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The Nature of Latin American Markets in the Presence of Credit Events

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Abstract:

In the past two decades the Latin American region has experienced a number of credit crises stemming from large sovereign debt levels and sharp currency devaluations. This study aims to discover whether or not the sovereign credit default swaps (CDS) in the Latin American region lead equity markets prior to these sovereign credit events. Through a sample of the seven largest Latin American economies and daily return data from 2001 to 2018, I try to empirically test this question through a Generalized Least Squared model. The paper finds little significant evidence of CDS leading equity markets in price discovery prior to sovereign credit events. Additionally, the paper observes a potential momentum effect present amongst Latin American equity market returns. However, this effect is more likely serial correlation amongst equity market returns due to the illiquidity of these equity markets.

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In memory of Guillermo Aguilar Alvarez

Table of Contents

1. Introduction:

Berkshire Hathaway Chairman and famous investor Warren Buffett notoriously referred to credit default swaps (CDS) as “financial weapons of mass destruction.” Other individuals describe CDS as analogous to “taking out fire insurance on a neighbor’s home.”[1] During the Global Financial Crisis, CDS played a central role in the bankruptcies of Lehman Brothers and AIG following the crash of the subprime mortgage market. Despite their central role in the Global Financial Crisis, CDS have also had positive effects on capital markets: they provide investors with a liquid market to trade credit risk and demonstrate the ability to capture information yet to be priced in stocks or bonds. This paper aims to explore the information captured by sovereign CDS and the extent to which this market is more efficient than local equity markets in pricing sovereign credit risk events.

Since the advent of these credit derivatives in 1994, the outstanding notional amount of CDS contracts peaked at $61.2 trillion in 2007 and fell to $9.4 trillion dollars in 2017.[2] A CDS is a contract in which the buyer purchases insurance on the default risk of a reference entity’s debt. The main components that define a CDS contract are the reference entity, a list of credit events that trigger the protection payment, the term or maturity of the contract, the reference obligation, and the notional amount of the contract.[3] The reference entity can be either a corporate or sovereign creditor. During the time of the Eurozone Crisis, the notional amount outstanding of sovereign CDS peaked at over $3 trillion. By 2017, the notional amount of sovereign CDS dropped to around $1.5 trillion, but grew to

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[1] Maiello.
[2] Aldasoro.
[3] Tuckman, 545.

around 15% of the overall CDS market. The reference obligation is a specified debt obligation of the reference entity. CDS are available in maturities of 1, 2, 3, 5, 7, and 10 years, although the 5-year CDS is the most liquid.[4] Exhibit 1 provides the current makeup of the CDS market and its historical growth while Exhibit 2 provides a list of generally accepted credit events by the International Swaps and Derivatives Association (ISDA).

A CDS buyer will make periodic payments, referred to as the CDS spread, to the CDS seller for the duration of the contract, or until a "credit event" occurs. These payments come from an annualized spread of basis points on the notional amount of the contract. If there is a credit event, the CDS seller agrees to buy the reference entity's debt from the buyer for the face value of the contract.[5] The CDS spread increases – and thus purchasing CDS protection becomes more expensive – as the creditworthiness of the reference entity deteriorates.

In recent years, the CDS market has shown to be a better source of pricing information than other markets. Academics have observed that the CDS market can be a superior source of credit risk information than both credit ratings and bond yield default spreads (Blanco et al., 2005; Norden and Weber, 2004; Flannery et al., 2010; Hull et al., 2004). In prior years, investors focused on information provided by credit rating agencies and reference entity borrowing costs as chief credit risk indicators. However, the relative illiquidity of bond markets and rating agencies' failure to adequately convey default risk compelled investors to look elsewhere for credit risk indicators. The CDS market was a

[4] Hull, 571.

[5] This is only the case in contracts with physical settlement. Under the now more common cash settlement, ISDA organizes a formal auction process in which the cash payoff to the CDS buyer is determined by the cheapest-to-deliver (CTD) bond after the credit event. In this case, the buyer's cash proceed is the loss given default times the face value of the CTD bond.

good place to start since the market was (and still is) more liquid than bond markets and the probability of default (PD) of reference entities is reflected in current market prices rather than periodic rating changes.

This study aims to add to previous studies focusing on the anticipation of adverse credit events in both CDS and equity markets. More specifically, I intend to contribute to existing literature by focusing on the sovereign CDS markets rather than corporate CDS markets. The Eurozone crisis showed the adverse effects of sovereign credit risk and there have been many post-hoc studies looking at market fluctuations during the period (Afonso et al, 2012; da Silva, 2014). I expand on these previous studies and analyze the reaction of sovereign CDS and equity markets prior to credit events. The central question I hope to answer is whether the sovereign CDS markets leads equity markets in price discovery during credit events.

Moreover, instead of focusing on the Eurozone or other developed markets, this study focuses on emerging markets (EM) in Latin America. My decision to choose this sample set was driven by both the less developed literature on this region and the more volatile nature of this region's CDS markets. The Latin American region has gone through a number of financial crises over the past twenty five years. These crises include Argentina's defaults in 2001 and 2014, Mexico's Tequila Crisis in 1995, Venezuela's default in 2017, and the Global Financial Crisis in 2008. While this paper will not cover all of these individual examples, it will provide insight on the nature of Latin American sovereign credit risk and market reaction prior to sovereign credit events.

The importance of this study is based on the higher risk assumed by emerging market investors. EM investors tend to take on risky, more volatile positions in developing markets. This is perhaps to exploit the ability to generate higher yields while developed markets are in a steady state – the "reaching for yield" phenomenon. For example, during periods of falling interest rates, an investor can buy sovereign bonds from a non-investment grade country and be able to both generate higher yields and capitalize on falling interest rates.[6]

However, investing in EM leaves investors exposed to risk factors such as political instability, liquidity risk, and potential corporate governance issues in some of the individual investment prospects. In times of pronounced market volatility, this makes the potential losses in emerging markets much higher than developed markets and leads to a "flight to quality and liquidity," whereby investors shift the allocation of their money towards low-risk, liquid assets. This means that a more volatile region like Latin America will be the first to experience a widespread market sell-off during times of economic uncertainty or volatility. Furthermore, the absence of developed liquid markets in Latin American makes it difficult for investors to sell off their positions without having to take losses on their investments. Through looking at the nature of sovereign CDS and equity markets in Latin America, this paper can help pinpoint certain patterns to help EM investors notice and anticipate future market behavior before a detrimental credit event occurs.

[6] Bond prices increase as interest rates fall, so investors gain from both higher yields and price appreciation perspective.

Through a sample of seven Latin American countries, I assess how corresponding sovereign CDS and equity markets move prior to "credit events" in the sample countries. In order to empirically test this, I will use a Generalized Least Squared (GLS) regression to look at the movements of both markets prior to "credit events." This follows the same econometric analysis used to investigate the presence of trading in CDS markets under normal and adverse market conditions (Acharya and Johnson, 2007; Berndt and Ostrovnaya, 2014; Qiu and Yu, 2012). Unlike the aforementioned studies, which focus on corporate credit risk, my paper focuses on the nature of sovereign credit risk. This fundamental difference could alter my results based on the different risk drivers of the two reference entities. Corporate credit risk is driven by firm-specific default risk, which is driven by metrics like leverage and asset volatility (Merton, 1974). Sovereign credit risk is more tied to macroeconomic factors like foreign exchange rates and geopolitical factors. Additionally, sovereign credit risk is also linked to U.S. market fundamentals like the CBOE Volatility Index (VIX) and U.S. high yield indices (Longstaff et al., 2011) Furthermore, my focus is on Latin American markets, which are less liquid than those in the U.S., might change the results of the study.

The results of this study show little significant evidence of CDS innovations leading equity market returns prior to a credit event. There was little indication of CDS innovations influencing equity returns prior to sovereign credit events for the entire sample. However, when splitting the sample of countries into those that were investment grade and non-investment grade, the study showed that CDS innovations do lead equity returns five and 30 days prior to a sovereign credit event. Furthermore, the study found results consistent with a serial correlation in Latin American equity market returns. The coefficient sum indicating this serial correlation was larger within the sample of investment grade countries and is very likely attributed to the absence of liquidity in underdeveloped Latin American equity markets (de la Torre and Schmukler, 2006).

The remainder of this paper proceeds as follows. Section 2 analyzes the relevant literature used to conduct this research and states the relevant hypotheses. Section 3 will describe the methodology through specifying the data collection process and describing the model specifications used to empirically test the hypotheses. Section 4 will describe the results from the econometric analysis. Lastly, Section 5 will make concluding remarks on the results and explain certain areas that could be further investigated in future research.

2. Literature Review:

The core of this paper focuses on the efficiency of credit derivatives markets and equity markets in Latin American countries. Therefore, the majority of the relevant literature focuses on sovereign CDS, sovereign credit risk, emerging market equity markets, and the relationship between CDS and equity markets. Since most of the available literature looks at the empirical relationship at the firm level, my paper will try to analyze things at a more aggregate macro level.

2.1. The Relationship Between CDS and Equity Markets:

The first part of the literature relevant in this paper is that regarding the relationship and information flow between CDS and equity markets. Since a CDS contract is essentially insurance protection against the outstanding debt of a reference entity, this relationship reduces to the relationship between the two sources of funding: debt and equity. Merton (1974) first looked at the relationship between debt and equity as contingent claims on firm assets. Through the Merton (1974) Model, he was able to map out probability of default as a nonlinear function of the assets' market value, asset volatility, and the debt-to-equity ratio. As such, the correlation between the return on both securities should increase as PD increases. From the model one should also be able to determine the CDS spread while any deviations in these expected returns would mean that there are model specifications or potential arbitrage opportunities.[7]

Longstaff et al. (2005) looked at the relationship between equity, CDS, and bond markets and observed that both stocks and CDS lead the corporate bond markets, but did not find any indication on whether or not one market consistently leads the other. Norden and Weber (2004) studied the cointegration between CDS, equity, and bond markets. The study concluded that the CDS market is the strongest contributor to price discovery and that the negative intertemporal relationship between CDS and equity returns is more strongly pronounced for firms with lower creditworthiness. Although both results provide insight on the CDS and equity relation in corporate bonds, there was no indication on this relation at the sovereign level or how this relationship might differ in the presence of adverse credit conditions.

Afonso et al. (2012), explored the reaction of sovereign CDS and sovereign bond yield spreads before and after credit rating announcements in a sample of European countries. The study observed that the reaction of sovereign CDS spreads to negative rating events increased after the Lehman Brothers bankruptcy. The study also noted that there is no anticipation of rating and outlook announcement 1-2 months prior, but there is evidence of bidirectional causality between credit ratings and CDS spreads in a 1-2 week

[7] The Merton Model assumes that volatility is constant. This means that with increasing asset volatility, CDS and equity returns could both be positive, which makes model misspecifications more likely.

window. Lastly, the study concluded that between two countries with the same rating, the one that had been downgraded in the past six months carried a much higher CDS spread. While the study did not observe any anticipation of rating announcements the 1-2 months prior, it might be because a credit event itself extends to far more than a sovereign rating downgrade. Perhaps the "credit event" entails the CDS markets significantly moving prior to the announcement could be the "credit event" itself.

Acharya and Johnson (2007) investigated insider trading in CDS markets. In their study, they observed statistically significant information flow between CDS and equity markets with firms that are likely to have a credit event in the future. This information flow is even greater for firms that actually experience some sort of credit deterioration. Their study, however, did not find that insider trading had significantly adverse effects on liquidity provisions in the credit markets. Only Acharya and Johnson applied the study within the context of market distress and found conditions as to how markets react under adverse conditions. Furthermore the study provided a more flexible definition of "credit event", which considers the market movement prior to a rating announcement the credit event itself. My study differs from theirs in that the reference entities of focus are sovereigns rather than corporates. Furthermore, my study is not centered on investing insider trading activity in the markets.

Qiu and Yu (2011) replicated Acharya and Johnson's (2007) for the determination of liquidity provision in the single-name CDS market. From a sample of 732 reference entities from 2001 to 2008, they observed that CDS innovations lead stock returns prior to large changes in CDS spreads. Furthermore, the coefficient used to measure the lead-lag relationship gets larger as the credit event gets closer and the conditional information flow from CDS to equity markets is stronger when isolating the dates close to the Global Financial Crisis and thereafter. These results suggest that there is greater information flow from CDS to equity markets when the CDS market is more liquid. Batta et al. (2016) find that U.S. corporate CDS lead stocks ahead of earnings announcements and analyst forecasts have become more accurate after the advent of CDS. The information of these two studies is relevant because perhaps these presence of insiders in the CDS markets makes this market more informational.

Chan et al. (2009) observed the absence of CDS and equity cointegration amongst a sample of Asian countries. What this means is that there is a deviation from the expected negative correlation between CDS and equity markets. Because the stock markets are less developed in many of these countries, price discovery took place in CDS markets primarily. The reason for this might be due to serial correlation of daily stock returns, which means CDS and equity prices could move in the same direction because of the difficulty in executing large buy or sell orders. Accompanied by the development of the credit derivatives market, the lack of cointegration allows investors to exploit arbitrage opportunities that would otherwise not exist in an efficient market. In Latin America, equity markets are less developed and it would be interesting to see if there is also a lack of cointegration in the region.

Chan-Lau et al. (2004) found that no arbitrage causes convergence between CDS and credit spreads, which means that CDS and bond yield spreads will converge in such a way that investor will be unable to profit from arbitrage opportunities. However, for most EM there was no cointegration between bond spreads and equity prices and CDS and equity prices. This means that it is possible to observe some form of deviation (or lag) between

CDS and local equity markets. The paper also found CDS have an edge over bond markets in price discovery, which reflects the illiquidity of bonds.[8] It would be interesting to see if these behaviors are consistent within the lesser developed equity markets in Latin America.

2.2. Price Discovery of Credit Risk:

Blanco et al. (2005) looked at CDS basis deviations in a sample of investment grade firms in the United States and Europe and found strong evidence of CDS spreads leading credit spreads.[9] A strong explanation for this observation was the CDS market being an overall better market to trade credit risk than the sovereign bond market. This is because bonds are often held until maturity, while CDS contracts are more heavily traded. In addition, the study concluded that corporate CDS spreads are strongly influenced by factors of idiosyncratic risk. The study, however, did not look at either sovereign CDS markets or below investment-grade markets. Because carrying a speculative credit rating might make the bond market even less liquid, it would be interesting to study the relationship in the context of sovereign entities that carry different default risk profiles.

Wengner et al. (2015), studied the impact of S&P Global rating announcements on a sample of corporate firms. Their study is consistent with results observed in the past, observing a positive median increase (CAS) in CDS spreads of 1.70 basis points i two days before credit rating downgrades and -0.79 basis points around credit rating upgrades. Creighton et al. (2004), studied the reaction of bond and equity markets to rating announcements in Australia. Their study observed that corporate firms subject to

[8] Most bonds are held to maturity, so they are illiquid compared to CDS, which are more heavily traded.
[9] The credit spread is the spread between the bond's yield and the risk-free rate, so this would imply a serious problem with relying on credit spreads as credit risk indicators.

downgrades on average underperformed the market by around 12% within their designated estimation window. On the announcement day and the subsequent day, stocks experience a negative cumulative abnormal return (CAR) of -1.3%, which is small compared to what is seen in the longer window.

Martell (2005), observed that local stock indices for 29 emerging economies react to negative sovereign rating announcements in a statistically significant manner and S&P ratings were more informative than those from Moody's. Although the study is consistent with previous studies, it does not provide additional insight on whether or not local stock indices lead or lag sovereign credit rating changes. Furthermore, it is very likely that the market has already reacted to the credit event before the rating agencies announce their analysis on the situation. As a result, it makes sense to look at where the markets are moving prior to this in order to paint a better picture of this relationship.

Kaminsky et al. (2001), studied emerging market behavior for both stocks and bonds in response to credit rating changes. As part of the event study they looked at a time frame of +/-10 days prior to the rating announcement and observed that equity markets decline around 7% in the window before the rating announcement.

With regards to the difference between sovereign and corporate CDS spreads, Packer et al. (2003), investigated the difference between sovereign and corporate CDS spreads for Emerging Market economies. From their study they concluded that there is asymmetry between the pricing of each type of CDS depending on the credit rating of the sovereign. For highly rated sovereigns, CDS spreads were generally lower than those for similarly rated corporations. For low-rated sovereigns, however, CDS spreads were on average much higher than those for similarly rated corporates. While the direction and degree of deviation is different, the same information could be observed in the sovereign CDS than what was observed previously for corporate firms.

Flannery et al. (2010) looked at whether CDS spreads are a viable substitute for credit ratings. In their study they observed that in 2007, certain financial institutions' CDS spreads reflected significantly more risk than equity prices. This was a major early warning indicator of the subsequent economic fallout. Although the study provided insight in the viability of CDS spreads as early warning indicators, it was limited to American financial institutions and does not extend to below investment-grade entities. Hull et al. (2004) found that CDS changes contain relevant information about the probability of a credit rating downgrades. The study was predominantly focused on corporates and was consistent with the notion that credit rating agencies prefer stable rating transitions to avoid moving the markets.

Zhang (2003) noted that when Argentina defaulted in 2001, the credit rating agencies lagged the credit market. More specifically, the PD reflected in credit ratings was much lower than the PD reflected in CDS prices. Furthermore, they studied three "implied state variables" that showed correlations with the negative slope of the U.S. treasury term structure, the 10-year treasury yield, and a spread of the 10-year yield and JP Morgan EMBI Index respectively. This is important to note because deteriorations in developed markets most often lead to a "flight to quality" and "flight to liquidity" movements in which investors go for safe and less volatile securities during times of financial distress.

At country level, da Silva (2014), looked at the relationship between sovereign credit risk and stock index performance of Eurozone countries the correlation between CDS and stock index returns does not get stronger with sovereign financial distress.

2.3. Equity Markets in Latin America:

Although many economists and policy makers once had optimistic prospects for capital market development in Latin America, countries in the region are still plagued by illiquid equity markets where trading is concentrated on a small number of firms. De la Torre and Schmukler (2006) studied the effect of institutional reform on the development of Latin American capital markets. Their study observed that market size in terms of capitalization is limited to only a few firms and an increasing number of firms have actually opted to list on foreign markets in New York and London. Furthermore, they note that the response to institutional financial reforms are even more underwhelming when compared to the development of equity markets in East Asian economies.

An OECD study (2017) notes two different theories behind the underdevelopment of Latin American equity markets. Firstly, companies are afraid that taking initial or secondary listings will not receive a sufficient value relative to other funding sources. This indicates that shareholders command a high rate of return on their investment, which makes it costly for the company. Additionally, Latin American countries struggle with deep systematic corruption issues, which in turn make investors reluctant to undertake investments with potential exposure to many corporate governance issues. These issues combined with a number of domestic corporations opting to list abroad holds back equity markets from having the serious booms that other EM equity markets have experienced since 1990.

2.4. Hypotheses:

From the available literature and past studies analyzed, I hypothesize the following results:

H1: CDS returns will lead equity index returns in the sample of Latin American countries.

H2: Prior to a sovereign "credit event", the reaction proposed in H1 will be even stronger.

H3: During times of sovereign credit events, the reaction proposed in H1 will be more severe for countries that are already below investment grade.

3. Methodology:

The seven countries of focus in this study are Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela. These countries were chosen because of their status as the seven largest economies in Latin America (LAC-7). These countries have varying levels of creditworthiness, which allows me to test if CDS and equity market reactions vary depending on the country's current perceived credit risk. Of the sample countries, Chile, Colombia, Mexico, and Peru are investment grade while Argentina, Brazil, and Venezuela are speculative. Therefore, the empirical analysis will investigate the effects both in the context of the entire sample of countries and in the context of two sub-samples split between investment-grade and speculative grade countries.

Data for this study is split into three components: stock index returns and five-year sovereign CDS spreads on U.S. Dollar-denominated debt. The stock indices used are the following: Merval Index (Argentina), Bovespa Index (Brazil), S&P/CLX IGPA Index (Chile), COLCAP Index (Colombia), S&P/BMV Index (Mexico), S&P/BVL Index (Peru), and IBVC

Index (Venezuela). The return component for the indices is the daily percent change in closing prices quoted in USD. The data downloaded from Bloomberg on daily index returns, included dividends. For the regression lags, I took up to five lags for CDS changes, Index returns, and the CDS innovation variables. Lastly, I created three different credit dummy variables. The purpose of these variables was to indicate if the two market return for the countries in the sample fell within 5 days, 30 days, or 90 days before a "credit event." The reason for this was not only to determine if there is information flow from CDS to equity markets prior to a credit event, but how far behind one can anticipate this reaction if present. The model defines the credit condition dummy under two different specifications.

I used Bloomberg to obtain the data on sovereign CDS changes and equity index returns. The time window of this data ranges from 2001 until 2018. The reason for this time period is because it is the earliest the data on CDS spreads was available and it covers market turmoil periods such as the Global Financial Crisis and credit deterioration in countries like Argentina, Brazil, and Venezuela. I had to drop some observations because there were missing observations for equity index prices on some of the corresponding dates for CDS spreads. The most likely reason for these missing observations was national holidays. On these dates local equity markets were probably closed while sovereign CDS were still trading globally. In total the entire data se ended up consisting of 26,431 observations. For the econometric analysis of the data sample, I used STATA under both the panel and time series packages. Descriptive statistics for each country are displayed in Table 1 and graphs of CDS and equity market prices are in Exhibit 5.

The first step of the analysis entails examining the individual correlation of CDS and equity market returns. More specifically, for each country in the sample, the correlation will be between CDS returns and lagged equity market returns. For the range period, $k = -5, -4, \dots, +5$, the correlation between daily index returns at time $t + k$ and contemporaneous percent changes in CDS prices at time t would imply information from equity to CDS markets.

Similar to Acharya and Johnson (2007), the first part of the empirical test is examining the pure effect of CDS changes at time t on index returns at time $t + k$. This entails isolating the information that the CDS market captures before the equity market. The first step to doing this is regressing changes in CDS spreads on contemporaneous stock returns and isolate the residual component. This is done through separate time series regressions for each country, along with five lags for both CDS changes and stock returns to obtain any lagged information transmission in the credit market. For this regression, CDS returns are the log difference between CDS spreads over a two-day period. Based on the Merton (1974) Model and Acharya and Johnson (2007), the relation between CDS changes and index returns should be nonlinear.

To examine the pure effect of CDS returns on future stock returns, I ran individual time series regressions for each country *i* in the sample. As part of this, I regressed CDS returns on some constant, five lags of CDS returns, contemporaneous index returns, the product of the return and the reciprocal CDS spread, and five lags of the previous two terms. The interpretation for the residual term, u_{it} (referred to as *CDS innovation* hereafter) is unique information arriving in CDS markets that can be helpful in predicting future equity market returns.

$$(CDS\ return)_{i,t} = \alpha_i + \sum_{k=0}^{5}\left[\beta_{i,t-k} + \frac{\gamma_{i,k}}{(CDS\ level)_{i,t}}\right](Index\ return)_{i,t-k}$$

$$+\sum_{k=1}^{5}\delta_{i,t-k}(CDS\ return)_{i,t-k} + u_{it} \quad (1)$$

The next step in the analysis involves determining information flow from CDS to equity markets. The regression used for this is a panel regression of contemporaneous index returns on five lags CDS innovations, the product of those five lags and a credit dummy variable, five lags of index returns, and the product of the five index return lags and the credit dummy variable. The dummy variable indicates whether one of the countries in the sample experienced a credit event during the sample period. The panel regression looks as follows:

$$(Index\ return)_{it} = a + \sum_{k=1}^{5}[b_k + b_k^D(Credit\ Dummy)_t](CDS\ innovation)_{t-k}$$

$$+\sum_{k=1}^{5}[c_k + c_k^D(Credit\ Dummy)_t](Index\ return)_{t-k} + \varepsilon_{it} \quad (2)$$

The terms $\sum_{k=1}^{5} b_k$ and $\sum_{k=1}^{5} b_k^D$ respectively measure unconditional and conditional permanent information flows from CDS to equity markets. What this allows us to do is look at the sampled countries as having the same dynamic properties with the exception of the conditioning provided by the lagged response terms. More importantly, the interpretation of the coefficient $\sum_{k=1}^{5}(b_k + b_k^D)$ measures information flow from the CDS to equity markets conditional on some credit event happening in the future.

Under Acharya and Johnson's (2007) model, the specification for a credit event included any one-day increase in CDS spreads over 50 basis points. However, within the

LAC-7 sample there were over 600 instances of this specification. These was very likely attributed to the volatile nature of some of the countries in the region, so this specification needed some modifications to provide a more accurate representation. As a result the specification for the credit event was a one-day jump exceeding 50 basis points for investment-grade countries and a one-day jump exceeding 100 basis points for non-investment-grade countries. After that, I established three different windows of five, 30, and 90 days prior to the credit event where the credit condition dummy took the value of one if the lagged dates corresponded to the respective time window.

Additionally, I also provided an additional specification that follows what Berndt and Ostrovnaya (2008) and Qiu and Yu (2011) used to define credit events. This specification defines a credit event as a one-day increase in CDS spreads satisfying the following condition:

$$\Delta CDS_{it} > average(\Delta CDS_i) + 4 \cdot stdev(\Delta CDS_i)$$

What this alternate specification does is account for the scale of variation in each of the LAC-7's sovereign CDS spreads. Implementing this definition showed credit events for stable countries like Chile and Peru in which the one-day increase was less than 50 basis points and ruled out credit events for unstable countries like Argentina and Venezuela in which the one-day increase in CDS spreads was greater than 100 basis points.

Once all these events were accounted for, I proceeded by eliminating events that were very close to each other. Since one can expect the markets to be more volatile after the credit event, I took the earliest date in these "clusters" and defined that as the date of the credit event. Just as with the previous specification, I established three different windows of five, 30, and 90 days prior to the credit event where the credit condition dummy took the value of one if the lagged dates corresponded to the respective time window.

In order to look at this issue further, I decided re-run the same regressions on two different sub-samples: investment grade countries and non-investment grade countries. There is a large gap in perceived sovereign credit risk between some of the countries in the LAC-7 sample. For example, Chile and Mexico are large, more stable economies in the region while Venezuela and Argentina have a notorious history for debt crises and economic meltdowns. As a result, splitting the sample up might identify if different Latin American markets react in different ways based on already perceived credit risk from rating agency sentiment.

4. Results:

4.1. Individual Correlation between Contemporaneous CDS returns and Lagged Equity Market Returns:

From a preliminary correlation analysis, we can see some degree of negative correlation between CDS returns and future equity returns. This negative correlation varies from country to country, but the results appear to be the strongest in the case of Colombia and Peru. The negative correlation appears most frequently with the contemporaneous CDS return and the equity market returns for the two following days. What this appears to show is that CDS returns might have certain information that takes an additional two days to be priced into equity market returns. However, this negative correlation does not appear to show between contemporaneous CDS and equity market returns. This might be attributed to the macro nature of this research question. There might be enough companies traded in these indices to diversify away firm-specific risk, which appears with single-name CDS and equity returns. The correlation matrices for each country are shown in Table 2.

4.2. Results from First Stage Regression:

The results from the first stage time series regression show that contemporaneous CDS returns are explained mostly by the CDS return of the prior day, the contemporaneous equity index return and that of the day before, as well as the past two lags of the CDS product (Results in Table 3). The r-squared of these regressions range from 5-44%, which show that a significant amount of the variation (at least half for every country in the sample) in CDS returns is not explained by the model.

The country with the highest r-squared in our sample was Brazil (0.44) while the lowest was Venezuela (5%). These results make sense when considering the size and robustness of the respective stock markets. There is not a lot of trading in Venezuela's stock market relative to its GDP. Furthermore, Venezuela is a country devastated by hyperinflation and market unfriendly policies. As a result, it is reasonable to expect that CDS returns will be influenced more by macroeconomic fundamentals, geopolitical activity, and country-relevant factors like oil prices and volatility. On the other hand, Brazil has the largest economy in Latin America and the stock market with the highest trading activity relative to GDP. Therefore, it is more reasonable to expect that sovereign credit risk reflected in CDS prices will can be better explained by factors related to equity returns. Exhibit 4 shows stock market activity as a percentage of GDP for all LAC-7 countries.

The portion of CDS returns that remains to be explained, is the CDS innovation coefficient that is plugged into the second stage regression of the analysis. The intention of this variable is to try and see if this unique information in CDS prices does in fact lead Latin American equity markets prior to sovereign credit events.

4.3. Results for the Entire Sample of LAC-7 Countries:

The sum of the lagged coefficients from the secondary regression of the entire LAC-7 sample are summarized in Table 4. The secondary regression of the entire sample shows that there is no significant unconditional information flow from CDS to equity markets. In other words, $\sum_{k=1}^{5} b_k$ is essentially equal to zero. These results are consistent with what Acharya and Johnson (2007).

The main result of interest, however, is whether there is information flow from CDS to equity markets prior to a credit event. The sum of lagged CDS innovations, $\sum_{k=1}^{5}(b_k + b_k^D)$, is negative for some of the specifications in the sample and positive for others. Under the entire LAC-7 sample, there is only statistical significance for the flow effect, $\sum_{k=1}^{5} b_k^D$, five days before a credit event defined by Specification A. This flow effect demonstrates around 6.6% information transmission from CDS innovations to equity markets. Ultimately, these results do not give compelling evidence of lagged CDS innovations predicting equity returns during sovereign credit events.

The direction of this coefficient, however, is unexpectedly positive. Given the negative correlation between CDS and equity returns, one would expect that statistically significant lagged CDS innovations prior to a credit event would lead to negative future equity market returns. Both Acharya and Johnson (2007) and Qiu and Yu (2011) found the summed coefficients to be negative for this case. This deviation in my results could be due to a number of reasons. Mainly, their studies focused on individual firms for which CDS innovations represent idiosyncratic risk. Since this study looks at sovereign CDS and equity index returns, the risk measured is systematic. Additionally, Acharya and Johnson (2007) sought to determine if insiders (mainly large financial institutions) were using the CDS market to trade on private information. At a sovereign level, perhaps there are little or no individuals with insider information. This makes sense because information relating to sovereign credit risk is publically available, allowing anyone to hypothetically trade this information. Additionally, despite their relative liquidity to bonds, CDS are still thinly traded. As a result, investors trading sovereign CDS might not be trading a large enough size carry a spillover effect into local equity markets. These results show some, although not an overwhelming amount, of evidence that sovereign CDS price in information about credit quality deterioration prior to equity markets.

Lastly, both Acharya and Johnson (2007) and Qiu and Yu (2012) found that there was negative serial correlation in this regression. Inside the credit condition dummy period, this is the period in which CDS spreads keep going up while stock prices fall. In the context of their study this corresponds to insiders buying CDS while uninformed traders continue to buy shares for the corresponding reference entity. In my results, there was a positive serial correlation, which is likely attributed to market illiquidity. Therefore, this positive serial correlation is reflected in the positive coefficient for the flow component. Since there is less liquidity in Latin American equity markets, it might take several days to execute a large trade order. From this observation, it might be beneficial to use monthly data on CDS and equity returns to address this issue.

The coefficients $\sum_{k=1}^{5} c_k$ and $\sum_{k=1}^{5} c_k^D$ indicate unconditional and conditional information transmission from past equity returns to future equity returns respectively. Under the Efficient Market Hypothesis (EMH), these coefficients should both be zero. In our model results, however, both coefficients showed statistical significance. The unconditional coefficient sum $\sum_{k=1}^{5} c_k$ was statistically significant for all of the different cases in Table 1 except 90 days prior to the credit event defined by Specification B. The effect specified by these coefficients represents a magnitude of around 21%. The conditional coefficient sum $\sum_{k=1}^{5} c_k^D$ was statistically significant 30 days prior to the credit event defined by Specification B. The effect of this coefficient is around 17%. These results indicate a potential momentum effect in Latin American equity market returns, which is consistent with what Muga and Santamaria (2007) found in their study. What this means is that theoretically investors in Latin American Markets can benefit from some trading strategy that buys "winners" and sells "losers," and implementing this strategy during periods of adverse credit conditions could potentially yield even higher profits.

However, given the relative illiquidity of Latin American equity markets, the statistical significance in this sum of coefficients is more likely attributed to serial correlation in Latin American equity market returns. De la Torre and Schmukler (2006) note that capital markets in Latin America are underdeveloped relative to not only developed countries but also EM in East Asia. They note that even with intense capital market reform, Latin American countries lack domestic activity in equity capital markets in terms of market cap, capital raising, and trading activity. Given the absence of significant trading activity in these markets, it could take a long period of time for a trader to execute a large buy or sell order. Since it takes a longer time for this trade order to go through, one could expect market prices to move in the same direction for a while, which generates the serial correlation observed in the results. Until higher activity on the three areas noted above injects liquidity to Latin America's equity markets, the presence of serial correlation in equity returns will persist. Because the length of the serial correlation effect is short (90 days at its maximum according to the model results), it is difficult to ascertain that this is a true momentum effect in Latin American markets. When Jegadeesh and Titman (1993) found a momentum effect present in U.S. equity markets, the effect persisted for several months following. Furthermore, the effect was observed in the most liquid stock market in the world, which rules out potential serial correlation issues that could be present in Latin American markets.

4.4. Results for Investment Grade Countries:

Although the results observed in the regression for the entire LAC-7 sample show compelling results, especially regarding momentum return anomalies, there is still no strong evidence on either the informational power of sovereign CDS or how sovereign CDS might lead equity markets in price discovery prior to credit events in the region. When reducing the sample to only investment grade countries, we can see statistical significance in that unconditional CDS innovations are negative and statistically significant across the board. More specifically, the results demonstrate lagged CDS innovations (unconditional) having an effect of around 2-5% on contemporaneous equity market returns. All of these results are significant at a 1% level except 90 days before the credit event under Specification B (significant at a 10% level). The results from the investment grade sample are shown in Table 2 below.

The sum of the coefficients on both lagged CDS innovations are mostly positive (driven by the larger and more positive coefficient on the flow effect). Lastly, the coefficients for the flow effect are statistically significant five and 30 days prior to a credit event under Specification A and five days prior to a credit event under Specification B.

These coefficients represent an information transmission from CDS innovations to equity returns of 7% and 12% under Specifications A and B respectively. The direction of the coefficient, however, is still positive.

What these results might show is that there is a larger amount of trading occurring in higher credit quality markets. However, the group of markets that are part of this sample still remain among some of the least developed in the region (Peru, for example). As a result, what this might actually mean is that there is a more severe reaction to credit events in regions that are known for less volatility and higher credit quality. It might be that investors who enter more volatile markets like Argentina are aware of the country's track record for credit crises and might already have this priced in.

Similar to the results observed with the entire sample, there is also a statistically significant coefficient sum for unconditional equity market returns across the board. All coefficients are statistically significant at a 1% level and represent a magnitude of about 30%, which is larger than what was observed with the entire LAC-7 sample. This again is indication of serial correlation in the sample returns. For the conditional lagged equity market returns, there is only statistical significance for this under Specification B and only 30 and 90 days prior to the credit event. These coefficients represent a magnitude of around 10-15%. For the same reasons noted previously it is difficult to conclude that these are momentum returns rather than serial correlation.

4.5. Results for Non-Investment Grade Countries:

When run only with the sample of non-investment grade countries, the second regression did not show a lot of statistical significance. Firstly, the unconditional flow effect was statistically insignificant across the board. The conditional flow effect was only statistically significant five days before a credit event under Specification A (5% level) and 90 days before a credit event under Specification B (1% level). These two coefficients represent information flow from CDS innovations to equity markets of 6.7% and -6.2% respectively. In this instance there was a negative coefficient, which is what was originally expected, for the conditional information flow 90 days prior to the credit event.[10]

The reason why there might be less statistical significance for these results might be because there is little trading in the equity markets of non-investment grade Latin American countries. As noted by de la Torre and Schmukler. (2006), trading activity in Latin American equity markets is a small fraction than that in East Asia or developed markets. Value traded in domestic markets is still a small fraction of GDP. This is especially true for all the non-investment grade countries excluding Brazil. What this means is that the total value accounted for in stock market trading activity is not large enough to display statistically significant results for below-investment grade nations in the sample. This liquidity problem may be a strong hindrance in finding statistically significant results with the non-investment grade countries in the sample.

With this sub-sample, there still appears to be serial correlation on lagged equity market returns, with statistically significant coefficients in the range of 22-24%. This is persistent for all cases of the regression except 90 days prior to a credit event under Specification B. The magnitude and level of statistical significance however, is lower than that observed for the sub-sample of investment grade countries. The reason this might be lower is due to the presence of Brazil in the sub-sample. Brazil's stock market (BOVESPA)

[10] For a lot of the statistically insignificant "flow effect" coefficients, the direction is negative, which shows something more in line with was originally expected. Perhaps this is something that needs to be further looked at.

has the most value traded relative to GDP. As a result, this shows at least a larger degree of liquidity relative to the other LAC-7 equity indices. Since Brazil's stock market would at least be the most liquid in the entire sample, it might lower the degree of serial correlation observed in this sample.

Lastly there is significant information flow in lagged equity returns to future equity returns 90 days prior to a credit event under Specification B. What this indicates is serial correlation in equity returns conditional on a credit event happening in the future, are only noticed 90 days in advance during our sampling period. This is mostly in line with the results from the entire LAC-7 sample and the investment grade sub-sample. Since serial correlation is already present absent of a credit event, the presence of a credit crisis down the line should not change this. However, given the more artificial nature of Specification B, there might be certain dates deemed as "credit events" that do not really meet the criteria of a sovereign credit event. As a result, it could be beneficial to find a more natural criteria to classify credit events given the list of macroeconomic factors that affect sovereign credit risk.

When looking only at the investment grade sub-sample of countries, the regression results were different than the results from the entire LAC-7 sample. Mainly, there was consistent statistical significance for lagged unconditional CDS innovation and statistical significance for the conditional flow coefficient 30 and 90 days prior to the credit event. Isolating the sample to only below-investment grade does not really change the results from what was observed in the entire sample.

The most likely reason for an absence of significant results is due to macro nature of this analysis. Past studies like Acharya and Johnson (2007) look at this relationship at a firm level. The nature of their analysis was finding whether or there was insider trading in corporate CDS markets. These insiders would include large Financial Institutions or corporate insiders who realized that trading activity on private information in equity markets would ultimately be reported to the SEC. As a result, an OTC derivatives market would allow these individuals to maintain a degree of anonymity. The information affecting the single-name corporate CDS was private corporate information. As a result, single-name corporate CDS that are otherwise out of the public eye are prone to potential manipulation by insiders such as hedge funds and other financial institutions.

For sovereign CDS spreads, information pertinent to sovereign credit risk is publically available and frequently traded on. News channels talk on upcoming elections, geopolitical tensions, foreign exchange rates, and other factors affecting sovereign credit risk. As a result, this information is available to all investors. Even though the sovereign CDS market is not the largest component of the entire CDS market, financial institutions and other investor closely follow this information to determine risks associated with corresponding government bonds and other securities. This fundamental difference is a potential reason for lacking significant information in the flow coefficient.

Factors that affect sovereign CDS and EM equity returns are different than the idiosyncratic factors driving single-name corporate CDS and stock returns. Mainly these include macroeconomic variables like foreign exchange (FX) rates and U.S. market factors including corporate bond yields, high yield indices, and market volatility indicators, such as the VIX. As a result, it is perhaps these other factors that perhaps lead local equity index returns prior to credit events in the Latin American region. Historically credit crises in EM come as a result of sharp currency devaluations. Therefore, mapping out currency volatility as an indicator of credit events might be better than looking at sovereign CDS spread changes.

5. Conclusion:

The informational power of credit default swaps has been a subject of importance to academia ever since their role in the Global Financial Crisis. Due to their relatively higher liquidity to bonds and OTC structure investors have adopted these contracts as a better mechanism for hedging credit risk or speculating on future default events. The past research done on the nature of corporate CDS and their price discovery power has provided insight into both the good and bad that has come to capital markets following their advent.

One might expect the relationship observed between single-name corporate CDS and corresponding stock returns to translate to an aggregate country-level. Compared to my original hypotheses, CDS markets are do not necessarily lead equity markets in pricing information on sovereign credit events. Furthermore, the instances in which these results were statistically significant were in the case of investment grade countries and not the non-investment grade ones as I originally hypothesized. These results of what I originally conjectured. Furthermore, although statistically significant in some instances, the direction of the coefficients for the information flow were positive instead of negative. This makes any statistical significance somewhat dubious as it goes against an already empirically proven relationship between CDS and stocks.

Yet it seems that the fundamental difference between systematic and idiosyncratic risk drivers presents a roadblock in this paper establishing a true empirical relationship between these two markets at a sovereign level. Although it was not the original intention, this paper did add to existing literature of momentum effects in EM equity returns. Furthermore, it was able to illustrate how these effects change in EM of different levels of perceived credit risk. More specifically it was successful in noting a larger momentum effect among equity indices of countries with investment grade ratings. Further research could explore the exact nature of this contrast and whether it is attributed to liquidity constraints in Latin American equity markets.

Furthermore, there could be further research done on the nature of these credit events and what potential variables can at least provide some level of anticipatory information before markets truly take a turn for the worst. Based on the principle components noted by Longstaff et al. (2011) one could look at whether or not movements in high yield indices or the VIX lead changes in EM CDS spreads or EM equity returns.

Even though the relationship provided by Acharya and Johnson (2007) does not exist at a country level in Latin America, it would be interesting to see if this relationship holds at a firm level. By taking the ten most traded firms in each of the sample countries, one could look at corresponding CDS changes to see if the previously observed leading relationship exists. As a result, there should be further studies done to investigate whether or not there might there are insiders trading on non-public information in corporate CDS markets in Latin America. Perhaps future research could attempt to establish a concrete relationship between these two markets, while also striving to better explain the underdevelopments of Latin American equity markets in the regions strive for growth.

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7. Appendix:

Exhibit 1: Example of a CDS Contract

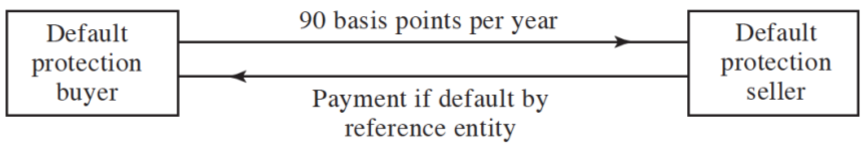


Exhibit 2: Examples of Credit Events (per ISDA)

Commonly Established CDS Credit Events	
Bankruptcy	The reference entity becomes insolvent or is unable to pay its debts
Failure to Pay	The reference entity fails to make interest or principal repayments when due
Debt Restructuring	The configuration of debt obligations is changed in such a way that the credit holder is unfavorably affected
Obligation Acceleration or Obligation Default	The debt obligations of the issuer become due before their originally scheduled maturity date
Repudiation/ Moratorium	The issuer of the underlying bond (the reference entity) rejects their debt, effectively refusing to pay interest and principal

Source: International Swaps and Derivatives Association

Exhibit 3: Breakdown of CDS contracts by reference entity and change in reference entity breakdown over time

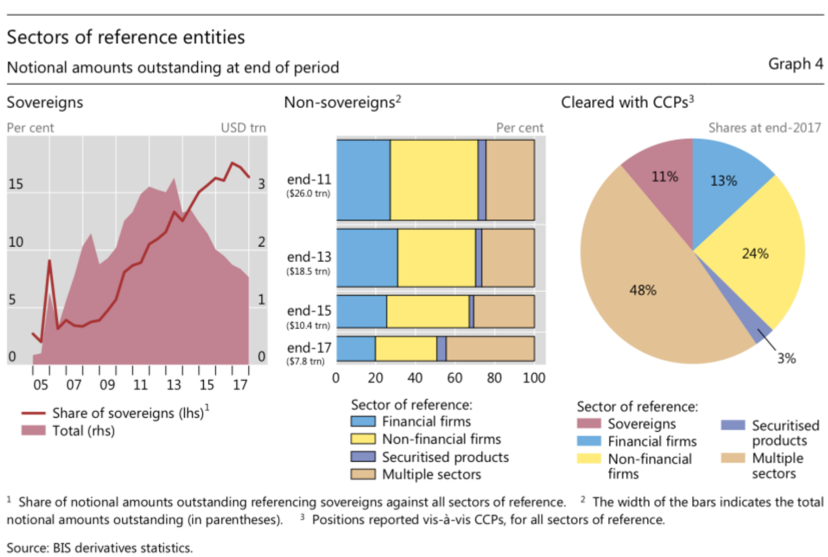
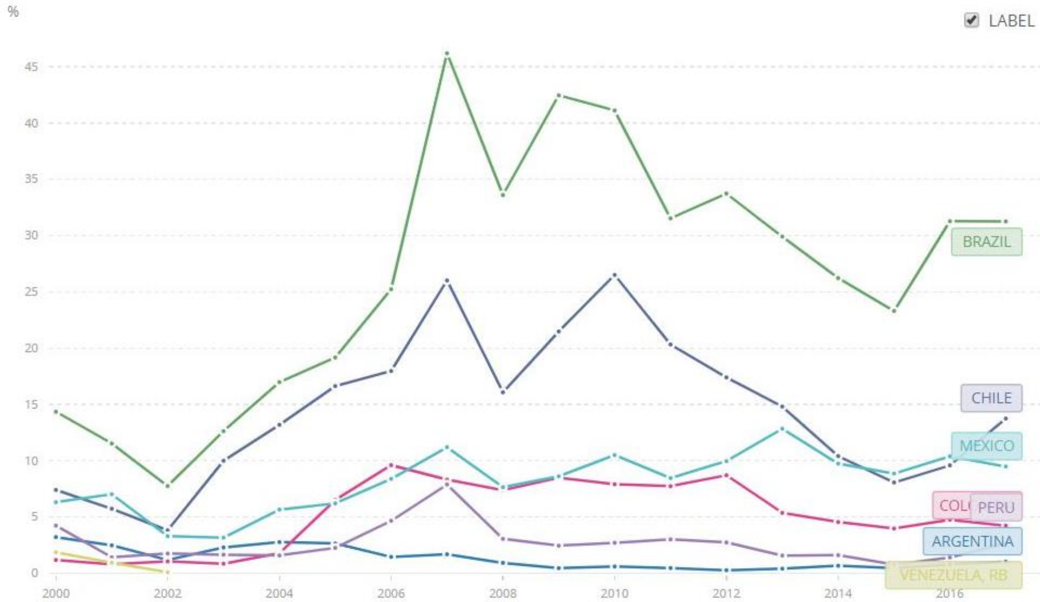


Exhibit 4: LAC-7 Stock Market Trade Value as a % of GDP



Source: World Bank Data

Table 1: Descriptive Statistics for the Sample

1= Argentina, 2= Brazil, 3= Chile, 4= Colombia, 5= Mexico, 6= Peru, 7= Venezuela

-> ccode = 1

Variable	Obs	Mean	Std. Dev.	Min	Max
cdslevel	2,940	1103.172	1078.863	182.532	6937.675
cdsret	2,937	-.0007803	.0499597	-.590528	.8377156
indexprice	2,940	777.5256	316.2341	248.7592	1804.217
indexret	2,940	.000429	.0209611	-.145105	.1545299

-> ccode = 2

Variable	Obs	Mean	Std. Dev.	Min	Max
cdslevel	4,132	350.8291	489.0308	61.5	3951.5
cdsret	4,131	.0003997	.0364826	-.4047818	.372582
indexprice	4,132	21271.09	10908.87	2165.816	44672.31
indexret	4,132	.0006493	.0236023	-.1608093	.2083805

-> ccode = 3

Variable	Obs	Mean	Std. Dev.	Min	Max
cdslevel	3,876	74.99169	44.97766	12.498	318.333
cdsret	3,875	.0002906	.0386154	-.5407472	.5500932
indexprice	3,876	29.9208	11.1028	6.63638	49.71015
indexret	3,876	.0005058	.0114731	-.0859772	.1183087

-> ccode = 4

Variable	Obs	Mean	Std. Dev.	Min	Max
cdslevel	3,818	199.7454	134.7133	64.7	850
cdsret	3,817	.0004789	.0367169	-.3977032	.3737097
indexprice	3,818	.550283	.2703858	.0572	1.06849
indexret	3,818	.0006353	.0164574	-.132101	.197688

-> ccode = 5

Variable	Obs	Mean	Std. Dev.	Min	Max
cdslevel	4,206	132.1044	70.33168	28.167	601.206
cdsret	4,205	.000188	.0360627	-.4544988	.4160361
indexprice	4,206	2239.129	861.6669	525.2297	3680.46
indexret	4,206	.0003405	.015444	-.1089159	.1095954

-> ccode = 6

Variable	Obs	Mean	Std. Dev.	Min	Max
cdslevel	3,740	154.9587	86.29002	59.659	605.833
cdsret	3,739	.000361	.036194	-.4800162	.3718138
indexprice	3,740	4775.609	2185.749	599.4793	9018.23
indexret	3,740	.0006577	.0152908	-.1324678	.1160219

-> ccode = 7

Variable	Obs	Mean	Std. Dev.	Min	Max
cdslevel	3,719	1952.575	2494.705	117.626	15559.45
cdsret	3,718	-.000403	.0374344	-.744153	.3122749
indexprice	3,719	5.958811	28.42469	.016	298.7042
indexret	3,719	.0038752	.0324247	-.4907407	.5369197

Table 2: Correlation between Contemporaneous CDS Returns and Lagged Equity Returns

Argentina

(obs=2,910)

	cdsret	L5. indexret	L4. indexret	L3. indexret	L2. indexret	L. indexret	indexret	F. indexret	F2. indexret	F3. indexret	F4. indexret	F5. indexret
cdsret	1.0000											
indexret												
L5.	0.0409	1.0000										
L4.	0.0010	0.0326	1.0000									
L3.	-0.0007	-0.0038	0.0316	1.0000								
L2.	0.0510	0.0273	-0.0040	0.0315	1.0000							
L1.	0.3189	0.0248	0.0268	-0.0038	0.0317	1.0000						
--.	0.0348	-0.0780	0.0241	0.0269	-0.0027	0.0320	1.0000					
F1.	0.0424	-0.0437	-0.0792	0.0243	0.0260	-0.0029	0.0327	1.0000				
F2.	0.0400	0.0075	-0.0439	-0.0786	0.0244	0.0262	-0.0024	0.0326	1.0000			
F3.	-0.0007	0.0401	0.0084	-0.0438	-0.0779	0.0253	0.0256	0.0003	0.0334	1.0000		
F4.	0.0035	-0.0071	0.0403	0.0087	-0.0426	-0.0773	0.0245	0.0271	0.0008	0.0305	1.0000	
F5.	-0.0099	0.0076	-0.0082	0.0412	0.0083	-0.0424	-0.0761	0.0240	0.0271	0.0034	0.0324	1.0000

Brazil

(obs=4,122)

	cdsret	L5. indexret	L4. indexret	L3. indexret	L2. indexret	L. indexret	indexret	F. indexret	F2. indexret	F3. indexret	F4. indexret	F5. indexret
cdsret	1.0000											
indexret												
L5.	-0.0059	1.0000										
L4.	-0.0248	0.0362	1.0000									
L3.	-0.0109	-0.0213	0.0366	1.0000								
L2.	0.0683	-0.0358	-0.0213	0.0369	1.0000							
L1.	0.6244	-0.0044	-0.0362	-0.0220	0.0372	1.0000						
--.	0.1800	-0.0066	-0.0041	-0.0362	-0.0217	0.0368	1.0000					
F1.	-0.0002	-0.0488	-0.0064	-0.0036	-0.0366	-0.0216	0.0372	1.0000				
F2.	0.0234	-0.0030	-0.0493	-0.0068	-0.0036	-0.0360	-0.0218	0.0368	1.0000			
F3.	-0.0060	0.0122	-0.0026	-0.0491	-0.0065	-0.0043	-0.0360	-0.0212	0.0363	1.0000		
F4.	0.0090	-0.0064	0.0121	-0.0027	-0.0491	-0.0064	-0.0044	-0.0360	-0.0211	0.0362	1.0000	
F5.	-0.0462	0.0279	-0.0064	0.0124	-0.0030	-0.0488	-0.0061	-0.0048	-0.0362	-0.0207	0.0362	1.0000

Chile

(obs=3,866)

	cdsret	L5. indexret	L4. indexret	L3. indexret	L2. indexret	L. indexret	indexret	F. indexret	F2. indexret	F3. indexret	F4. indexret	F5. indexret
cdsret	1.0000											
indexret												
L5.	-0.0039	1.0000										
L4.	-0.0094	0.1341	1.0000									
L3.	0.0220	0.0354	0.1344	1.0000								
L2.	0.0995	-0.0061	0.0359	0.1341	1.0000							
L1.	0.3149	0.0198	-0.0060	0.0358	0.1338	1.0000						
--.	0.1422	-0.0377	0.0198	-0.0060	0.0359	0.1337	1.0000					
F1.	-0.0027	-0.0268	-0.0376	0.0197	-0.0061	0.0357	0.1338	1.0000				
F2.	0.0236	0.0141	-0.0267	-0.0377	0.0197	-0.0063	0.0357	0.1338	1.0000			
F3.	0.0044	-0.0116	0.0142	-0.0268	-0.0379	0.0197	-0.0063	0.0357	0.1337	1.0000		
F4.	-0.0126	0.0290	-0.0115	0.0140	-0.0270	-0.0380	0.0197	-0.0063	0.0356	0.1337	1.0000	
F5.	-0.0084	-0.0174	0.0293	-0.0118	0.0135	-0.0268	-0.0380	0.0195	-0.0066	0.0356	0.1335	1.0000

Colombia

(obs=3,808)

	cdsret	L5. indexret	L4. indexret	L3. indexret	L2. indexret	L. indexret	indexret	F. indexret	F2. indexret	F3. indexret	F4. indexret	F5. indexret
cdsret	1.0000											
indexret												
L5.	-0.0204	1.0000										
L4.	0.0023	0.1397	1.0000									
L3.	0.0482	0.0136	0.1397	1.0000								
L2.	0.1323	-0.0288	0.0137	0.1397	1.0000							
L1.	0.4809	0.0000	-0.0288	0.0137	0.1397	1.0000						
--.	0.0735	-0.0259	0.0000	-0.0289	0.0138	0.1397	1.0000					
F1.	0.0164	-0.0565	-0.0260	-0.0001	-0.0290	0.0136	0.1394	1.0000				
F2.	-0.0328	-0.0015	-0.0566	-0.0261	-0.0002	-0.0290	0.0135	0.1391	1.0000			
F3.	-0.0047	0.0147	-0.0015	-0.0567	-0.0262	-0.0002	-0.0292	0.0131	0.1390	1.0000		
F4.	-0.0433	0.0593	0.0147	-0.0016	-0.0567	-0.0262	-0.0003	-0.0293	0.0131	0.1389	1.0000	
F5.	-0.0068	0.0376	0.0594	0.0147	-0.0014	-0.0567	-0.0263	-0.0008	-0.0296	0.0128	0.1389	1.0000

Mexico

(obs=4,196)

	cdsret	L5. indexret	L4. indexret	L3. indexret	L2. indexret	L. indexret	indexret	F. indexret	F2. indexret	F3. indexret	F4. indexret	F5. indexret
cdsret	1.0000											
indexret												
L5.	-0.0107	1.0000										
L4.	-0.0055	0.1203	1.0000									
L3.	0.0019	-0.0002	0.1204	1.0000								
L2.	0.1156	-0.0243	-0.0003	0.1195	1.0000							
L1.	0.5986	-0.0248	-0.0243	-0.0006	0.1190	1.0000						
--.	0.1420	-0.0064	-0.0252	-0.0245	-0.0001	0.1191	1.0000					
F1.	0.0502	0.0248	-0.0065	-0.0256	-0.0255	-0.0003	0.1193	1.0000				
F2.	-0.0174	0.0102	0.0249	-0.0066	-0.0263	-0.0257	-0.0004	0.1191	1.0000			
F3.	-0.0069	0.0060	0.0100	0.0245	-0.0077	-0.0265	-0.0254	-0.0007	0.1189	1.0000		
F4.	0.0043	-0.0166	0.0061	0.0102	0.0247	-0.0076	-0.0267	-0.0254	-0.0006	0.1189	1.0000	
F5.	0.0216	0.0019	-0.0169	0.0052	0.0080	0.0242	-0.0069	-0.0272	-0.0259	-0.0011	0.1190	1.0000

Peru

(obs=3,730)

	cdsret	L5. indexret	L4. indexret	L3. indexret	L2. indexret	L. indexret	indexret	F. indexret	F2. indexret	F3. indexret	F4. indexret	F5. indexret
cdsret	1.0000											
indexret												
L5.	0.0569	1.0000										
L4.	0.0507	0.1784	1.0000									
L3.	0.0573	0.0523	0.1784	1.0000								
L2.	0.1415	0.0635	0.0524	0.1784	1.0000							
L1.	0.4656	0.0630	0.0636	0.0523	0.1784	1.0000						
--.	0.0717	0.0429	0.0630	0.0636	0.0523	0.1784	1.0000					
F1.	-0.0107	-0.0065	0.0429	0.0630	0.0636	0.0522	0.1784	1.0000				
F2.	-0.0067	0.0384	-0.0063	0.0429	0.0630	0.0635	0.0522	0.1783	1.0000			
F3.	0.0156	0.0322	0.0384	-0.0063	0.0429	0.0630	0.0635	0.0522	0.1783	1.0000		
F4.	0.0024	0.0007	0.0323	0.0384	-0.0063	0.0429	0.0630	0.0634	0.0521	0.1783	1.0000	
F5.	-0.0133	0.0377	0.0009	0.0323	0.0383	-0.0064	0.0428	0.0629	0.0633	0.0521	0.1782	1.0000

Venezuela

(obs=3,709)

	cdsret	L5. indexret	L4. indexret	L3. indexret	L2. indexret	L. indexret	indexret	F. indexret	F2. indexret	F3. indexret	F4. indexret	F5. indexret
cdsret	1.0000											
indexret												
L5.	-0.0222	1.0000										
L4.	0.0194	0.2429	1.0000									
L3.	-0.0043	0.1957	0.2431	1.0000								
L2.	0.0223	0.1104	0.1941	0.2409	1.0000							
L1.	-0.0001	0.0185	0.1093	0.1943	0.2391	1.0000						
--.	0.0297	0.0405	0.0173	0.1095	0.1928	0.2378	1.0000					
F1.	-0.0110	0.0115	0.0402	0.0173	0.1084	0.1925	0.2375	1.0000				
F2.	-0.0308	-0.0482	0.0115	0.0402	0.0099	0.1083	0.1923	0.2372	1.0000			
F3.	0.0023	0.0366	-0.0470	0.0115	0.0396	0.0118	0.1103	0.1930	0.2372	1.0000		
F4.	0.0187	0.0442	0.0371	-0.0470	0.0111	0.0402	0.0123	0.1105	0.1929	0.2369	1.0000	
F5.	0.0092	0.0143	0.0443	0.0371	-0.0469	0.0112	0.0404	0.0123	0.1104	0.1929	0.2369	1.0000

Exhibit 5: CDS (Blue) and Equity Market (Green) Prices for the LAC-7 Sample (per Bloomberg)

Argentina

Brazil

Chile

Colombia

Mexico

Peru

Venezuela

Track
Annotate
News
Zoom
Last Price
VENZ CDS USD SR 5Y D14 Corp (R1) 8502.344
IBVC Index (L1) 776.140
776.140
800
600
400
200
0
16000
14000
12000
10000
8502.344
8000
6000
4000
2000
0
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018

Table 3: First Stage Individual Time Series Regressions

1= Argentina, 2= Brazil, 3= Chile, 4= Colombia, 5= Mexico, 6= Peru, 7= Venezuela

-> ccode = 1

Source	SS	df	MS			
				Number of obs	=	2,922
				F(17, 2904)	=	23.16
Model	.874349559	17	.051432327	Prob > F	=	0.0000
Residual	6.4477562	2,904	.002220302	R-squared	=	0.1194
				Adj R-squared	=	0.1143
Total	7.32210576	2,921	.002506712	Root MSE	=	.04712

cdsret	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
indexret						
--.	.0631738	.0652878	0.97	0.333	-.0648414	.1911889
L1.	.636233	.0649915	9.79	0.000	.5087989	.7636671
L2.	.1230828	.0660872	1.86	0.063	-.0064996	.2526653
L3.	.1042272	.066467	1.57	0.117	-.0261001	.2345546
L4.	-.0630809	.0666576	-0.95	0.344	-.1937819	.0676201
L5.	.1471174	.0668565	2.20	0.028	.0160265	.2782084
cdsproduct	9.18794	36.33304	0.25	0.800	-62.05321	80.42909
cdsproductL1	89.84675	35.82375	2.51	0.012	19.60421	160.0893
cdsproductL2	5.242408	35.5128	0.15	0.883	-64.39042	74.87523
cdsproductL3	-22.07198	35.31808	-0.62	0.532	-91.32301	47.17904
cdsproductL4	18.92817	35.21376	0.54	0.591	-50.1183	87.97464
cdsproductL5	-27.6656	35.22542	-0.79	0.432	-96.73493	41.40374
cdsret						
L1.	-.0439263	.0185537	-2.37	0.018	-.0803061	-.0075464
L2.	-.0889224	.0185746	-4.79	0.000	-.1253431	-.0525017
L3.	.0374709	.0186255	2.01	0.044	.0009504	.0739915
L4.	-.0364054	.0185808	-1.96	0.050	-.0728383	.0000274
L5.	-.0273568	.0175762	-1.56	0.120	-.0618198	.0071062
_cons	-.0013206	.0008742	-1.51	0.131	-.0030348	.0003936

```
-> ccode = 2

      Source |       SS           df       MS      Number of obs   =     4,126
-------------+----------------------------------   F(17, 4108)     =    187.42
       Model |  2.40027371        17  .141192571   Prob > F        =    0.0000
    Residual |  3.09478268     4,108  .000753355   R-squared       =    0.4368
-------------+----------------------------------   Adj R-squared   =    0.4345
       Total |   5.4950564     4,125  .001332135   Root MSE        =    .02745

------------------------------------------------------------------------------
      cdsret |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    indexret |
         --. |   .3749106   .0341911    10.97   0.000     .3078774    .4419437
         L1. |   .6625079   .0349134    18.98   0.000     .5940587    .7309572
         L2. |   .0213816   .0364196     0.59   0.557    -.0500206    .0927838
         L3. |   .0492399   .0363469     1.35   0.176    -.0220198    .1204995
         L4. |   .0622839   .0365021     1.71   0.088    -.0092799    .1338477
         L5. |   .0319162   .0363817     0.88   0.380    -.0394117    .1032441
             |
  cdsproduct |   -28.5366   6.417949    -4.45   0.000    -41.11926   -15.95394
cdsproductL1 |   63.10873   6.429026     9.82   0.000     50.50436     75.7131
cdsproductL2 |   7.642976   6.469247     1.18   0.237    -5.040253    20.32621
cdsproductL3 |  -2.716169   6.403643    -0.42   0.671    -15.27078     9.83844
cdsproductL4 |  -5.438894    6.38349    -0.85   0.394    -17.95399    7.076203
cdsproductL5 |   -3.71176   6.362767    -0.58   0.560    -16.18623    8.762709
             |
      cdsret |
         L1. |   .0315573    .015582     2.03   0.043     .0010081    .0621064
         L2. |    -.02286    .015633    -1.46   0.144    -.0535092    .0077892
         L3. |  -.0382702   .0156277    -2.45   0.014    -.0689089   -.0076315
         L4. |  -.0035219   .0156505    -0.23   0.822    -.0342053    .0271616
         L5. |  -.0423902   .0119842    -3.54   0.000    -.0658857   -.0188947
             |
       _cons |  -.0003323    .000429    -0.77   0.439    -.0011733    .0005087
------------------------------------------------------------------------------
```

```
-> ccode = 3

      Source |       SS           df       MS      Number of obs   =     3,870
-------------+----------------------------------   F(17, 3852)     =     37.33
       Model |  .816888748        17  .048052279   Prob > F        =    0.0000
    Residual |   4.9583761     3,852  .001287221   R-squared       =    0.1414
-------------+----------------------------------   Adj R-squared   =    0.1377
       Total |  5.77526485     3,869  .001492702   Root MSE        =    .03588

------------------------------------------------------------------------------
      cdsret |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    indexret |
         --. |   .4430393   .0770717     5.75   0.000     .2919341    .5941445
         L1. |   1.457429   .0782897    18.62   0.000     1.303936    1.610922
         L2. |   .3715731   .0817915     4.54   0.000     .2112143    .5319319
         L3. |   .1568279   .0823391     1.90   0.057    -.0046046    .3182604
         L4. |   .1024875   .0830876     1.23   0.217    -.0604123    .2653874
         L5. |  -.0636672   .0835094    -0.76   0.446     -.227394    .1000596
             |
  cdsproduct |  -6.872357   3.544178    -1.94   0.053      -13.821    .0762869
cdsproductL1 |  -26.38952    3.55869    -7.42   0.000    -33.36662   -19.41242
cdsproductL2 |  -3.232252    3.55959    -0.91   0.364    -10.21111    3.746609
cdsproductL3 |  -3.539382   3.561664    -0.99   0.320    -10.52231    3.443545
cdsproductL4 |  -7.779536   3.607814    -2.16   0.031    -14.85294   -.7061286
cdsproductL5 |   1.901529   3.622876     0.52   0.600     -5.20141    9.004468
             |
      cdsret |
         L1. |  -.1195431   .0161191    -7.42   0.000    -.1511459   -.0879402
         L2. |   -.052434   .0162318    -3.23   0.001    -.0842577   -.0206103
         L3. |   -.004685   .0162514    -0.29   0.773    -.0365471    .0271771
         L4. |   .0175601   .0161795     1.09   0.278    -.0141611    .0492814
         L5. |   .0086071   .0152163     0.57   0.572    -.0212258    .0384399
             |
       _cons |   -.000349   .0005803    -0.60   0.548    -.0014868    .0007888
------------------------------------------------------------------------------
```

-> ccode = 4

Source	SS	df	MS			
Model	1.27320531	17	.07489443	Number of obs	=	3,812
Residual	3.87014212	3,794	.001020069	F(17, 3794)	=	73.42
				Prob > F	=	0.0000
				R-squared	=	0.2475
				Adj R-squared	=	0.2442
Total	5.14334743	3,811	.001349606	Root MSE	=	.03194

cdsret	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
indexret						
--.	-.2729314	.0823931	-3.31	0.001	-.4344704	-.1113924
L1.	1.118062	.0825745	13.54	0.000	.9561672	1.279957
L2.	.0702644	.0844864	0.83	0.406	-.0953788	.2359076
L3.	.1346677	.0854506	1.58	0.115	-.0328658	.3022013
L4.	.1448216	.0866696	1.67	0.095	-.0251019	.3147451
L5.	-.0198513	.0869299	-0.23	0.819	-.190285	.1505825
cdsproduct	51.76918	13.60696	3.80	0.000	25.09152	78.44684
cdsproductL1	-13.33794	13.61315	-0.98	0.327	-40.02773	13.35185
cdsproductL2	-.552555	13.56752	-0.04	0.968	-27.15289	26.04778
cdsproductL3	-16.84577	13.60646	-1.24	0.216	-43.52245	9.830917
cdsproductL4	-17.29825	13.71236	-1.26	0.207	-44.18255	9.586051
cdsproductL5	.5058967	13.67013	0.04	0.970	-26.29561	27.30741
cdsret						
L1.	.068672	.0162235	4.23	0.000	.0368644	.1004797
L2.	.0188356	.016257	1.16	0.247	-.0130377	.0507089
L3.	-.0219548	.0162496	-1.35	0.177	-.0538136	.0099039
L4.	-.0205508	.016251	-1.26	0.206	-.0524123	.0113107
L5.	-.0356018	.014261	-2.50	0.013	-.0635617	-.0076418
_cons	-.0004015	.0005243	-0.77	0.444	-.0014294	.0006264

-> ccode = 5

Source	SS	df	MS
Model	2.0186566	17	.118744506
Residual	3.44452487	4,182	.000823655
Total	5.46318147	4,199	.001301067

Number of obs	=	4,200
F(17, 4182)	=	144.17
Prob > F	=	0.0000
R-squared	=	0.3695
Adj R-squared	=	0.3669
Root MSE	=	.0287

cdsret	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
indexret						
--.	.0538273	.0541097	0.99	0.320	-.0522563	.159911
L1.	1.443145	.0546673	26.40	0.000	1.335968	1.550322
L2.	.1175654	.0589178	2.00	0.046	.0020552	.2330756
L3.	-.0249969	.058706	-0.43	0.670	-.1400918	.090098
L4.	.0981391	.0587708	1.67	0.095	-.0170829	.2133611
L5.	-.09524	.0583338	-1.63	0.103	-.2096053	.0191253
cdsproduct	14.66698	5.801856	2.53	0.012	3.292264	26.0417
cdsproductL1	-9.714948	5.7757	-1.68	0.093	-21.03839	1.608493
cdsproductL2	-4.647708	5.738847	-0.81	0.418	-15.8989	6.603482
cdsproductL3	3.539393	5.701677	0.62	0.535	-7.638923	14.71771
cdsproductL4	-4.727204	5.687956	-0.83	0.406	-15.87862	6.424213
cdsproductL5	11.5891	5.619542	2.06	0.039	.5718151	22.60639
cdsret						
L1.	.0238162	.0154599	1.54	0.124	-.0064933	.0541258
L2.	-.0106106	.0154574	-0.69	0.492	-.0409152	.0196941
L3.	-.0222747	.0154595	-1.44	0.150	-.0525836	.0080341
L4.	.0195657	.0154477	1.27	0.205	-.0107199	.0498514
L5.	-.0394874	.0124397	-3.17	0.002	-.0638758	-.0150991
_cons	-.0004435	.0004444	-1.00	0.318	-.0013146	.0004277

-> ccode = 6

Source	SS	df	MS
Model	1.18204721	17	.069532189
Residual	3.71397317	3,716	.000999455
Total	4.89602038	3,733	.001311551

Number of obs	=	3,734
F(17, 3716)	=	69.57
Prob > F	=	0.0000
R-squared	=	0.2414
Adj R-squared	=	0.2380
Root MSE	=	.03161

cdsret	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
indexret						
--.	-.3196638	.0838291	-3.81	0.000	-.4840194	-.1553082
L1.	1.474661	.0865133	17.05	0.000	1.305043	1.644279
L2.	.0911	.0894363	1.02	0.308	-.084249	.2664489
L3.	.1076705	.0904791	1.19	0.234	-.069723	.285064
L4.	.1918665	.0916326	2.09	0.036	.0122114	.3715217
L5.	.0790952	.0900924	0.88	0.380	-.0975401	.2557305
cdsproduct	42.83705	11.66311	3.67	0.000	19.97032	65.70377
cdsproductL1	-60.22554	11.95853	-5.04	0.000	-83.67146	-36.77962
cdsproductL2	-8.964308	11.90888	-0.75	0.452	-32.31289	14.38427
cdsproductL3	-11.58529	11.96686	-0.97	0.333	-35.04755	11.87697
cdsproductL4	-22.26226	12.01624	-1.85	0.064	-45.82132	1.296814
cdsproductL5	3.478563	11.74091	0.30	0.767	-19.54069	26.49781
cdsret						
L1.	.0839348	.0163926	5.12	0.000	.0517955	.1160741
L2.	.0076486	.0164319	0.47	0.642	-.0245678	.0398649
L3.	-.0165698	.0164186	-1.01	0.313	-.0487602	.0156206
L4.	-.0538828	.0164123	-3.28	0.001	-.0860607	-.0217048
L5.	-.0411893	.014466	-2.85	0.004	-.0695514	-.0128271
_cons	-.0005552	.00052	-1.07	0.286	-.0015747	.0004644

-> ccode = 7

Source	SS	df	MS			
				Number of obs	=	3,713
				F(17, 3695)	=	13.58
Model	.306397137	17	.018023361	Prob > F	=	0.0000
Residual	4.90234552	3,695	.001326751	R-squared	=	0.0588
				Adj R-squared	=	0.0545
Total	5.20874265	3,712	.001403217	Root MSE	=	.03642

cdsret	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
indexret						
--.	.0373107	.0227624	1.64	0.101	-.0073175	.0819388
L1.	-.0485905	.0233785	-2.08	0.038	-.0944265	-.0027546
L2.	.0291862	.0235153	1.24	0.215	-.016918	.0752904
L3.	-.035065	.0234226	-1.50	0.134	-.0809875	.0108576
L4.	.030925	.0231515	1.34	0.182	-.014466	.076316
L5.	-.0323698	.0224181	-1.44	0.149	-.0763228	.0115833
cdsproduct	11.17482	13.50135	0.83	0.408	-15.296	37.64564
cdsproductL1	33.26548	13.22583	2.52	0.012	7.334839	59.19613
cdsproductL2	9.562037	13.13643	0.73	0.467	-16.19333	35.3174
cdsproductL3	18.95223	13.01807	1.46	0.146	-6.571081	44.47553
cdsproductL4	13.14115	12.77067	1.03	0.304	-11.89711	38.17941
cdsproductL5	-5.38854	12.85348	-0.42	0.675	-30.58915	19.81206
cdsret						
L1.	.2349745	.0164547	14.28	0.000	.2027133	.2672356
L2.	-.0571279	.016891	-3.38	0.001	-.0902444	-.0240113
L3.	.0108011	.0169128	0.64	0.523	-.0223583	.0439605
L4.	-.0296896	.0168888	-1.76	0.079	-.0628019	.0034226
L5.	.0115671	.0164401	0.70	0.482	-.0206655	.0437997
_cons	-.0005059	.0006136	-0.82	0.410	-.0017089	.0006971

Table 4: Entire Sample of LAC-7

Here we observe the effect of unconditional and conditional lagged CDS innovations and lagged equity returns on contemporaneous equity returns. We define the credit event under two different specifications (A) a day-to-day CDS spread jump exceeding 50 basis points for investment grade countries and 100 basis points for non-investment grade countries; (B) a day-to-day jump in CDS spreads exceeding four standard deviations above the average CDS spread jump in the sampling period.

		Spec A			**Spec B**	
	5 days	30 days	90 days	5 days	30 days	90 days
$\boldsymbol{a}$	0.00083***	0.00082***	0.00082***	0.00081***	0.00081***	0.00080***
	(2.92)	(2.86)	(2.97)	(2.92)	(2.88)	(3.05)
$\sum_{k=1}^{5} \boldsymbol{b_k}$	-0.02518	-0.02153	-0.02124	-0.01798	-0.01665	-0.01492
	(1.38)	(1.10)	(1.23)	(0.96)	(0.86)	(0.89)
$\sum_{k=1}^{5} \boldsymbol{b_k^D}$	0.06583*	0.02179	0.01288	0.01619	0.02179	-0.00142
	(1.95)	(0.72)	(0.47)	(0.17)	(0.72)	(0.04)
$\sum_{k=1}^{5} \boldsymbol{c_k}$	0.21199**	0.21476**	0.21082**	0.21285**	0.20783**	0.18975
	(2.19)	(2.24)	(2.24)	(2.20)	(2.15)	(0.04)
$\sum_{k=1}^{5} \boldsymbol{c_k^D}$	0.18795	-0.01661	0.02726	0.00431	0.17220***	0.02726
	(1.18)	(0.17)	(0.56)	(0.04)	(2.64)	(5.04)

z-values displayed below coefficients in parentheses
** Significance at 10% level*
*** Significance at 5% level*
**** Significance at 1% level*

Table 5: Sample with Investment Grade Countries

Here we observe the same regression results from Table 1, but with only the investment grade countries of the sample (Chile, Colombia, Mexico, and Peru).

	Spec A			**Spec B**		
	5 days	30 days	90 days	5 days	30 days	90 days
$\boldsymbol{a}$	0.00098**	0.00099**	0.00097**	0.00097**	0.00097**	0.00093**
	(2.08)	(2.08)	(2.08)	(2.05)	(2.08)	(2.13)
$\sum_{k=1}^{5} \boldsymbol{b_k}$	-0.04068***	-0.04269***	-0.03837***	-0.03506***	-0.03411***	-0.02901*
	(4.52)	(3.78)	(2.78)	(3.44)	(2.97)	(1.86)
$\sum_{k=1}^{5} \boldsymbol{b_k^D}$	0.07739***	0.07172**	0.04201	0.12929*	0.79528	0.00976
	(2.83)	(1.98)	(1.10)	(1.78)	(0.30)	(0.16)
$\sum_{k=1}^{5} \boldsymbol{c_k}$	0.29956***	0.29768***	0.29263***	0.30224***	0.29759***	0.27769***
	(4.55)	(4.43)	(4.30)	(4.77)	(4.71)	(4.70)
$\sum_{k=1}^{5} \boldsymbol{c_k^D}$	0.33263	0.13395	0.10393	-0.00915	0.14285***	0.10393***
	(1.34)	(1.44)	(1.52)	(0.10)	(4.48)	(11.19)

z-values displayed below coefficients in parentheses
** Significance at 10% level*
*** Significance at 5% level*
**** Significance at 1% level*

Table 6: Sample with Non-Investment Grade Countries

Here we observe the same regression results from Table 1, but with only the non-investment grade countries of the sample (Argentina, Brazil, and Venezuela).

		Spec A			**Spec B**	
	5 days	30 days	90 days	5 days	30 days	90 days
$\boldsymbol{a}$	0.00133** (2.10)	0.00132** (2.02)	0.00131** (2.10)	0.00131** (2.10)	0.00130*** (2.05)	0.00124*** (2.07)
$\sum_{k=1}^{5} \boldsymbol{b_k}$	-0.02737 (0.89)	-0.01962 (0.60)	-0.01686 (0.58)	-0.01305 (0.41)	-0.01089 (0.34)	-0.00324 (0.12)
$\sum_{k=1}^{5} \boldsymbol{b_k^D}$	0.06749** (2.53)	0.02309 (1.27)	-0.00393 (0.13)	-0.08015 (0.40)	-0.09856 (0.79)	-0.06194*** (7.96)
$\sum_{k=1}^{5} \boldsymbol{c_k}$	0.23538* (1.81)	0.24097* (1.90)	0.23744* (1.89)	0.23360* (1.74)	0.22873* (1.71)	0.20368 (1.55)
$\sum_{k=1}^{5} \boldsymbol{c_k^D}$	0.05171 (0.98)	-0.10313 (1.10)	-0.01922 (0.44)	-0.17540* (1.93)	0.11048 (1.07)	-0.01922*** (2.97)

z-values displayed below coefficients in parentheses
**   Significance at 10% level*
***   Significance at 5% level*
**** Significance at 1% level*