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Tail systemic risk and contagion: Evidence from the Brazilian and Latin America banking network

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A B S T R A C T

In this study the tail systemic risk of the Brazilian banking system is examined, using the conditional quantile as the risk measure. Multivariate conditional dependence between Brazilian banks is modelled with a vine copula hierarchical structure. The results demonstrate that Brazilian financial systemic risk increased drastically during the global financial crisis period. Our empirical findings show that *Bradesco* and *Itaú* are the origin of the larger systemic shocks from the banking system to the financial system network, the real economy, and the region. The results have implications for the capital regulation of financial institutions and for risk managers' decisions.

1. Introduction

The recent financial crisis of 2007/2008 drew the attention of both regulators and investors, as it exposed the financial system's fragility and the potential risks arising from bank defaults. Since the collapse of *Lehman Brothers* in mid-September 2008, the assessment of systemic risk turned out to be crucial for decision makers, since regulators started to evaluate the impacts of small, fragile, and seemingly isolated portfolios from one financial institution in compromising the safety and soundness of other institutions. In consequence, systemic risk is necessary to determine the amount of regulatory capital of financial institutions (Sanjiv Ranjan Das, 2004; Rosenberg and Schuermann, 2006). The Financial Stability Oversight Council (*FSOC*; Dodd-Frank, 2010) remarked that financial institutions that are systemically important must be forced to have a greater capacity for risk absorption, given their larger contribution to the systemic risk of the global financial system.

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Banking network links are determinant factors when measuring systemic risk. Glasserman and Young (2016) review the literature[1] and classify the different methodologies for assessing the systemic risk in: (i) studies where the existence and the strength of a network provide a better infrastructure for the member institutions to endure financial stress and (ii) studies where the existence of the network links increases the possibility of big shocks affecting the functioning of the member institutions. Our research focuses on the second group of papers. Bartram et al. (2007) and Diebold and Yilmaz (2014) are in the second group – systemic risk spillover. Bartram et al. (2007) used three methodologies to assess the systemic risk of the world financial system: the first methodology measures the systemic risk as the abnormal returns from negative shocks to the markets; Diebold and Yilmaz (2014) construct a network topology to measure the variance spillover in the financial system. In our study we use a similar approach to the Bartram et al. (2007) and Diebold and Yilmaz (2014) methods.

Our research defines and calculates systemic risk as (i) the risk contribution from one bank to another, i.e. bank's conditional α-quantile – see Reboredo and Ugolini's (2016) implementation of Adrian and Brunnermeier (2016) $CoVaR$– and (ii) the risk contribution from each bank to the Brazilian financial system (*BFIndex*), i.e. system's conditional α-quantile. The selection of the bank's and the system's conditional α-quantile ($CoVaR$) for measuring systemic risk, is based on the rapid success of the Adrian and Brunnermeier (2016) measure in the literature.[2] Adrian and Brunnermeier (2016) proposed $CoVaR$ (VaR conditional on financial distressed institutions) as a new systemic risk measure. $CoVaR$ captures the spillover risks between financial institutions, providing more information about the Value-at-Risk VaR of the financial system conditional on the instability or default. In $CoVaR$, the systemic risk contribution from an institution is measured as the difference between the $\Delta CoVaR$ of an institution and the benchmark $CoVaR$, where $\Delta CoVaR$ is the linear sensitivity of the institution $CoVaR$.[3,4]

We describe a hierarchical banking network model with copulae for the banks' dependence. The hierarchical copula modeling considers bank interconnectedness, conditional systemic dependence, and specific peer-to-peer tail dependence. Using this model, we calculate the effects from the vulnerability of one bank to another measuring the VaR of the recipient institution, and disentangling direct and indirect effects. In addition a bivariate copula dependence model is used to measure the contribution of each bank within the *BFIndex*. Previous research by Silva et al. (2016) found evidence of the strong network interconnectedness in the Brazilian banking system; nevertheless they used complex mathematical measures that are based on topology, while we use a conditional quantile that can easily be compared to the traditional industry adopted measures such as the unconditional quantile (VaR) and conditional VaR.

VaR continues to be the most widely used measure of risk which assesses the potential losses in time using a probabilistic model with a defined interval of confidence under normal market circumstances. VaR was proposed during the 1990s by JP Morgan and adopted as the standard market risk measure for individual institutions; nevertheless, it neglects the collateral effects of defaults over other institutions. The academic literature on macroprudential policies has thus focused on examining the individual risk contributions from one institution to another, and from one institution to the financial system, developing different risk measures (see, for example, Bisias et al., 2012; Bernal et al., 2014).

Previous studies of the Brazilian banking network include (i) new theoretical systemic risk measures calibrated with some empirical data such as in Santos and Cont (2010), Tabak et al. (2014), Silva et al. (2016), and Silva et al. (2017a); (ii) numerical simulations assessment such as in Barnhill and Souto (2009). Barnhill and Souto (2009) proposed a new portfolio simulation methodology to test the Brazilian banking system's strength during the 2007/2008 financial crisis; they found that once sovereign risk is included in the model, the Brazilian banking system is fragile to the effects of the financial crisis. Similar empirical studies of the implications of the banking network for another Latin America country (Mexico) are provided in Martínez-Jaramillo et al. (2010).

In this study we measure the systemic impact of the financial crisis on listed banks[5] of the Brazil stock index (*Bovespa*), using bank and index daily prices from January 1, 2008 to January 18, 2016. The results demonstrate that the multivariate dependence structure of Brazilian banks is given by a C-vine copula hierarchical structure, on which *Bradesco* is the main influence bank in determining the conditional dependence structure of the financial system. This result can be a consequence of the bank size and characteristics, and the Brazilian macroeconomic reforms applied to the banking system: a large private bank that absorbed many small institutions during the Brazilian banking reforms – fragile small banks with multiple business links to the

1 Silva et al. (2017b) provide a compelling revision of the publications about financial systemic risk.

2 Other risk spillover approaches include: Huang et al. (2009), that developed a systemic risk index that measures financial fragility using the prices of credit default swaps (*CDS*); Segoviano and Goodhart (2009), that used *CDS* to develop an index of financial stability that measured interbank dependence during extreme events; Acharya et al. (2016), that used the expected shortfall (*ES*) and the marginal expected shortfall (*MES*) as measures for quantifying risks in extreme situations, and for estimating financial institutions' contributions to system risk; Brownlees and Engle (2012), that defined a systemic risk measure (*SRISK*), that is the required capital in demand to restore the minimum level of mandatory regulatory capital; Allen et al. (2012), that proposed a systemic risk measure (*CATFIN*) to predict the decline in aggregated loan activity within 6 months; and Engle and Manganelli (2004) that developed a model of conditional autoregressive VaR ($CaViaR$) using quantile regression to capture the conditional distribution of the returns in the tails of the distribution. Previous empirical studies that use these methodologies include Rodríguez-Moreno and Peña (2013), that found empirical evidence of the adequacy of *CDS* in estimating systemic risk; and Billio et al. (2012), that tested five systemic risk measures that capture contagion and exposure in financial institutions' relationships.

3 López-Espinosa et al. (2012) identified the determinants of systemic risk for a large set of international banks, applying $CoVaR$ as in Adrian and Brunnermeier (2016).

4 Girardi and Ergün (2013), extended the $CoVaR$ measure, including returns below the VaR of the conditional distress event, in comparison to Adrian and Brunnermeier (2016) that considered only returns equal to the VaR of the conditional distress event. Girardi and Ergün (2013) defined a systemic risk $CoVaR$ calculation different from that of Adrian and Brunnermeier (2016)'s quantile regression; this new method adjusted the financial system joint returns' density to a multivariate generalised autoregressive conditional heteroskedastic (*MGARCH*), calculating the $CoVaR$ by numerical methods from this adjusted distribution.

5 *Bovespa* listed banks are: *ABC*, *Banco do Brasil*, *Bradesco*, *PanAmericano*, *Banrisul*, *Itaú*, and *Paraná*.

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