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Systemic Risk in Latin America: From Tequila Crisis to Oil Bust

Abstract

In this article, we estimate measures of systemic risk in Latin America using a network approach. We find that the period from the late 1990s until the oil bust of 2014-2015 has included modest declines in Latin American financial sector connectivity, as measured by the prevalence of default risk spillovers between institutions, and substantial declines in the overall level of default risk. Connectivity is pro-cyclical with real regional output, with the notable exception of the global financial crisis of 2007-2009, during which it was countercyclical. High credit risk institutions drive credit risk in the system during times of economic turmoil. Although the overall response of default risk and leverage in the system to the recent oil bust has been surprisingly muted, Brazilian institutions currently represent a major concentration of credit risk, while institutions in the broader group of Brazil, Chile and Argentina appear to have the greatest spillover effects on credit risk in the rest of Latin America.
Systemic Risk in Latin America: From Tequila Crisis to Oil Bust

BY SAMUEL W. MALONE AND ALEJANDRA CARO

Major financial crises—in particular banking and currency crises—in Latin American countries during the 1990s made headlines in the region and around the world. Few homegrown crisis episodes in Latin America stand out as clearly as the Tequila Crisis in 1994. That year, a sudden stop in capital flows to Mexico precipitated what was, as Musacchio (2012) notes, the worst financial distress in that country’s history. In 1995, Mexico’s output contracted by 5.7%, and the crisis spread swiftly to other economies in the region. For various reasons, including but not limited to fallout from the Tequila Crisis, nearly all Latin American countries, with the exception of Panama and Chile, experienced a banking crisis during the period from 1994 to 2002 (Jácome, 2008). These events prompted increased focus by regulators and the regions’ banks on their ability to withstand future financial shocks. Given the capital outflows from regional economies and significant exchange rate depreciations that have accompanied the 2014-2015 oil bust, such a shock is happening now.

The benefits of house-cleaning by financial institutions in major Latin American countries around the turn of the millennium became evident in 2007-2009 in the form of a muted response of financial sector default risk in many Latin American countries to the events of the global financial crisis. However, the recent commodity bust, and in particular the oil bust that began in July 2014, has left many policymakers in the region acutely aware of the many significant vulnerabilities still facing their economies.

New approaches to systemic and counterparty risk developed since the global financial crisis can help regulators and bank risk managers stay better informed about emergent trends and potential dangers originating at the national, regional, and global scales. We believe that systemic risk tools can be most useful when developed as a natural extension of credit risk metrics that many banks and regulators already use.

In this article, we apply the network-based approach of Hughes and Malone (2015) to measure credit risk spillovers between all major publicly traded Latin American financial institutions with greater than $1 billion of assets on their books at some point during the period from January 1997 until May 2015. We report trends in financial sector credit risk and its main drivers: leverage and asset volatility. Our systemic risk measures quantify the extent of spillovers between institutions in the regional financial system over time, and allow us to identify the institutions with the greatest combination of size, default risk, and influence on the credit risk of other institutions. Our tools are extensions of those discussed in Billio et al. (2012) and Merton et al. (2013), who focus on spillovers in equity returns and the expected loss component of financial institution debt instruments, respectively. In our setup, the credit risk metric of interest is the probability of default, or PD. We obtain default probabilities from Moody’s Analytics CreditEdge, in the form of the industry-leading Expected Default Frequency, or EDF, metric, which is available for nearly all publicly traded firms worldwide.

In recognizing the value of network-based techniques for understanding systemic risk in Latin American financial systems, we follow in the footsteps of several researchers at prominent central banks of the region who have already seen the utility of such an approach. We briefly review that work, and then describe our methods and our main findings from applying the network model to financial institutions in Latin America.

Network research in Latin American central banks

The adverse impact of multiple financial crises in Latin America during the past several decades has sparked interest in systemic risk on the part of researchers in central banks across the region.

Cepeda López (2008) and Machado et al. (2010), of the Central Bank of Colombia, for instance, have evaluated the stability of Colombia’s payment system by analyzing the
topology of the network of transfers. They use the amount and number of bilateral transactions as measures of connectivity between pairs of institutions. Most institutions in the Colombian payment system are able to grapple with a temporary lack of liquidity, they find. However, because of the structure and specificity of their business, Colombian stockbrokers face special challenges when it comes to liquidity risk management.

Márquez and Martínez-Jaramillo (2009), from the Central Bank of Mexico, estimate the loss distribution of the financial system in Mexico resulting from an initial random shock to the system and its ensuing contagion process. They assume contagion is a deterministic process and depends on the level of exposure between banks.

Miranda Tabak et al. (2012), from the Central Bank of Brazil, identify risk sources in the Brazilian payments system by estimating scale free networks. As in the case of Cepeda López (2008), they estimate their networks using data on transactions between institutions. In other work from the Central Bank of Brazil, de Castro Miranda and Miranda Tabak (2013) assess how shocks in the real sector propagate to the Brazilian financial sector. To analyze inter-sector spillovers, they use two network structures: an inter-bank graph describing interactions within the financial system, and a bipartite graph linking firms to a subset of institutions in the inter-bank network. They find that distress to firms can have contagious effects in the inter-bank network, in part because of the existence of common exposures among banks to institutions in the real sector.

Our method of measuring network spillovers differs from the above contributions in a few key ways. First, by measuring directly the strength of linkages between default probabilities of different financial firms over time, our measures of systemic risk and counterparty credit risk sensitivities are explicitly dynamic. They are also market-based, as the underlying EDF measures themselves use firm equity market values as inputs. Furthermore, although our model does not employ granular counterparty exposure data of the sort typically available to regulators, it has the compensating advantage of scope. In particular, we can easily capture risk-transfer originating outside as well as inside the national boundaries of any one country by specifying the scope of our financial network appropriately. We view our approach as being highly complementary to the more granular, but less scalable and sometimes low-frequency, counterparty exposure-based approaches that many national regulators currently employ. We now describe our framework in more detail.

A network-based approach to assess systemic risk

As in Hughes and Malone (2015), we take systemic risk to mean the “potential for a shock, endogenous or exogenous to the financial system, to cause broad-based financial system failure while inflicting collateral damage on other economic sectors.” Following the methodology used in that paper, we estimate the presence and strength of dynamic linkages between the EDFs of individual financial institutions.

A link from one institution to another is said to exist whenever movements in the EDF of the first institution Granger-cause movements in the EDF of the second. Granger-causality is a statistical notion of causality, which exists whenever the history of one variable can be used to explain variations in another variable after controlling for lagged values of the latter.

Formally, denote by $X_t$ and $Y_t$ the one-year ahead (log) default probability of each of two publicly traded financial institutions measured at time $t$. We estimate vector autoregression models of the form

$$Y_t = a_1 + \sum_{j=1}^{p} b_{1j} Y_{t-j} + \sum_{j=1}^{p} c_{1j} X_{t-j} + \epsilon_{1t}$$

$$X_t = a_2 + \sum_{j=1}^{p} b_{2j} Y_{t-j} + \sum_{j=1}^{p} c_{2j} X_{t-j} + \epsilon_{2t}$$

In particular, we estimate the above model with $p = 2$ for each pair of financial institutions, at each point in time, using a 60-month rolling data window. We say that $X$ Granger-causes $Y$ at time $t$ if the joint F-test of the coefficients associated with the $p$ lags of $X$, that is the $c_{21}^1$, is statistically significant at the 5% level in rejecting the null hypothesis that these coefficients are both equal to zero. Likewise, if the relevant F-test of the $b_{12}^1$ is significant at the 5% level, we say that $Y$ Granger-causes $X$.

In addition to our focus on the EDF metric of default probability, we also compute and report weighted-average measures of financial system leverage and asset volatility. For an individual firm, leverage is calculated as the ratio of the default point to the estimated market value of the firm’s assets. The default point is the asset value at which the firm is assumed to default, which is approximately equal to the net present value of the firm’s liabilities. The firm’s asset volatility, as well as the default point and implied market value of assets, are all sourced from CreditEdge.

Based on the graph structure estimated using the aforementioned techniques, we compute several additional systemic risk measures. These include the degree of Granger-causality, which represents the proportion of links in the system as a whole that are active at a given time, and a systemic influence measure for each institution. The specific components used to compute the systemic influence measure include Out, Out plus and Closeness.

The Out indicator measures the fraction of other banks in the system that are Granger-caused by a given institution; the Out plus indicator measures the fraction of other firms whose EDF is significantly increased at the one-month horizon by a positive shock to the institution in question; and the Closeness measure is the average length of the shortest path from a given institution to each of the other institutions in the network.

We compute weighted-average EDF, leverage and volatility measures for the system using two separate schemes: one in...
which institutions are weighted in proportion to their size, as measured by the book value of their assets, and another in which institutions are weighted in proportion to their systemic influence score. A detailed description of all indicators used in this paper can be found in Hughes and Malone (2015).

**Empirical results**

Our dataset includes all publicly traded financial institutions in Argentina, Brazil, Chile, Colombia, Mexico, Peru and Venezuela with asset values exceeding $1 billion at least once from January 1997 to May 2015.

Our first set of results is contained in Table 1, which ranks institutions in decreasing order by the value of their Out measure in May 2015, and contains information on their Out measure, probability of default, and size. The top 20 firms by Out measure are shown.

Although the largest companies by value of book assets are from Brazil, those with the most downstream linkages to other firms are from Chile. Further, we find that the linkage between institution size, as measured by book assets, and the extent of outward linkages, as measured by Out, is weak. The Spearman rank correlation between both measures for May 2015 for all firms in our sample is actually negative, at -0.15. This finding is consistent with a robust stylized fact documented by Hughes and Malone (2015) for financial institutions in the U.S. and Southeast Asia: An institution’s size is, by itself, usually not a reliable proxy for the degree of influence it has on credit risk in the rest of the financial system.

A third observation, if we rank institutions in decreasing order by their EDFs (not shown), is that the top 10 institutions by default probability are all Brazilian. This finding is consistent with the fact that Brazil’s output has experienced negative year-on-year growth rates since the second quarter of 2014 (Moody’s Analytics Dismal Scientist, 2015).

To help gain insight on the relationship between systemic risk and macroeconomic fluctuations in the region, Figure 1 displays the degree of Granger-causality for publicly traded institutions in the Latin American financial sector, alongside the de-trended real GDP of the countries in this study (on the right axis), over time. All countries were included in the GDP calculation except for Venezuela, for which recent GDP data were unavailable. We find that from 1997 to 2015, the average degree of financial network connectivity in Latin America declined, but with significant variations around the downward trend.

We find that financial network connectivity in Latin America is pro-cyclical with respect to regional real output before and after the global financial crisis of 2007-2009, but strongly countercyclical during the crisis. Our regional output series is constructed by using the cyclical component obtained after de-trending the total real GDP, in constant U.S. dollars, of the countries in our study excluding Venezuela. When we repeat the exercise using the cyclical real output component obtained after applying the Hodrick-Prescott filter to the raw output series, we obtain qualitatively identical results. In particular, the Pearson correlation coefficient between

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**Table 1: Top LatAm Firms Ranked by Out Measure**

*Data as of May 2015*

<table>
<thead>
<tr>
<th>Financial institution</th>
<th>Country</th>
<th>Out Value</th>
<th>Quan tile</th>
<th>EDF Value (%)</th>
<th>Quan tile</th>
<th>Book assets Value ($ mil)</th>
<th>Quan tile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Salfacorp S.A.</td>
<td>CHL</td>
<td>0.263</td>
<td>1.000</td>
<td>1.466</td>
<td>0.805</td>
<td>1386.478</td>
<td>0.156</td>
</tr>
<tr>
<td>Parana Banco S.A.</td>
<td>BRA</td>
<td>0.250</td>
<td>0.987</td>
<td>0.870</td>
<td>0.688</td>
<td>1948.361</td>
<td>0.286</td>
</tr>
<tr>
<td>Grupo Security S.A.</td>
<td>CHL</td>
<td>0.250</td>
<td>0.974</td>
<td>0.369</td>
<td>0.260</td>
<td>12343.337</td>
<td>0.662</td>
</tr>
<tr>
<td>Banco Estado Do Rio Grande Do Sul S.A.</td>
<td>BRA</td>
<td>0.250</td>
<td>0.961</td>
<td>3.470</td>
<td>0.974</td>
<td>19566.840</td>
<td>0.766</td>
</tr>
<tr>
<td>Banco Macro S.A.</td>
<td>ARG</td>
<td>0.250</td>
<td>0.948</td>
<td>0.418</td>
<td>0.364</td>
<td>7567.709</td>
<td>0.584</td>
</tr>
<tr>
<td>Cielo S.A.</td>
<td>BRA</td>
<td>0.237</td>
<td>0.935</td>
<td>0.309</td>
<td>0.195</td>
<td>8955.523</td>
<td>0.623</td>
</tr>
<tr>
<td>Impulsoira Del Desarrollo Y El Empleo</td>
<td>MEX</td>
<td>0.237</td>
<td>0.922</td>
<td>0.090</td>
<td>0.026</td>
<td>5736.594</td>
<td>0.506</td>
</tr>
<tr>
<td>Sociedad Comercial Del Plata S.A.</td>
<td>ARG</td>
<td>0.237</td>
<td>0.909</td>
<td>0.041</td>
<td>0.013</td>
<td>176.315</td>
<td>0.026</td>
</tr>
<tr>
<td>Cyrela Brazil Realty S.A.</td>
<td>BRA</td>
<td>0.224</td>
<td>0.896</td>
<td>0.586</td>
<td>0.558</td>
<td>4249.741</td>
<td>0.429</td>
</tr>
<tr>
<td>Emprendimientos E Participaciones</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Grupo De Inversiones Suramericana S.A.</td>
<td>COL</td>
<td>0.224</td>
<td>0.883</td>
<td>0.398</td>
<td>0.338</td>
<td>18320.918</td>
<td>0.753</td>
</tr>
<tr>
<td>Corporacion Financiera Colombiana S.A.</td>
<td>COL</td>
<td>0.224</td>
<td>0.870</td>
<td>0.236</td>
<td>0.104</td>
<td>4630.622</td>
<td>0.455</td>
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<tr>
<td>Banco Mercantil De Inversiones S.A.</td>
<td>BRA</td>
<td>0.211</td>
<td>0.857</td>
<td>0.590</td>
<td>0.571</td>
<td>25.216</td>
<td>0.013</td>
</tr>
<tr>
<td>Sociedad De Inv Oro Blanco S.A.</td>
<td>CHL</td>
<td>0.211</td>
<td>0.844</td>
<td>2.244</td>
<td>0.857</td>
<td>1729.356</td>
<td>0.260</td>
</tr>
<tr>
<td>Corporativo Gbm, S.A.B. De C.V.</td>
<td>MEX</td>
<td>0.197</td>
<td>0.831</td>
<td>0.427</td>
<td>0.403</td>
<td>2344.134</td>
<td>0.338</td>
</tr>
<tr>
<td>Banestes Sa-Bco Estado Espirito Santo</td>
<td>BRA</td>
<td>0.197</td>
<td>0.818</td>
<td>1.901</td>
<td>0.844</td>
<td>5062.691</td>
<td>0.494</td>
</tr>
<tr>
<td>Grupo Financiero Galicia S.A.</td>
<td>ARG</td>
<td>0.197</td>
<td>0.805</td>
<td>0.386</td>
<td>0.299</td>
<td>12899.089</td>
<td>0.714</td>
</tr>
<tr>
<td>Cyrela Commercial Properties S.A.</td>
<td>BRA</td>
<td>0.184</td>
<td>0.792</td>
<td>0.709</td>
<td>0.623</td>
<td>1369.303</td>
<td>0.143</td>
</tr>
<tr>
<td>Rimac Seguros Y Reaseguros</td>
<td>PER</td>
<td>0.171</td>
<td>0.779</td>
<td>0.918</td>
<td>0.714</td>
<td>2569.449</td>
<td>0.351</td>
</tr>
<tr>
<td>Jhsf Participacoes S.A.</td>
<td>BRA</td>
<td>0.171</td>
<td>0.766</td>
<td>2.643</td>
<td>0.896</td>
<td>1900.054</td>
<td>0.273</td>
</tr>
<tr>
<td>Banco Do Estado De Sergipe S.A.</td>
<td>BRA</td>
<td>0.171</td>
<td>0.753</td>
<td>5.384</td>
<td>0.987</td>
<td>1317.035</td>
<td>0.130</td>
</tr>
</tbody>
</table>

Source: Moody’s Analytics
DGC and the de-trended output series shown in Figure 1 is 0.51 for the 1997-2006 period, -0.73 for the 2007-2009 period, and 0.38 for the 2010-May 2015 period.

Insights on why financial sector connectivity is typically pro-cyclical in the region can be gained by a closer examination of the years 1997 to 2003, when the DGC fell to a historical low. During that time, several financial institutions were either bailed out by their country's central bank, merged, or purchased by other financial institutions (Jácome, 2008). According to Levy Yeyati and Micco (2003), the reduction in the number of banks from 1996 to 2003 for the major economies of the region was noteworthy. The numbers of bank reductions, by country, were: Mexico, 9; Argentina, 37; Brazil, 76; Colombia, 12; Chile, 6; and Peru, 7. Since interventions by central banks in the region showed marked increases in their default probabilities during the 1998-2001 period.

Figure 2 is the significant decrease in the average level of default risk in Latin American financial institutions over time. The systemic influence-weighted average EDF displayed a slight uptick in late 2007 and then again in 2009 in response to the global financial crisis. Other than that fairly transient, exogenous shock to credit risk in the region’s banks, however, the new normal weighted-average EDFs are around 1% following the global financial crisis, as opposed to 5% pre-2004.

Figure 3, which depicts leverage measures versus time, shows that large institutions are more highly leveraged than systemically influential institutions. Further, the degrees of leverage weighted by size and systemic influence diverged in 2009, and the wedge between them has remained significant to the present day, with larger institutions significantly more leveraged than the set of institutions with more spillovers to the rest of the system. Latin American financial institutions deleveraged from 2003 to 2007, only for leverage to spike from 2007 to 2009 during the global financial crisis. This spike was transitory for the systemically influential firms, but leverage in larger firms has remained high.

Figure 4 depicts asset volatility measures over time. Size-weighted volatility has been consistently lower than systemic importance-weighted volatility, as is the case in other regions (Hughes and Malone, 2015; Hamilton, Hughes, and Malone, 2015). However, this generalization masks three separate regimes in Latin American bank asset volatility. In 1998, the average volatility of systemically important institutions spiked, whereas the volatility of large institutions was quite low at that time. From 2000 to 2005, the series converged. Beginning in 2006, and from the global financial crisis until the present day, the levels of the series have diverged once more, with the series themselves fluctuating around what appear to be relatively stable post-crisis average levels.

Putting the results from Figures 2 to 4 together, we can conclude that larger financial institutions in Latin America are more highly leveraged and have higher levels of volatility compared to smaller institutions.
leverage and have lower asset volatility, and that the higher asset volatility of systemically influential firms explains why their spike in leverage at the time of the global financial crisis caused a temporary spike in their EDFs that was not as evident in many larger firms in the region.

Figure 5 displays two additional measures we have found to be useful in diagnosing the state of the financial system: the EDF-Out measure correlation, and the Leverage-Volatility correlation. Both correlations are Spearman rank correlations, and are computed at a given time using values of each underlying measure obtained from the cross section of firms in the system during only that period. Several findings emerge from Figure 5. First, the EDF-Out correlation across firms tends to be positive during and immediately following times of economic distress. This is consistent with the idea that high-EDF firms drive credit risk in the network in times of market stress. Second, the Leverage-Volatility correlation, which is always negative, has become highly negative and very stable during the post-2006 period. The negative correlation between leverage and asset volatility supports the hypothesis that banks follow a Value-at-Risk rule, as proposed in Adrian and Shin (2014). According to this logic, financial intermediaries deleverage as asset volatility increases to maintain their target Value-at-Risk levels. Empirical work for global megabanks, the U.S. and Southeast Asia shows that the correlation between leverage and volatility often becomes less negative preceding turbulent periods (Hughes and Malone, 2015).

Figures 6 and 7 show snapshots of the network, in the form of network graphs, for the set of financial firms included in our analysis as of January 2008 and May 2015, respectively. The direction, color and thickness of the edges are related to the type of relationship that exists between each node, or firm, at the time the snapshot was taken. The size of each node is proportional to the logarithm of the institution’s book assets.

The number of financial institutions in the region has grown significantly in the last seven years. Particularly, the number of firms in Brazil has proliferated during that time. In both network snapshots, we see that although there is an import number of damping connections (in red), which correspond to situations where an increase in the EDF of one bank lowers the EDF of the other bank in the following month, most links are forcing relations (in blue). In forcing relationships, positive shocks to credit risk in one bank propagate the next month to connected banks in the form of positive shocks to their EDFs.

The network for January 2008 does not show a clustering pattern for many countries. However, in this and other network graphs during the same period (not shown), Colombian financial institutions and the three largest Brazilian banks do tend to cluster on account of the strength of their relationships with each other. The extent of clustering appears to go down over time as more institutions join the system.

From Figure 7, we see that financial institutions from Peru and Mexico in particular are located in the periphery of the network in May 2015. Interestingly, although Mexican firms are some of the largest by asset size, they are not as connected as those from Chile or Colombia, which appear to be more central. This may reflect the omission of U.S. financial firms from the network, as stronger trade ties between the U.S. and
Mexico are likely to be reflected by stronger banking ties between those two countries as well.

**Counterparty risk sensitivities**

To close, we will highlight the ability of the Hughes-Malone (2015) framework to examine more granular issues pertaining to counterparty risk between individual pairs of financial firms. For this purpose, we graph the F-statistics used to determine the presence (or absence) of Granger-causality from one firm’s credit risk to that of another firm versus time. We focus on a pair of Colombian banks and a pair of Brazilian banks to illustrate the tool.

Figures 8a and 8b concern the bank pair Banco de Bogota—Bancolombia SA, both from Colombia, and Figures 9a and 9b display results for the bank pair Itau Unibanco Holding—Banco do Brasil, both from Brazil.

The first panel of each Figure (for example, Figure 8a) shows the F-test statistic for Granger-causality of the second bank by the first, whereas the second panel of each Figure (for example, Figure 8b) displays the F-test statistic for Granger-causality of the first bank by the second. Critical values for the F-statistics at the 5% confidence level are displayed as orange horizontal lines.

In Figure 8a, we see that Banco de Bogota drove default risk in Bancolombia SA in 2000 and briefly in 2012. Conversely, as is evident from Figure 8b, Bancolombia SA drove Banco de Bogota for the period from 2003 until 2007, as well as briefly in 2011 and 2014.

Turning to the Brazilian banks, in Figure 9a we see that the EDFs of Itau Unibanco Holding and Banco do Brasil drove each other during 1999 and early 2000, as evidenced by highly significant Granger-causal relationships. Since then, only Banco do Brasil has Granger-caused movements in Itau’s EDF, during the 2007-2009 turmoil of the global financial crisis.

From both pairs of results, it is evident that counterparty credit risk spillovers have the potential to go up substantially during crisis periods such as the late 1990s or the global financial crisis. Also, counterparty risk exposures are time-varying, and banks interested in performing counterparty risk management that is scalable across the region and with respect to global counterparties may find these tools useful.

**Conclusion**

The effects of economic and regulatory policies during the last two decades in Latin America highlight the need for tools to accurately measure systemic and counterparty risk. In this paper, we apply the scalable,
customizable systemic and counterparty risk tool kit of Hughes and Malone (2015) to the set of publicly traded Latin American financial institutions. Our approach provides a set of indicators that allows regulators to identify which institutions are most systemic, and which help financial institutions gauge their levels of exposure with respect to other nodes in the network. Variations in the leading indicators from the framework track important macroeconomic events in Latin America and reflect noteworthy changes to the region’s financial system during the 1997-2015 period in an intuitive manner.
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