	(0.00547)	(0.00596)	(0.00466)	(0.00487)	(0.00488)	(0.00398)	(0.00423)	(0.00502)
η_1				-0.146***	0.00346	-0.0498***	-0.0849***	0.00915*	-0.0183***
				(0.00618)	(0.00646)	(0.00647)	(0.00430)	(0.00482)	(0.00542)
η_2				0.148***	0.125***	0.156***	0.0522***	-0.000339	0.0509***
				(0.00393)	(0.00410)	(0.00411)	(0.00319)	(0.00389)	(0.00423)
θ_i							0.0219	0.238***	0.374***
							(0.0140)	(0.0143)	(0.0151)
θ_j							0.657***	0.539***	0.304***
							(0.0134)	(0.0145)	(0.0160)
λ_0	0.328***	0.390***	0.317***	0.295***	0.347***	0.269***	0.141***	0.0947***	0.0948***
	(0.00266)	(0.00236)	(0.00258)	(0.00262)	(0.00273)	(0.00274)	(0.00462)	(0.00568)	(0.00503)
Observations	3173	3173	3173	3173	3173	3173	3173	3173	3173
F	893.8	859.5	546.6	1408	702.9	867.1	2605	1303	1141
F (p-value)	0	0	0	0	0	0	0	0	0
Adjusted R^2	0.220	0.213	0.147	0.571	0.399	0.450	0.804	0.672	0.642

Notes. Evolution of market correlations of MILA stock markets. The model is: $\hat{\rho}_{ij,t} = \lambda_{i,0} + \lambda_{i,1} DMILA_t + \sum_{k=1}^{2} \eta_k \, DC_{k,t} + \theta_i \hat{\rho}_{iUS,t} + \theta_j \hat{\rho}_{jUS,t} + \epsilon_t, for\ i \neq j$, where $\hat{\rho}_{ij,t}$, $\hat{\rho}_{iUS,t}$ and $\hat{\rho}_{jUS,t}$ are the conditional correlations of the stock market returns predicted from the DCC-GARCH in Table 4. $DMILA_t$ is a dummy variable that is equal to one after 05/29/2011, zero otherwise. $DC_{k,t}$ are dummy variables to control for financial contagion. The first one ($DC_{1,t}$) is part of the dot-com bubble (03/10/2000 – 09/27/2002) and the second one ($DC_{2,t}$) captures the most recent financial crisis (01/01/2008-12/30/2011). The t-statistics based on robust standard errors are in parentheses. **, and *** significant at 5% and 1%, respectively.

Table 7: Dynamic Correlation Coefficients in MILA and No-MILA Countries

Countries i and j:	MILA Countries			No-MILA Countries			All Countries		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
λ_1^{MILA}	0.143***	0.145***	0.0266***				0.143***	0.140***	0.0190**
	(0.00169)	(0.00190)	(0.00165)				(0.00728)	(0.00650)	(0.00860)
λ_1^{NoMILA}				0.0178***	0.00969***	-0.0473***	0.0178***	0.0146***	-0.0351***
				(0.00270)	(0.00235)	(0.00133)	(0.00266)	(0.00309)	(0.00233)
η_1		-0.0712***	-0.0297***		-0.168***	0.0205***		-0.119***	-0.0255**
		(0.00287)	(0.00219)		(0.00353)	(0.00259)		(0.0188)	(0.0107)
η_2		0.128***	0.0247***		0.154***	0.0167***		0.141***	0.0332***
		(0.00158)	(0.00158)		(0.00187)	(0.00142)		(0.00861)	(0.00579)
θ_i			0.389***			0.551***			0.419***
			(0.00482)			(0.00489)			(0.0739)
θ_j			0.389***			0.551***			0.419***
			(0.00482)			(0.00489)			(0.0739)
λ_0	0.353***	0.317***	0.0747***	0.515***	0.483***	-0.0935***	0.434***	0.400***	0.0503***
	(0.00101)	(0.00107)	(0.00194)	(0.00136)	(0.00163)	(0.00342)	(0.000723)	(0.00264)	(0.0159)
Observations	19038	19038	19038	19038	19038	19038	38076	38076	38076
F	7242	3863	13243	43.59	4572	12201	216.6	252.7	897.3
F (p-value)	0	0	0	0	0	0	0	0	0
H_0: $\lambda_1^{MILA} > \lambda_1^{NoMILA}$							262	262.66	38.33
H_0: $\lambda_1^{MILA} > \lambda_1^{NoMILA}$ (p-value)							0	0	0
Adjusted R^2	0.181	0.453	0.715	0.00175	0.356	0.766	0.0915	0.484	0.767

Notes. Evolution of market correlations of MILA (Chile, Colombia and Peru) and No-MILA (Argentina, Brazil and Mexico) stock markets. The estimated model is the panel version of Equation (8): It pools across country pairs ij. All specifications include country-pair ij dummies. The t-statistics are in parentheses based on robust standard errors. ** and *** indicate the significance levels of 5% and 1%, respectively.

Table A1: Order Selection for the Mean Equation

	$s=1$	$s=2$	$s=3$	$s=4$	$s=5$
$p=1$	39114.39	39111.16	39129.47	39149.04	39154.22
$p=2$	39118.31	39135.18	39153.52	39173.10	39178.32
$p=3$	39124.74	39140.29	39168.46	39189.03	39193.76
$p=4$	39126.54	39141.75	39170.32	39201.38	39206.67
$p=5$	39126.20	39140.95	39169.44	39200.52	39224.83

Notes: Figures reported are Bayesian Information Criteria statistics for the DCC-GARCH model. p and s are the orders of the mean equation $r_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i r_{t-i} + \sum_{i=1}^{s} \delta_i r_{r-i}^{US} + \varepsilon_t$.