

Securitization and Credit Risk in the Brazilian Economy

Vivian Íris Barcelos

Fluminense Federal University
Department of Economics

email: vivianiris@uol.com.br

Helder Ferreira de Mendonça

Fluminense Federal University
Department of Economics and
National Council for Scientific and Technological
Development (CNPq)

Address: Rua Dr. Sodré, 59 – Vila Suíça
Miguel Pereira – Rio de Janeiro – Brazil
CEP: 26900-000

email: *helderfm@hotmail.com*

phone: +55(24)2484-4143

Abstract

This paper presents empirical evidence from the Brazilian experience for the analysis on securitization transactions and credit risk. Based on panel data framework that takes into account 60 financial institutions from December 2002 to October 2012, we observe if there is some effect of the securitization transactions on credit risk and also whether credit risk stimulates securitization. Our findings indicate that securitization transactions imply an increase in the credit risk whereas credit risk is not relevant to explain securitization in Brazil.

Resumo

Este artigo apresenta evidências empíricas da experiência brasileira a partir da análise das operações de securitização e risco de crédito. Por meio da aplicação da metodologia de dados em painel, que leva em conta 60 instituições financeiras entre dezembro de 2002 e outubro de 2012, observamos se há algum efeito das operações de securitização sobre o risco de crédito e também se o risco de crédito estimula a securitização de ativos. Os resultados indicam que as operações de securitização implicam um aumento do risco de crédito, enquanto o risco de crédito não é relevante para explicar a securitização no Brasil.

Key words: securitization assets, credit risk, financial system, Brazilian economy.

JEL Classification: G14, G21, G28.

Área ANPEC: 8 - Microeconomia, Métodos Quantitativos e Finanças

1. Introduction

With the objective of increasing liquidity in the financial systems, financial innovations proliferated. Among financial innovations there was a rapid development of credit risk transfer markets. In particular, structured finance allows different classes of assets being regrouped and their risk dispersed among different agents. As identified by Affinito and Tagliaferri (2010), it is possible to identify four main determinants in deciding to securitize bank loans: the need for new sources of funding, the transfer of credit riskiness, the search for new profit opportunities, and the role of capital.

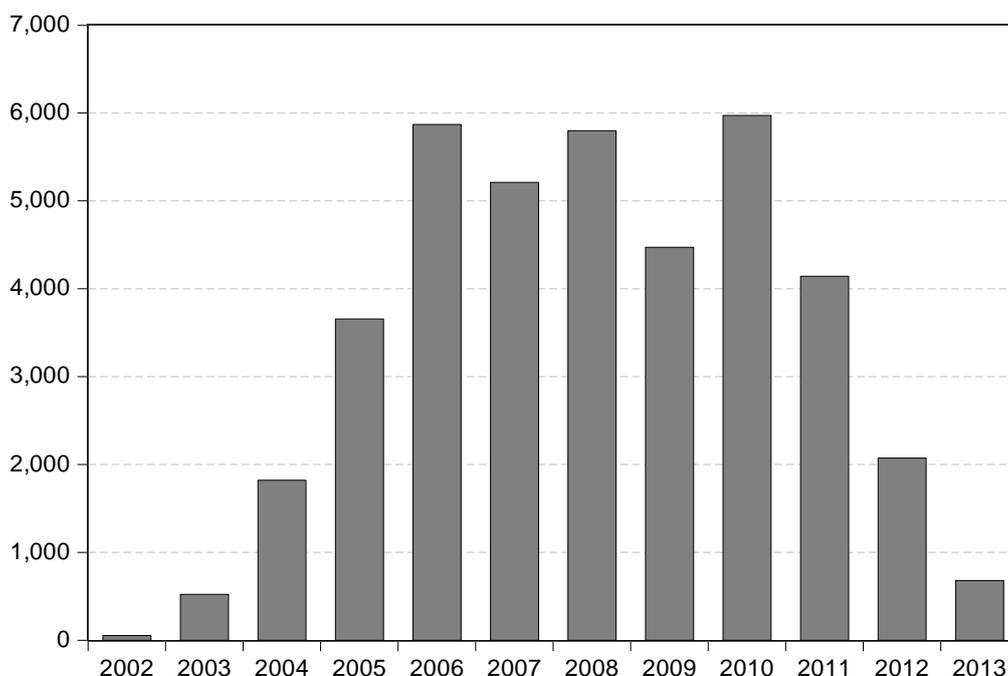
The idea that the development of credit derivatives contributed to the stability of the banking system was well accepted before the subprime crisis (Duffie, 2008). After the subprime crisis the perception that credit derivatives are beneficial for the financial system is doubtful. Some authors such as Uhde and Michalak (2010) found evidence that credit risk transfer operations weaken the stability of the financial system. This result can be connected with the possibility that transfer of credit risk can reduce the monitoring of borrowers by the financial institutions (Keys *et al*, 2010). In contrast, according to Dionne and Harchaoui (2003), in the case of securitization of assets, financial institutions transfer only good quality credit in order to obtain high credit ratings.

In short, there is no clear evidence regarding the effect of securitization transactions on the risk in the financial system. This literature is incipient for emerging economies and, in particular, for Latin American countries. A possible justification for this fact can be a lack of a developed financial system in these countries. However, since 1999, Brazilian economy is marked by a macroeconomic stability which contributes to the development of financial markets (see World Economic Forum, 2011). A good example is that the Central Bank of Brazil, through resolution n. 2,907 of 2001, created the receivables investment fund (FIDC) and opened a new capital market alternative. As a result, the issuance volume of FIDC is not negligible (see figure 1) and the domestic market represented 45% of the volume of securitization of Latin America in 2012 (Moody's, 2012). Therefore, analysis on securitization of receivables in Brazil allows one to extract some empirical evidence.

This paper makes a contribution to the empirical literature on securitization transactions and credit risk through empirical evidence from the Brazilian experience.

Using Ordinary Least Squares (OLS) and dynamic panel data framework (Difference Generalized Method of Moments - D-GMM and System Generalized Method of Moments - S-GMM) that draws on 60 financial institutions from December 2002 to October 2012, our analysis is divided into two parts. First part of the empirical analysis assesses the effect of the securitization transactions on credit risk. Second part evaluates the determinants of securitization. Special attention is given to checking whether credit risk stimulates securitization transactions. Our findings indicate that securitization transactions imply an increase in the credit risk. On the other hand credit risk is not relevant to explain securitization transactions in Brazil.

Figure 1
Total FIDC issuance amount (in millions of US\$)



Source: Securities and Exchange Commission of Brazil (CVM).

This paper is organized as follows. Section 2 describes data and variables as well as the empirical model and methodology. Section 3 presents estimation results for the credit risk focusing the analysis on the effect caused by securitization operations. Section 4 presents a robustness analysis through estimation of determinants of the securitization transactions. Section 5 concludes the paper.

2. Methodology and data

Due to the fact that the main objective of this study is to provide empirical evidence regarding securitization and credit risk, a first point to be considered is the information of these main variables in the empirical model. Hence, with the intention of gathering data on securitization in Brazil, we have identified all Credit Rights Investment Funds (FIDC - Fundos de Investimento em Direitos Creditórios) in the period from December 2002 to October 2012 through information available from Securities and Exchange Commission of Brazil (CVM). During this period there were 594 operations of FIDC, however 213 of them were exempted from registration in CVM. As a consequence, due to the difficulty in finding information on those operations and also due to the fact that their volume is negligible, they have been dropped from the sample. Moreover, since the focus of the study is on the financial market, 253 operations from non-financial institutions are also excluded from the sample. Hence the initial sample corresponds to 128 FIDC issuances by 32 financial institutions (80% which are multiple banks).

With the objective of improving the analysis regarding the impact caused by securitization of assets, the final sample included another 28 financial institutions with the same profile (small or medium size taking into account the total assets) but which did not utilize securitization. In other words, the inclusion of the financial institutions that did not used securitization, but that have similar characteristics of those that used securitization, is important because it eliminates the risk of bias selection in the sample (the list of financial institutions used in the sample is available in table 1).

In the same way as Bannier and Hänsel (2008), we use dummy variables for observing differences between securitizing and non-securitizing financial institutions over time. As a consequence, securitization in the empirical model (*SEC*) corresponds to a dummy variable that assumes value equal to 1 from the first issuance of FDIC by the financial institutions and value equal to 0 otherwise. In short, this is a simple manner for detecting the impact caused after financial institutions make use of the securitization.

Table 1
Financial institutions in the sample

Financial institutions that issued FIDC			Financial institutions that did not issue FIDC		
ABC	CREDIBEL	NEGRESKO	ALVORADA	FIAT	RABOBANK
ABN	CRUZEIROSUL	OMNI	BANRISUL	FIBRA	SAFRA
BANCOOB	DAYCOVAL	OURINVEST	BASA	HIPERCARD	SICREDI
BANIF	FICSA	PANAMERICANO	BBI	HSBC	SOCIETE
BGN	GMAC	PARANA	BNPPARIBAS	ITAUBBA	UNIBANCO
BIC	IBIBANK	PAULISTA	BRADESCOCARTOES	ITAUCARD	VOTORANTIM
BMC	INTERMEDIUM	PINE	BRB	ITAULEASING	
BMG	LUSO	RURAL	BTGPACTUAL	JPMORGAN	
BONSUCESSO	MATONE	SCHAHIN	CITIBANK	JSAFRA	
BVA	MAXIMA	VOLKSWAGEN	CITICARD	MERCEDES	
BVFINANCEIRA	MERCANTIL		DEUTSCHE	NORDESTE	

According to Santomero and Babbel (1997, p. 240), “credit risk is the risk that borrower will not perform in accordance with its obligations”. Furthermore, securitization of assets can influence credit risk in two ways: (i) financial institution transfer assets of good quality through securitization and thereby increases the credit risk in its portfolio thus worsening its financial wealth, and (ii) financial institution transfer credit risk to other market agents which, in turn can increase the risk in the financial system. In this case, the assets with worse quality are transferred and those with good quality are held by the institution implying an improvement in its portfolio. With the objective of observing whether the Brazilian financial institutions have employed securitization as a way of transferring part of their credit risk, we use two variables for measuring this type of risk. As suggested by Cardone-Riportella, Samaniego-Medina, and Trujillo-Ponce (2010), we use the following variables:

- Loan Loss Reserve/Gross Loans ratio (*CR1*) – this ratio indicates how much of the total loan portfolio is covered by the entity’s current reserves. A higher ratio indicates a lower quality loan portfolio.
- Non-performing Loans/Gross Loans ratio (*CR2*) – this ratio denotes the amount of the total doubtful loans and thus lower ratios denote a better asset quality.

As pointed out by Santomero and Babbel (1997), credit risk is difficult to eliminate completely. Therefore, we assume that the current credit risk is not independent from that observed in the past. In other words, there is a “persistence effect”. Furthermore, it is reasonable to consider that the effect of the securitization

operations on the credit risk is not instantaneous. In addition, with the objective to avoid potential problems of simultaneity and endogeneity, as observed in Michalak and Uhde (2012) and Cardone-Riportella, Samaniego-Medina, and Trujillo-Ponce (2010), the variables are lagged by one period in the model. Hence, to verify the effect of securitization activity on credit risk (CR), our general specification is as follows:

$$(1) \quad CR_{i,t} = f(CR_{i,t-1}, SEC_{i,t-1}, Z_{i,t-1}),$$

where: CR is the credit risk measured by two alternative variables: Loan Loss Reserve/Gross Loans ratio (CRI) and Non-performing Loans/Gross Loans ratio ($CR2$); SEC is a dummy as described earlier; Z covers mostly financial institutions' individual characteristics; sub-index i refers to financial institutions and t to the time periods.

With the intention of mitigating omitted variable biases we consider well-accepted variables present in the literature on the relation between credit risk and securitization. As most studies take into consideration the influence from liquidity, equity or regulatory capital, and performance in the analysis on securitization (see Cardone-Riportella, Samaniego-Medina, and Trujillo-Ponce, 2010) we included the following variables in the empirical model:

- Liquidity – as highlighted by Loutskina and Strahan (2009), due to the fact that loans have become more liquid, credit supply has become less sensitive to changes in bank financial condition. In particular, the same authors highlight that liquidity provides a substitute source of finance for loan origination because the originator need not hold the loan. As a consequence, we consider liquid assets/total assets ratio (LIQ) as a proxy for liquidity in the empirical model.

- Indebtedness – as pointed out by Michalak and Uhde (2012), there is a relationship between credit risk securitization and the bank's financial soundness. The relevance of this relation is also recognized, for example, in Affinito and Tagliaferri (2010). Hence, we take into account total liabilities/total liabilities and the owner's equity ratio (IND) as an indicator that reflects the solvency of the financial institutions.

As recognized by Bannier and Hänsel (2008) the wealth effects of securitization transactions cannot be neglected. In this respect, we also include in the empirical model a variable traditionally used as proxy for the performance of a financial institution:

- Return on equity (ROE) – measures the rate of return on the shareholders' equity of the common stock owners. Then, it is a result of net income/shareholder's equity ratio.

Data is gathered from Central Bank of Brazil (balance sheet of independent

financial institutions - documents 7002/4010) regarding information of 60 financial institutions from December 2002 to October 2012 with quarterly frequency (table 2 presents the descriptive statistics).

Based on the variables described above, we consider three models for observing a possible effect caused by the securitization process on the credit risk of the financial institutions. The baseline model which is given by:

$$(2) \quad CR_{i,t} = \beta_0 + \beta_1 SEC_{i,t-1} + \beta_2 CR_{i,t-1} + \beta_3 LIQ_{i,t-1} + \varepsilon_{i,t},$$

where the subscript $i=1,2,\dots,60$ is the financial institution; $t=1,2,\dots,40$ is the period, and $\varepsilon_{i,t}$ is the disturbance.

The next two models include the variables *IND* and *ROE*, respectively. As a consequence:

$$(3) \quad CR_{i,t} = \beta_4 + \beta_5 SEC_{i,t-1} + \beta_6 CR_{i,t-1} + \beta_7 LIQ_{i,t-1} + \beta_8 IND_{i,t-1} + \varepsilon_{i,t}, \text{ and}$$

$$(4) \quad CR_{i,t} = \beta_9 + \beta_{10} SEC_{i,t-1} + \beta_{11} CR_{i,t-1} + \beta_{12} LIQ_{i,t-1} + \beta_{13} IND_{i,t-1} + \beta_{14} ROE_{i,t-1} + \varepsilon_{i,t}.$$

Table 2
Descriptive statistics

	Mean	Median	Maximum	Minimum	Standard dev.	Observations
<i>CRI</i>	0.089	0.050	1.000	0.000	0.116	2279
<i>CR2</i>	0.105	0.051	1.109	0.000	0.139	2279
<i>LIQ</i>	0.006	0.002	0.156	0.000	0.012	2279
<i>IND</i>	0.728	0.773	1.306	0.024	0.168	2279
<i>ROE</i>	0.051	0.037	5.384	-4.069	0.208	2279

This study uses panel data analysis. Besides usual OLS methods for panel data analysis found in the literature for estimations of credit risk, this study makes use of dynamic panel data framework (D-GMM and S-GMM). It is important to note that there is the possibility of simultaneity problem in the analysis due to the fact that the financial wealth of banking firms may be influenced by credit risk, which, in turn, suggests endogeneity problem in the regressions. The use of instrumental variables allows the estimation of parameters more consistently, even in the case of endogeneity in explanatory variables (Bond, Hoeffler, and Temple, 2001). An additional justification for using GMM is that including lagged dependent variables in panel models generates a dynamic panel bias (Wooldridge, 2002). Furthermore, as pointed out by Affinito and Tagliaferri (2010), the use of GMM estimators can be a useful tool to analyze the

relation between securitization and credit risk due to the heterogeneity among the financial institutions.

As for the issue of endogeneity, Arellano and Bond (1991) use the first difference of the data and then use lagged values of the endogenous variables as instruments. However, Blundell and Bond (1998) showed that the first-difference GMM has a bias (for large and small samples) and low accuracy. Furthermore, the use of lagged levels can generate weak instruments (Arellano and Bover, 1995; and Staiger and Stock, 1997). As a way of improving the efficiency by mitigating the weak problem in the D-GMM, Arellano and Bover (1995) and Blundell and Bond (1998) suggest the addition of moment conditions. As a result, S-GMM combines regression equations in differences and in levels into one system and uses lagged differences and lagged levels as instruments.¹

While D-GMM and S-GMM estimation approaches are suitable for a small number of time periods (t) and a large number of individuals (i) in small samples, when the instruments are too many, they tend to over-fit the instrumented variables and bias the results (Roodman, 2009). Hence, with the objective of avoiding the use of an excessive number of instruments in the regressions and thus lose the power of above-mentioned tests, the number of instruments/number of cross-sections is less than 1 in each regression. Moreover, in order to confirm the validity of the instruments in the models, the test of over-identifying restrictions (J-test) was used as suggested by Arellano (2003). In addition, tests of first-order (AR1) and second-order (AR2) serial correlation were performed.

It is important to highlight that although we perform two-step GMM estimation, our sample is not characterized by a case of small number of periods t ($t=40$) and it is not small relative to the number of financial institutions ($i=60$). Thus there is not the risk of over-fitting the instrumented variables and biasing the results, thereby making the two-step system GMM estimator consistent (see Hayakawa, 2012).²

¹ Besides lagged values of the endogenous variables, we use the Basel index and the return on assets (ROA) as instruments in the models.

² Hence, the Windmeijer's (2005) finite sample correction of the two-step estimator variance-covariance matrix to avoid downward biased estimations is not applied.

3. Estimation results

We present baseline empirical results in tables 3 and 4. Robustness checks regarding determinants of securitization are reported in tables 5 and 6. The use of both D-GMM and S-GMM do not change the signs and the statistical significance of the coefficient on securitization for both measures of credit risk presented in fixed effect models (see tables 3 and 4). Furthermore, all GMM regressions accept the null hypothesis in the Sargan tests (J-statistic) and thus the over-identifying restrictions are valid. Moreover, both serial autocorrelation tests (AR(1) and AR(2)) reject the hypothesis of the presence of serial autocorrelation.

The statistical significance and the positive coefficients on the variable *SEC* denote that the credit risk increases after the securitization of assets by financial institutions. One interpretation of this result is that the securitization operation would not be used for transferring credit risk to other financial institutions thus indicating good quality credit.³ Another possible interpretation for the positive relationship between securitization and credit risk is in line with Dionne and Harchaoui (2003). According to this view, it is possible that the current regulation may be too costly and securitization activity may therefore be used to reduce this cost.

Regarding the coefficients on lagged credit risk it is observed that there is statistical significance and the sign is positive (see tables 3 and 4). This result suggests that there exists a credit risk persistency probably caused by the long-term maturity of the banking operations. In addition, this result is in line with the idea present in Santomero and Babbel (1997) that credit risk is diversifiable but difficult to eliminate completely.

³ For an analysis regarding this interpretation, see: Uzun and Webb (2007); Ambrose, Lacour-Little, and Sanders (2005); and Palia and Sopranzetti (2004).

Table 3
Credit risk estimation (CR1)

Estimator: Regressors:	FOLS						DGMM						SGMM					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
Constant	0.011	***	0.004		0.003													
	(0.003)		(0.008)		(0.009)													
CR1(-1)	0.857	***	0.859	***	0.859	***	1.068	***	1.092	***	1.094	***	0.713	***	0.844	***	1.094	***
	(0.031)		(0.031)		(0.029)		(0.085)		(0.106)		(0.058)		(0.004)		(0.001)		(0.058)	
SEC(-1)	0.004	**	0.004	**	0.004	**	0.431	***	0.407	***	0.303	***	0.004	***	0.001	***	0.303	***
	(0.002)		(0.002)		(0.002)		(0.147)		(0.143)		(0.100)		(0.001)		(0.000)		(0.100)	
LIQ(-1)	0.056		0.059		0.058		0.007		0.044		0.022		0.118	***	0.405	***	0.022	
	(0.153)		(0.152)		(0.153)		(0.241)		(0.252)		(0.180)		(0.036)		(0.056)		(0.180)	
IND(-1)			0.010		0.011				0.024		0.0890	**			0.009	***	0.089	**
			(0.012)		(0.012)				(0.034)		(0.037)				(0.001)		(0.037)	
ROE(-1)					0.008						0.0570	***					0.057	***
					(0.011)						(0.020)						(0.020)	
N. Obs.	2225		2225		2212		1638		1643		1643		2050		1779		1643	
adj. R ²	0.88		0.88		0.88													
N. Inst./N. cross sec.							0.31		0.33		0.36		0.68		0.79		0.36	
J-stat.							19.50		16.95		16.48		45.38		45.32		16.48	
p-value							(0.15)		(0.26)		(0.35)		(0.19)		(0.30)		(0.35)	
AR(1)							-4.29		-16.02		-4.08		-0.44		-0.47		-0.46	
p-value							(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)	
AR(2)							0.87		0.82		0.71		0.02		0.03		0.03	
p-value							(0.39)		(0.41)		(0.47)		(0.31)		(0.18)		(0.18)	

Note: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. White's heteroskedasticity consistent covariance matrix was applied in regressions. Standard errors between parentheses. FOLS – OLS fixed effects. D-GMM – uses two-step of Arellano and Bond (2001) without time period effects. S-GMM – uses two-step of Arellano and Bover (1995) without time period effects. D-GMM estimator - tests for AR (1) and AR (2) check that the average autocovariance in first order and second-order residuals, respectively, is zero. S-GMM estimator - tests for AR (1) and AR (2) check for the presence of first order and second-order serial correlation in the first-difference residuals. The sample is an unbalanced panel of 60 financial institutions (see table 1) from December 2002 to October 2012.

Table 4
Credit risk estimation (CR2)

Estimator: Regressors:	FOLS						DGMM						SGMM					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
Constant	0.035 (0.008)	***	0.060 (0.025)	**	0.060 (0.024)	**												
CR2(-1)	0.648 (0.078)	***	0.643 (0.077)	***	0.643 (0.075)	***	0.007 (0.025)	0.042 (0.022)	***	0.456 (0.063)	***	0.387 (0.006)	***	0.542 (0.005)	***	0.486 (0.011)	***	
SEC(-1)	0.005 (0.006)		0.006 (0.006)		0.006 (0.006)		1.157 (0.211)	***	0.194 (0.098)	**	0.217 (0.119)	*	0.006 (0.002)	***	0.011 (0.003)	***	0.013 (0.004)	***
LIQ(-1)	0.152 (0.270)		0.141 (0.276)		0.134 (0.278)		0.141 (0.141)		0.609 (0.134)	***	1.041 (0.272)	***	3.204 (0.273)	***	4.956 (0.381)	***	7.882 (0.649)	***
IND(-1)			-0.034 (0.035)		-0.034 (0.033)				0.0580 (0.031)	*	0.040 (0.024)	*			0.094 (0.007)	***	0.138 (0.006)	***
ROE(-1)					0.014 (0.017)						0.045 (0.019)	**					0.104 (0.006)	***
N. Obs.	2225		2225		2212		1604		1462		1593		1722		1716		1627	
adj. R ²	0.73		0.73		0.73													
N. Inst./N. cross sec.							0.31		0.48		0.40		0.76		0.78		0.82	
J-stat.							14.75		23.80		24.25		41.41		43.13		44.84	
p-value							(0.40)		(0.36)		(0.11)		(0.37)		(0.30)		(0.28)	
AR(1)							-2.34		-2.22		-2.33		-0.50		-0.53		-0.50	
(p-value)							(0.02)		(0.03)		(0.02)		(0.00)		(0.00)		(0.00)	
AR(2)							0.95		1.01		1.38		0.03		0.04		0.01	
p-value							(0.34)		(0.31)		(0.17)		(0.25)		(0.12)		(0.62)	

Note: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. White's heteroskedasticity consistent covariance matrix was applied in regressions. Standard errors between parentheses. FOLS – OLS fixed effects. D-GMM – uses two-step of Arellano and Bond (2001) without time period effects. S-GMM – uses two-step of Arellano and Bover (1995) without time period effects. D-GMM estimator - tests for AR (1) and AR (2) check that the average autocovariance in first order and second-order residuals, respectively, is zero. S-GMM estimator - tests for AR (1) and AR (2) check for the presence of first order and second-order serial correlation in the first-difference residuals. The sample is an unbalanced panel of 60 financial institutions (see table 1) from December 2002 to October 2012.

In a general way, the coefficients on liquidity, indebtedness, and ROE are positive in all models and have statistical significance in some specifications (see tables 3 and 4). Although the coefficients on liquidity are positive, most of them are not significant and thus are in consonance with the Affinito and Tagliaferri (2010) observation that bank liquidity becomes less important in the presence of securitization. Regarding the positive relation between indebtedness and credit risk there is no surprise. A higher indebtedness indicates a higher liability of the institution which in turn reveals a higher credit risk (de Mendonça and Loures, 2009). Similar to that found by Ben Salah and Fedhila (2012), positive coefficient and significance statistics on ROE is observed in most specifications. As pointed out by Yu (2012), a higher ROE (a higher-risk portfolio may increase the chances of higher return) may be associated with potential credit losses (a higher-risk portfolio will increase the chances of higher losses). In short, there is an increase in risk appetite and thus a trade-off between risk and return.

4. Robustness analysis

The results from the estimation of the credit risk indicate that securitization increases the risk. This observation suggests that securitization of assets in Brazil does not transfer credit risk to other financial institutions. Therefore, it is important to identify which factors stimulate the securitization in Brazil. In general, the literature highlights three factors for securitization: (i) transfer of the credit risk to other financial institutions; (ii) increase in the liquidity; and (iii) regulatory capital arbitrage. Moreover profitability and financial institutions' size are also factors considered in the analysis on determinant of securitization.⁴ With the objective of observing the direct relationship between credit risk and securitization we used the same methodology applied in the previous section. Hence, using the variables *CR*, *LIQ*, *IND*, *ROE*, and *SEC* lagged as regressors, the following specifications are considered:

$$(4) \quad SEC_{i,t} = \alpha_0 + \alpha_1 SEC_{i,t-1} + \alpha_2 CR_{i,t-1} + \alpha_3 LIQ_{i,t-1} + \varepsilon_{i,t},$$

$$(5) \quad SEC_{i,t} = \alpha_4 + \alpha_5 SEC_{i,t-1} + \alpha_6 CR_{i,t-1} + \alpha_7 LIQ_{i,t-1} + \alpha_8 IND_{i,t-1} + \varepsilon_{i,t}, \text{ and}$$

$$(6) \quad SEC_{i,t} = \alpha_9 + \alpha_{10} SEC_{i,t-1} + \alpha_{11} CR_{i,t-1} + \alpha_{12} LIQ_{i,t-1} + \alpha_{13} IND_{i,t-1} + \alpha_{14} ROE_{i,t-1} + \varepsilon_{i,t}.$$

We present the empirical results in tables 5 and 6.

⁴ See, Bannier and Hänsel (2008); Affinito and Tagliaferri (2010); Cardone-Riportella, Samaniego-Medina, and Trujillo-Ponce (2010).

Table 5
Securitization estimation – SEC

Estimator: Regressors:	FOLS			DGMM			SGMM				
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3		
Constant	0.040 (0.004)	*** 0.015 (0.014)	0.015 (0.014)								
SEC(-1)	0.917 (0.009)	*** 0.916 (0.009)	*** 0.916 (0.009)	*** 0.916 (0.009)	0.287 (0.168)	* 0.250 (0.073)	*** 0.109 (0.058)	*	0.004 (0.001)	*** 0.001 (0.000)	*** 0.859 (0.012)
CR1(-1)	0.013 (0.022)	0.020 (0.022)	0.020 (0.022)	0.054 (0.036)	0.054 (0.052)	0.012 (0.048)	0.713 (0.004)	*** 0.844 (0.001)	*** 0.004 (0.010)		
LIQ(-1)	0.232 (0.312)	0.240 (0.305)	0.237 (0.307)	0.937 (0.175)	*** 0.437 (0.253)	* 0.745 (0.296)	** 0.118 (0.036)	*** 0.405 (0.056)	*** 0.894 (0.436)		
IND(-1)		0.034 (0.018)	* 0.033 (0.018)	*	0.038 (0.043)	0.005 (0.018)	0.009 (0.001)	*** 0.039 (0.013)			
ROE(-1)			0.001 (0.004)			0.012 (0.011)			0.002 (0.004)		
N. Obs.	2242	2242	2229	1550	1597	1434	2050	1779	1504		
adj. R ²	0.94	0.94	0.94								
N. Inst./N. cross sec.				0.35	0.33	0.48	0.68	0.79	0.49		
J-stat.				12.52	18.39	18.77	45.38	45.32	17.13		
p-value				(0.71)	(0.19)	(0.60)	(0.19)	(0.30)	(0.76)		
AR(1)				-1.69	-2.72	-2.31	-0.50	-0.50	-0.49		
(p-value)				(0.09)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)		
AR(2)				1.22	0.87	0.35	0.00	0.00	0.00		
p-value				(0.22)	(0.38)	(0.73)	(0.91)	(0.88)	(0.87)		

Note: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. White's heteroskedasticity consistent covariance matrix was applied in regressions. Standard errors between parentheses. FOLS – OLS fixed effects. D-GMM – uses two-step of Arellano and Bond (2001) without time period effects. S-GMM – uses two-step of Arellano and Bover (1995) without time period effects. D-GMM estimator - tests for AR (1) and AR (2) check that the average autocovariance in first order and second-order residuals, respectively, is zero. S-GMM estimator - tests for AR (1) and AR (2) check for the presence of first order and second-order serial correlation in the first-difference residuals. The sample is an unbalanced panel of 60 financial institutions (see table 1) from December 2002 to October 2012.

Table 6
Securitization estimation – SEC

Estimator: Regressors:	FOLS						DGMM						SGMM					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
Constant	0.040	***	0.016		0.016													
	(0.004)		(0.014)		(0.014)													
SEC(-1)	0.917	***	0.916	***	0.916	***	0.192	0.252	*	0.141		0.899	***	0.881	***	0.854	***	
	(0.009)		(0.009)		(0.009)		(0.131)	(0.139)		(0.090)		(0.006)		(0.007)		(0.009)		
CR2(-1)	0.009		0.013		0.013		0.050	0.057		0.033		0.001		0.005		0.006		
	(0.015)		(0.016)		(0.016)		(0.033)	(0.060)		(0.022)		(0.003)		(0.007)		(0.011)		
LIQ(-1)	0.231		0.238		0.236		0.889	***	0.564		0.904	***	0.005		0.011		1.641	***
	(0.312)		(0.305)		(0.307)		(0.202)		(0.390)		(0.047)		(0.166)		(0.238)		(0.225)	
IND(-1)			0.032	*	0.032	*		0.132	***	0.131	***		0.055	***	0.042	***		
			(0.018)		(0.018)			(0.045)		(0.047)			(0.016)		(0.013)			
ROE(-1)					0.000					0.007						0.013	***	
					(0.004)					(0.013)						(0.005)		
N. Obs.	2242		2242		2229		1657	1607		1614		1661	1597		1646			
adj. R ²	0.94		0.94		0.94													
N. Inst./N. cross sec.							0.38	0.31		0.40		0.33	0.42		0.52			
J-stat.							18.80	10.78		19.32		16.97	19.50		21.04			
p-value							(0.40)	(0.63)		(0.31)		(0.32)	(0.43)		(0.69)			
AR(1)							-1.71	-1.95		-1.71		-0.50	-0.50		-0.49			
(p-value)							(0.09)	(0.05)		(0.09)		(0.00)	(0.00)		(0.00)			
AR(2)							0.97	0.83		1.07		0.00	0.00		0.00			
p-value							(0.33)	(0.41)		(0.28)		(0.98)	(0.93)		(0.95)			

Note: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. White's heteroskedasticity consistent covariance matrix was applied in regressions. Standard errors between parentheses. FOLS – OLS fixed effects. D-GMM – uses two-step of Arellano and Bond (2001) without time period effects. S-GMM – uses two-step of Arellano and Bover (1995) without time period effects. D-GMM estimator - tests for AR (1) and AR (2) check that the average autocovariance in first order and second-order residuals, respectively, is zero. S-GMM estimator - tests for AR (1) and AR (2) check for the presence of first order and second-order serial correlation in the first-difference residuals. The sample is an unbalanced panel of 60 financial institutions (see table 1) from December 2002 to October 2012.

Such as observed for the estimations in the previous section, the results indicate that there are no overidentification and autocorrelation problems in all models (see J-statistic, AR(1), and AR(2) reported in tables 5 and 6).

The estimation results confirm the hypothesis that credit risk is not a determinant factor for securitization in Brazil (there is no statistical significance in practically all models - see tables 5 and 6). Therefore, contrary to Bannier and Hänsel (2008) and Gorton and Souleles (2007) we cannot state that financial institutions with greater risk are more active in securitization operation.

The coefficients on liquidity are positive and have statistical significance in half of the specifications. This result matches with Agostino and Mazzuca (2008). A possible justification for this result is that the relationship between liquidity and securitization may assume a positive sign if the liquidity increases the collateral. Regarding the positive coefficient and statistical significance on indebtedness for most specifications, this result suggests that the financial institutions try to reduce their fragility through securitization. The positive coefficient on ROE without statistical significance is compatible with the idea that banks with higher profits are not likely to resort to loan securitizations to improve their profitability (Affinito and Tagliaferri, 2010).

5. Conclusion

Such as observed for the European case, the securitization of assets is relevant for small and medium financial institutions in Brazil.⁵ Therefore, as pointed out by Fabozzi and Kothari (2007), securitization represents an alternative tool for reducing fundraising costs. Our results support that the use of securitization operation has a positive impact on credit risk of the Brazilian financial institutions. This result indicates that it is possible that banks hold poor assets and thus transfer to others only credit with good quality.⁶ In short, a very important result is that securitization increases the credit risk in the Brazilian case. As a consequence, it is essential that the Central Bank of Brazil (financial regulator) draws regulation policies that avoid the increase in the financial fragility.

⁵ Regarding the European case, see Uzun and Webb (2007), and Uhde and Michalak (2010).

⁶ The result that securitization does not imply transfer of credit risk is in line with Cardone-Riportella, Samaniego-Medina, and Trujillo-Ponce (2010), and Affinito and Tagliaferri (2010).

6. References

- AFFINITO, M., TAGLIAFERI, E. (2010). "Why do (or did?) banks securitize their loans? Evidence from Italy." *Journal of Financial Stability*, 6(4), 189-202.
- AGOSTINO, M., MAZZUCCA, M. (2008). "Why Do Banks Securitise? The Case of Italy." Università della Calabria, Mimeo.
- AMBROSE, B.W., LACOUR-LITTLE, M., SANDERS, A.B. (2005). "Does regulatory capital arbitrage or asymmetric information drive securitization?" *Journal of Financial Services Research*, 28(1/2/3), 113-133.
- ARELLANO, M. (2003). "Panel data econometrics." Oxford University Press.
- ARELLANO, M., BOND, S. (1991). "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies*, 58(2), 277-297.
- ARELLANO, M., BOVER, O., (1995). "Another Look at the Instrumental Variables Estimation of Error-components Models." *Journal of Econometrics*, 68(1), 29-51.
- BANNIER, C.E., HÄNSEL, D.N. (2008). "Determinants of European banks' engagement in loan securitization." Discussion Paper, Deutsche Bundesbank.
- BEN SALAH, N., FEDHILA, H. (2012). "Effects of securitization on credit risk and banking stability: Empirical evidence from American commercial banks." *International Journal of Economics and Finance*, 4(5), 194-207.
- BOND, S., HOEFFLER, A., TEMPLE, J. (2001). "GMM Estimation of empirical growth models." Economics Papers W21, Economics Group, Nuffield College, University of Oxford.
- BLUNDELL, R., BOND, S. (1998). "Initial conditions and moments restrictions in dynamic panel data models." *Journal of Econometrics*, 86(1), 115-143.
- CARDONE-RIPORTELLA, C., SAMANIEGO-MEDINA, R., TRUJILLO-PONCE, A. (2010). "What drives bank securitisation? The Spanish experience." *Journal of Banking and Finance*, 34(11), 2639-2651.
- DE MENDONÇA, H.F., LOURES, R.V. (2009). "Market discipline in the Brazilian banking industry: an analysis for the subordinated debt holders." *Journal of Regulatory Economics*, 36(3), 286-307.
- DIONNE, G., HARCHAOUI, T.M. (2003). "Bank's capital, securitization and credit risk: an empirical evidence for Canada." Working paper, SSRN, Rochester, NY.
- DUFFIE, D. (2008). "Innovations in Credit Risk Transfer: Implications for Financial Stability." *Bank for International Settlements*. Working paper, n. 255.
- FABOZZI, F.J., KOTHARI, V. (2007). "Securitization: The Tool of Financial Transformation." ICF Working Paper n.7, International Center for Finance, Yale.
- GORTON, G.B., SOULELES, N.S. (2007). "Special Purpose Vehicles and Securitization." NBER Working Paper Series, n. 11190, National Bureau of Economic Research.
- HAYAKAWA, K. (2012). "The asymptotic properties of the system GMM estimator in dynamic panel data models when both B and T are large." Institute of Economic Research, Hitotsubashi University, Mimeo.
- KEYS, B.J., MUKHERJEE, T., SERU, A., VIG, V. (2010). "Did securitization lead to lax screening? Evidence from subprime loans." *Quarterly Journal of Economics*, 125(1), 307-362.

- LOUTSKINA, E., STRAHAN, P.E. (2009). "Securitization and the declining impact of bank financial condition on loan supply." *Journal of Finance*, 64(2), 861–889.
- MICHALAK, T.C., UHDE, A., (2012). "Credit risk securitization and bank soundness in Europe." *Quarterly Review of Economics and Finance*, 52(3), 272-285.
- MOODY'S (2012). "Latin America Securitization: 2012 Outlook." Special Report, January.
- PALIA, D., SOPRANZETTI, B.J. (2004). "Securitizing Accounts Receivable." *Review of Quantitative Finance and Accounting*, 22(1), 29-38.
- ROODMAN, D. (2009). "How to do xtabond2: An introduction to difference and system GMM in Stata." *Stata Journal*, 9(1), 86-136.
- SANTOMERO, A.M., BABEL, D.F. (1997) "Financial risk management by insurers: An analysis of the process." *Journal of Risk and Insurance*, 64(2), 321-270.
- UHDE, A., MICHALAK, T.C. (2010). "Securitization and systematic risk in European banking: Empirical evidence." *Journal of Banking and Finance*, 34(12), 3061-3077.
- UZUN, H., WEBB, E. (2007). "Securitization and risk: empirical evidence on US banks." *Journal of Risk Finance*, 8(1), 11-23.
- WINDMEIJER, F. (2005). "A finite sample correction for the variance of linear efficient two-step GMM estimators." *Journal of Econometrics*, 126 (1), 25–51.
- WOOLDRIDGE, J.M. (2002). "Econometric analysis of cross-section and panel data." Cambridge, MA. The MIT Press.
- WORLD ECONOMIC FORUM (2011). "The Financial Development Report." New York, USA.
- YU, K. (2012). "Risk appetite, stress testing, capital planning." *RMA Journal*, September, 42-47.