Effect of Transparency on Bank Credit:
Evidence from NYSE and NASDAQ*

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
CEP: 26900-000 – Brazil
helderfm@hotmail.com

Délio José Cordeiro Galvão
Central Bank of Brazil and
Fluminense Federal University
Department of Economics
Address: Rua Raul Pompéia, nº 148 aptº 1001
Copacabana – Rio de Janeiro
CEP: 22080-002 – Brazil
delio.galvao@yahoo.com.br

Renato Falci Villela Loures
Fluminense Federal University
Department of Economics
Coordination for the Improvement of Higher Education Personnel (CAPES)
Address: Avenida Atlântica, 3958/403
Copacabana – Rio de Janeiro
CEP: 22070-002 – Brazil
rloures@globo.com

Abstract

This paper makes an empirical analysis of the effect of bank transparency on credit. Therefore, an analysis of panel data which considers 310 banks that have shares traded on the NYSE and NASDAQ for the period extending from the first quarter of 1990 to the fourth quarter of 2009 is made. As a measure of bank transparency, an opacity index that represents the difference between the real risk taken by banks and the perception of the economic agents on that risk is built. Furthermore, this study considers how events of "credit sudden stop" may interfere in the relationship between transparency and bank credit. The findings indicate that an increase in the bank transparency contributes to creating an environment conducive to amplifying credit without generating speculative bubbles.

Key words: bank transparency; bank credit; financial crisis; credit sudden stop.

JEL classification: E51; G14, G15.

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1. Introduction

Nowadays, the prevailing view in the analysis focused on the subprime crisis indicates as the major cause for the occurrence of this event the gaps in regulation and supervision of the financial system. However, a more careful analysis of the crisis, allows one to conjecture that the lack of information transparency in the financial market is a centerpiece to this puzzle.

An important point in the subprime crisis refers to the scarcity of credit. The first signs of crisis were seen in August 2007 when New Century Financial, an institution specialized in subprime loans, filed for bankruptcy and laid off half its staff. A year later, Lehman Brothers was pointed out as a trigger of the crisis. However, the sudden lack of credit was the main reason for the crisis deepening and the spread of instability in the market.

The contraction of credit supply was the result of the uncertainty in the market about the value of assets accounted for by financial institutions. In other words, the lack of transparency about the real risk assumed by banks represented a source of uncertainty that infected the entire financial system. Therefore, in the search for a tool to avoid financial crisis, it becomes important to analyze the effect of transparency regarding the risks taken by banks on credit.

The main objective of this paper is to provide empirical evidence to the effect of bank transparency on credit. Therefore, a panel data analysis which considers 310 banks that have shares traded on the NYSE (New York Stock Exchange) and NASDAQ (National Association of Securities Dealers Automated Quotations) for the period extending from the first quarter of 1990 to the fourth quarter of 2009 is made.

As a way of measuring bank transparency to the market, an opacity index was developed. This index, which captures the lack of transparency, represents the difference between the real risk taken by banks and the perception of the economic agents on that risk. Moreover, as pointed out by Calvo (2009), credit sudden stop in the market is the main problem of financial crises. Therefore, the empirical analysis developed in this paper also considers how events of credit sudden stop may interfere in the relationship between transparency and bank credit.

Besides this introduction, this article is organized as follows. The next section highlights arguments for the importance of transparency on bank credit. Section 3 presents the opacity index and its performance on the NYSE and NASDAQ. Section 4 presents empirical evidence for the relationship between opacity of banks and credit through panel data analysis (system Generalized Method of Moments) for NYSE and NASDAQ (all banks in the sample and largest banks). The last section presents the conclusion.

2. Why transparency matters?

Enron is a good example of the several faults that were committed by those who should certify the health of companies to investors in the market.[1] Just over six months after the Enron scandal, in response to the outcry from investors for greater transparency, the Sarbanes-Oxley Act (SOX) of 2002 was issued directing special attention to the gatekeepers. The main objective was to increase the accountability of managers by implementing a series of corporate governance rules (see Coates IV, 2007).

Despite the SOX Act, with the outbreak of the subprime crisis in September of 2007, the Citigroup (the largest U.S. bank at the time) lost more than US$ 170 billion in assets, which represented 7.24% of its total assets. A year later (September of 2008), the uncertainty about the real value of the portfolio of assets based on mortgage securities wrecked investor confidence in Lehman Brothers (the fourth largest investment bank in the U.S.A. at the time). The suspicion regarding the safety of these investments led to a drop in the value of the bank's shares from US$ 82 to less than US$ 4 and drove Lehman Brothers to file for bankruptcy on September 15, 2008.

Another good example can be seen in Brazil. In September and October 2008, managers of the companies Sadia and Aracruz surprised investors by disclosing two facts related to financial transactions and derivative agreements, respectively. Hence, the day after the publication of these facts, the stocks of these companies fell substantially (35.5% Sadia and 17.7% Aracruz), and thus reflects the ignorance of investors about the real risk involved in the operations of these two institutions.

The above-mentioned cases have in common the lack of market perception regarding the risks faced by firms. In other words, a situation where there was lack of transparency and therefore created an environment conducive to the problems of adverse selection and moral hazard in credit markets. This observation is in connection

[1] For an analysis concerning the problems with gatekeepers, see Coffee Jr. (2002).

with the analyses made by Kwan (2009), Flannery, Kwan and Nimalendran (2010), and Pritsker (2010) where a tendency to increase the degree of banks' opacity in times of crisis is observed. Under this view, the uncertainty of investors affects the decision of banks offering loans between them and, as a consequence, credit sudden stop occurs.

In the major part of the literature regarding transparency, it is understood as the absence of asymmetric information among economic agents. Furthermore, as highlighted by Geraats (2002), there are two effects that are related to the analysis on transparency: (i) uncertainty effect - the asymmetric information creates uncertainty for economic agents who need to learn from experience, and allow others the opportunity to explore the presence of private information, and (ii) incentive effect - economic agents who have access to private information may try to influence the behavior of others through the dissemination of information.

Assuming the assumption that transparency is capable of eliminating asymmetric information among economic agents, it is possible to make an association with the first theorem of welfare economics. Under this perspective, an increase in transparency should enhance welfare of economic agents because there would be a decrease in forecast errors and also in the expected variability of the variables subject to uncertainty.

Therefore, a transparent financial system regarding its credit assets and risks in the operations allows an efficient allocation of resources of investors and provides the necessary conditions for developing sound and efficient markets. Moreover, bank transparency also implies a disciplining effect, since the perception of an increase in the risk assumed by the financial institution represents a cost that corresponds to the loss of investor who will migrate to another institution. In short, bank transparency can promote an increase in credit with lower risk.

3. Opacity index

With the purpose of measuring the degree of transparency that banks reveal to the market, an opacity index is developed. This index considers the real risk of banks (*RR*) and the perception of economic agents in relation to banks' risk (risk perception – *RP*). In a simple manner, the difference between real risk and perceived risk of banking firms is the opacity index (*OI*). The intuition of this analysis is that a high *OI* reflects that there is an asymmetry of information in the market which, in turn, creates myopia for the economic agents regarding the real risk assumed by banks.

This study considers 310 banks that have their shares traded on the NASDAQ and NYSE.[2] The sample consists of 39 banking firms which have their shares traded on the NYSE and 271 banking firms on the NASDAQ. The period of analysis includes information from the first quarter of 1990 to the fourth quarter of 2009, totaling 17,006 observations for unbalanced data.

The *RR* is defined as the risk of total loss of assets of the banking firms. In other words, the *RR* is how much assets a bank can lose in a period *t*. The *RR* is derived from the total assets (*TA*) of financial institutions.[3] The return on assets (*ROA*), is given by the *TA* at period *t* divided by *TA* at period *t-1*, minus 1 multiplied by 100, then

$$(1) \qquad ROA_t = 100\left[\left({TA_t}/{TA_{t-1}}\right) - 1\right].$$

After calculating the *ROA*, the *RR* of each bank is built. Therefore a rolling window to 5 years (20 periods) was considered.[4] Thus, information based on 20 periods, *RR* is measured through the Monte Carlo simulation method and the application of Value at Risk (VaR) of market for a significance level of 95%. In short, the RR_t is the result of:

$$(2) \qquad RR_t = VaR(ROA_{t-19}, ROA_{t-18}, \dots, ROA_{t-1}, ROA_t; \mu, \sigma, 0{,}05),$$

where μ is the mean and σ is the standard deviation of (ROA_{t-19},..., ROA_t), assuming a normal distribution.

The perception of economic agents about the risk of banking firms (*RP*) is obtained through closing price (*CP*) in quarter *t* of bank stocks. Similar to *AR*, the return on *CP* (*RCP*) is estimated according to the equation:

$$(3) \qquad RCP_t = 100\left[\left({CP_t}/{CP_{t-1}}\right) - 1\right].$$

With the objective of eliminating the volatilities from transitory type and consider just fundamental volatilities, the Hodrick-Prescott filter on *RCP* (that is, *RCP’*) was applied (see, Flannery, Kwan, and Nimalendran, 2010). After the measurement of *RCP’*, *RP* is calculated similarly to the *RR*. In short, considering it as a rolling window of five years, a Monte Carlo simulation is applied, and after the VaR methodology is

[2] Only financial institutions classified as “major banks” by Blommberg are considered for analysis.
[3] This analysis is to some extent similar to that developed by Allen and Bali (2007) for catastrophe risk. The variable total assets (total assets - BS_TOT_ASSET) of banks was extracted from the Bloomberg terminal.
[4] The justification for adopting a rolling window of 5 years is in accordance with that determined by Basel II for creating a data base for financial institutions which will adopt an advanced method for measuring credit risk and operational risk.

employed. Thus,

(4) $RP_t = VaR(RCP'_{t-19}, RCP'_{t-18}, \ldots, RCP'_{t-1}, RCP'_t; \mu, \sigma, 0{,}05)$,

where μ is the mean and σ is the standard deviation (RCP'_{t-19},..., RCP'_t), assuming a normal distribution.

As a way of capturing the asymmetric information and thus the opacity of the market regarding the risk of financial institutions, the gap between real risk and that perceived by economic agents (in modulus) is considered as an indicator of the lack of transparency. Furthermore, the opacity index (*OI*) can vary on a scale from 0 to 100 and can be represented by the following equation:

(5) $OI_t = |RR_t - RP_t|$.

For analysis, the 310 banking firms were divided according to the market in which their shares are traded, NYSE and NASDAQ. This division is justified because each market has different trading agreements, which may compromise the study (see Flannery, Kwan and Nimalendran, 2010). Moreover, it is noteworthy that in the 31 largest banks in the study (10% of the sample), 22 have their shares traded on the NYSE. Hence, in order to analyze banks considered too big to fail, the 10 largest banks in the NYSE and NASDAQ's 50 largest banks were studied separately.[5]

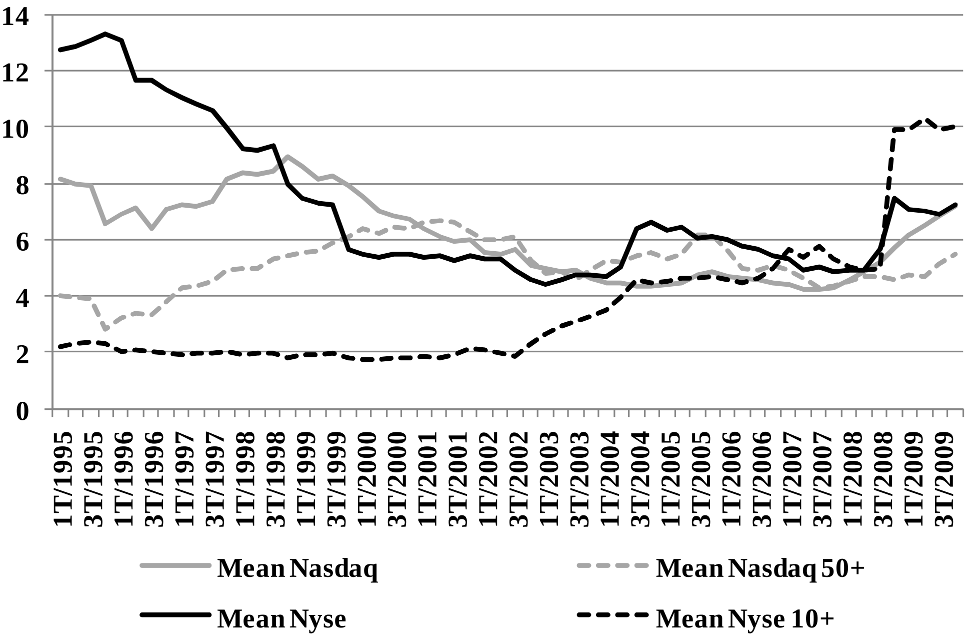
Figure 1 shows the evolution of the mean of opacity for banks that trade their shares on the NYSE and NASDAQ. Moreover, the mean for the 10 largest NYSE banks and 50 largest NASDAQ banks is also shown. Taking into consideration the rolling window previously mentioned, the period covers from the first quarter of 1995 to the fourth quarter of 2009. A trend of convergence is observed between the *OI* of the largest banks and the *OI* of other banking firms in the late 1990s and early 2000s. However, this trend is broken due to the subprime crisis in the late 2000s.

Considering the banks that have their shares traded on the NYSE, on average, there is a trend of decrease in *OI* in the late 1990s and early 2000s. After this period a stability of *OI* until the subprime crisis (sudden elevation of *OI*) is observed. In contrast, the 10 largest institutions in the NYSE showed, on average, an *OI* stable in the late 1990s and early 2000s. In the subsequent period (between third quarter of 2002 and third quarter of 2004) there was a significant increase in the indicator. This result can be explained by policies to stimulate the U.S. economy promoted by the Bush

[5] The division between the major and minor banks is based on total assets of financial institutions in the fourth quarter of 2009.

administration after the attacks of September 11, 2001 (see, Bordo, 2009; and Calomiris 2009). These policies can be leveraged loans to subprime levels which, in turn, in a process of securitization, created an incentive to increase the opacity of banks. After this period there was a new trend of stabilization of *OI*, which lasted until the subprime crisis which, in turn, caused an abrupt increase in the index.

Figure 1
Evolution of the Opacity Index (OI)



The banking firms that trade their shares on NASDAQ showed, on average, a drop in the opacity in the early 2000s, and after this period signs of stabilization. In the period of the subprime crisis the NASDAQ banks had their *OI* increased, although not as abruptly as observed in the NYSE banks. The 50 largest NASDAQ banks showed, on average, a bullish trend in the late 1990s and early 2000s, and later a relative stabilization of *OI*. As observed in the case for all NASDAQ banks, the 50 largest banks have not had a surge in the *OI* in the period referring to the subprime crisis. Finally, figure 1 shows the necessity for a separate analysis of the NYSE banks and NASDAQ banks and the division of the largest banks for others in this study.

4. Opacity index and bank credit

This section aims to study the relationship between the level of opacity of banks and the volume of credit extended by them through panel data analysis. Therefore the opacity index (*OI*) developed in the previous section and a proxy for bank credit (*BC*), which corresponds to the total loans by bank divided by its total assets, are considered.[6] The division by total assets is a way of standardizing data due to the presence of banks with different sizes. It is expected that there is a negative relationship between the *BC* and *OI* because a greater transparency contributes to reduce the market uncertainty. As a consequence, there is a reduction in the problems related to adverse selection and moral hazard and thus creates an environment propitious for increasing credit.

Based on Lown and Morgan (2006), the following control variables are used in the empirical analysis of the relation *OI*-*BC*:[7]

(i) U.S. interest rate expectation (TB) – is the U.S. interest rate expectations for 3 months (3-Month Treasury Bill Rate). A positive relationship between the *BC* and *TB* is expected. It is worth noting that fixed-rate loans are popular in the U.S. market, thus an expectation of rising interest rates causes an increase in demand for loans today.

(ii) U.S. real gross domestic product expectation (*GDP*) - *GDP* forecast for four quarters ahead. The GDP has a positive relationship with the *BC* because an increase in the product tends to raises the volume of loans.

(iii) Commodity price index (*COM*) – accumulated index (four quarters) and it is based on the Journal of Commerce-ECRI Industrial Commodities Price Index (*JOCIINDX* Index).[8] Then, *COM* is a result of:

$$(6) \qquad COM_t = 100\left[\left({JOCIINDX_t}/{JOCIINDX_{t-4}}\right) - 1\right].$$

A positive relationship is expected between the variables *BC* and *COM*. A rise in industrial production leads to an increase in demand for industrial commodities, raising their price, and thus increasing demand for credit.

Table 1 presents the descriptive statistics of variables. The *OI* presented variation between 0 and 85.82. The bank that had the highest *OI* has its shares traded on the NYSE. The *OI* of the NYSE banks showed a higher standard deviation compared to the NASDAQ banks. In other words, NYSE banks present more volatility on opacity of banks. Furthermore, considering *BC*, NYSE banks showed higher standard deviation compared to the NASDAQ banks. This observation indicates a greater volatility on

[6] Total loans are made available from Bloomberg terminal.
[7] Data regarding *TB* and *GDP* is gathered from Philadelphia Fed.
[8] This index was gathered from Bloomberg terminal and it considers the prices of 18 commodities.

volume of credit supplied by NYSE banks.

Table 1
Descriptive Statistics

	BC	*OI*	*TB*	*GDP*	*COM*
	NYSE –all banks				
Mean	61.46	6.82	3.54	4.85	3.93
Median	65.49	4.18	4.11	5.10	7.18
Maximum	88.18	85.82	6.40	5.96	37.51
Minimum	4.84	0.00	0.26	1.91	-46.95
Std. Deviation	15.66	9.42	1.84	0.90	17.65
OBS	1853	1853	1853	1853	1853
	NYSE - 10 largest banks				
Mean	52.33	6.41	3.21	4.83	4.67
Median	54.32	5.37	3.78	5.14	9.95
Maximum	75.34	31.01	6.40	5.96	37.51
Minimum	9.07	0.00	0.26	1.91	-46.95
Std. Deviation	15.90	5.39	1.86	1.01	19.09
OBS	356	356	356	356	356
	NASDAQ – all banks				
Mean	67.36	5.52	3.12	4.83	4.40
Median	68.61	3.47	3.30	5.14	9.95
Maximum	134.68	63.02	6.40	5.96	37.51
Minimum	1.03	0.00	0.26	1.91	-46.95
Std. Deviation	11.76	6.40	1.84	1.02	19.28
OBS	8953	8953	8953	8953	8953
	NASDAQ - 50 largest banks				
Mean	64.25	6.91	3.45	4.83	3.72
Median	66.60	4.36	4.09	5.10	7.57
Maximum	106.86	58.07	6.40	5.96	37.51
Minimum	29.01	0.00	0.26	1.91	-46.95
Std. Deviation	10.41	7.76	1.86	0.93	18.08
OBS	2210	2210	2210	2210	2210

4.1. Methodology

This study makes use of panel data analysis. The main reason is that the time series are short and the data is unbalanced. As a manner of eliminating the non-observed effects on regressions, dynamic panel data (Generalized Method of Moments - GMM) is used. As pointed out by Arellano and Bond (1991), an advantage of this method over others (Ordinary Least Squares - OLS and Generalized Least Squares - GLS) is that the estimates are reliable even in the case of omitted variables. In particular, the use of instrumental variables allows the estimation of parameters more consistently, even in the case of endogeneity in explanatory variables and the occurrence of measurement errors (Bond, Hoeffler and Temple, 2001).

Traditional econometric models have assumed the hypothesis that the error term is not correlated with their estimators. In cases where the estimators are correlated with the error term there is endogeneity problem and thus the result of regressions is inconsistent. Wooldridge (2001) presents three hypotheses for the existence of endogenous variables: omitted variables, measurement error, and simultaneity in regressions. Variables can be omitted when, for example, they are not known or not available. Measurement error can occur when one needs to measure the partial effect of a variable. Finally, simultaneity occurs when one of the explanatory variables is concomitant with the dependent variable.

The empirical model developed in this study is subject to the above-mentioned problems. In short, not all explanatory variables of the model are known and measurable. Furthermore, the opacity index (*OI*) can be influenced by bank credit (*BC)*, which, in turn, suggests simultaneity problem. Furthermore, regarding the endogeneity problem, for example, a macroeconomic shock affects *BC* and thereby *OI*.

A general solution to the problem of endogeneity is the use of instrumental variables. In particular, GMM models allow the use of instruments sequentially exogenous avoiding endogeneity problem. The model proposed by Arellano and Bond (1991) consists in the estimation of first-difference GMM panel data as a way of eliminating non-observed effects. However, Alonso-Borrego and Arellano (1998), and Blumdell and Bond (1998) showed that the first-difference GMM has a bias (for large and small samples) and low accuracy. Moreover, the use of lags can generate weak instruments (Staiger and Stock, 1997).

Blumdell and Bond (1998) found results that sustain the use of system GMM panel data estimation method instead of first-difference GMM. In the model proposed by Arellano and Bover (1995) and Blumdell and Bond (1998) regressions in levels and first differences are combined (see, Bond, Hoeffler and Temple, 2001).

In order to verify the relevance of the instruments in the models, the test of overidentifying restrictions (Sargan test) is performed as suggested by Arellano (2003). Moreover, White’s heteroskedasticity consistent covariance matrix is applied on regressions. Finally, as proposed by Arellano and Bond (1991), tests of first-order (m1) and second-order (m2) serial correlation are used. It is important to highlight that in the case of system GMM models one premise is the non-correlation of the first difference of endogenous regressors and thus implies that is not necessary to perform unit root tests.

4.2. Empirical evidence

Aiming to analyze the relationship between the opacity index and bank credit, four models using panel data (GMM system) were estimated taking into account: (i) all NYSE banks in the sample; (ii) 10 largest NYSE banks; (iii) all NASDAQ banks in the sample; and (iv) 50 largest NASDAQ banks. Moreover, for each panel data, three specifications are estimated including new control variables. Hence:

(7) $BC_t = \beta_0 BC_{t-1} + \beta_1 OI_t + \beta_2 TB_t + \beta_3 DC_t + \varepsilon_t^0$;

(8) $BC_t = \beta_4 BC_{t-1} + \beta_5 OI_t + \beta_6 TB_t + \beta_7 GDP_t + \beta_8 DC_t + \varepsilon_t^1$; and

(9) $BC_t = \beta_9 BC_{t-1} + \beta_{10} OI_t + \beta_{11} TB_t + \beta_{12} GDP_t + \beta_{13} COM_t + \beta_{14} DC_t + \varepsilon_t^2$,

$\varepsilon \sim N(0, \sigma^2)$.

Where *DC* is a dummy which corresponds to the subprime crisis (*DC*).

Table 2 shows the results for banks that trade their shares on the NYSE. It is noteworthy to highlight that all regressions accept the null hypothesis in the Sargan tests and thus the over-identifying restrictions are valid. Furthermore, both serial autocorrelation tests (first order and second order) reject the hypothesis of the presence of serial autocorrelation in all specifications.

The coefficients on *OI* are negative and statistically significant in all specifications. This result corroborates the hypothesis that a lower opacity (greater transparency) of the banking firms causes an increase in the credit supplied by them. Furthermore, in the models “all banks” and “largest banks”, the magnitude of the coefficients on *OI* are very close which, in turn, indicates that there is no difference between large and small banks in regard to the effect on credit.

The coefficient on lagged bank credit is positive and statistically significant in all models. In short, an increase in the credit today implies a rise in credit in the subsequent period. In regard to the control variables (*TB*, *GDP*, and *COM*), with the exception of the coefficient on *GDP* in the model “10 largest banks”, all coefficients are statistically significant. Moreover, the coefficients are positive in all models and thus are in accordance with the assumptions previously considered.

The results for banks that have their shares traded on NASDAQ are presented in table 3. As observed in the regressions of table 2, tests of Sargan and autocorrelation validate the instrumental variables and indicate the absence of serial autocorrelation, respectively.

Table 2

Effect on bank credit – NYSE (system GMM)

Regressors	NYSE – all banks						NYSE - 10 largest banks					
	Specification 1		Specification 2		Specification 3		Specification 1		Specification 2		Specification 3	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
BC_{t-1}	0.8974***	0.0008	0.9154***	0.0025	0.9185***	0.0027	0.9417***	0.0016	0.9431***	0.0024	0.9459***	0.0026
OI_t	-0.0160***	0.0012	-0.0152***	0.0037	-0.0138***	0.0036	-0.0179***	0.0028	-0.0156***	0.0030	-0.0127***	0.0035
TB_t	0.1634***	0.0065	0.1623***	0.0126	0.1487***	0.0133	0.1621***	0.0036	0.1574***	0.0055	0.1402***	0.0094
GDP_t			0.1714***	0.0488	0.1050*	0.0597			0.0508**	0.0251	0.0024	0.0260
COM_t					0.0043*	0.0023					0.0047***	0.0009
DC_t	0.1546***	0.0272	0.3583**	0.1738	0.2842*	0.1751	0.1187*	0.0671	0.2205***	0.0746	0.1777**	0.0761
N. instruments	22		22		22		26		26		26	
Obs.	1619		1619		1619		286		286		286	
Sargan test	34.2095		31.9943		31.2469		67.8805		67.7477		67.6474	
(p-value)	0.46		0.47		0.45		1.00		1.00		1.00	
m1	-2.8995		-3.8916		-3.5384		-3.5644		-3.6148		-3.6866	
(p-value)	0.00		0.00		0.00		0.00		0.00		0.00	
m2	0.3683		0.1925		0.1571		0.3201		0.3090		0.2915	
(p-value)	0.71		0.85		0.88		0.75		0.76		0.77	

Note: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1.

Table 3

Effect on bank credit – NASDAQ (system GMM)

Regressors	NASDAQ – all banks						NASDAQ - 50 largest banks					
	Specification 1		Specification 2		Specification 3		Specification 1		Specification 2		Specification 3	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
BC_{t-1}	0.8281***	0.0000	0.8360***	0.0001	0.8365***	0.0001	0.9021***	0.0061	0.9084***	0.0062	0.9067***	0.0093
OI_t	-0.0121***	0.0001	-0.0076***	0.0001	-0.0046***	0.0001	-0.0129***	0.0013	-0.0108***	0.0024	-0.0127*	0.0073
TB_t	0.2297***	0.0002	0.2150***	0.0001	0.1961***	0.0003	0.1835***	0.0049	0.1843***	0.0065	0.1868***	0.0078
GDP_t			0.1978***	0.0002	0.0930***	0.0002			0.4317***	0.0068	0.4397***	0.0146
COM_t					0.0080***	0.0000					-0.0005	0.0009
DC_t	0.3513***	0.0022	0.7189***	0.0032	0.6121***	0.0044	0.2561***	0.0686	1.1843***	0.0890	1.2126***	0.1146
N. instruments	19		19		19		26		26		26	
Obs.	7606		7606		7606		1854		1854		1854	
Sargan test	235.5922		235.5606		232.7850		45.7258		43.8107		43.7318	
(p-value)	0.35		0.33		0.35		0.36		0.39		0.36	
m1	-1.7120		-1.7864		-1.7919		-2.2257		-2.3101		-2.2830	
(p-value)	0.09		0.07		0.07		0.03		0.02		0.02	
m2	-1.1199		-1.1714		-1.1750		-0.6035		-0.6708		-0.6506	
(p-value)	0.26		0.24		0.24		0.55		0.50		0.52	

Note: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1.

As found for the case of models which consider NYSE banks, the coefficients on *OI* are negative and statistically significant. Therefore, this observation validates the hypothesis, also for NASDAQ banks, that a lower opacity raises the level of credit. Unlike the previous analysis on NYSE, the coefficients do not show the same magnitude for both models ("all banks" and "50 largest banks"). The coefficients on the model "all banks" are (on average) smaller than observed for the "50 largest banks". In other words, for the largest NASDAQ banks the *OI* has a greater effect on *BC*. Moreover, the results denote that the coefficients on *OI* for the case of NYSE banks are greater than observed for NASDAQ banks.

As observed for the case of NYSE banks, the coefficient on lagged bank credit is positive and statistically significant in all specifications. The results for the control variables (*TB*, *GDP*, and *COM*) show that, with the exception of the coefficient on *COM* in the model "50 largest banks", all coefficients are positive and statistically significant.

4.3. Test of robustness

This section aims to examine the effect of the opacity index on bank credit even in the presence of "credit sudden stops" (CSS). According to Calvo, Izquierdo, and Talvi (2006) a sudden stop is defined as an abrupt fall of credit in relation to its past history. Morever, as pointed out by Calvo (2009) credit sudden stops is a central problem of financial crises as observed in the subprime crisis.

In order to capture evidence of the importance of transparency for bank credit in the presence of events of CSS, the dependent variable (*BC*) in first difference is considered in the regressions. The use of the first difference allows one to observe how *OI* causes variations on *BC* (*ΔBC*). Based on the methodology used in the previous section, the following models are considered:

(10) $\Delta BC_t = \alpha_0 \Delta BC_{t-1} + \alpha_1 OI_t + \alpha_2 TB_t + \alpha_3 DC_t + \varepsilon_t^3$;

(11) $\Delta BC_t = \alpha_4 \Delta BC_{t-1} + \alpha_5 OI_t + \alpha_6 TB_t + \alpha_7 GDP_t + \alpha_8 DC_t + \varepsilon_t^4$; and

(12) $\Delta BC_t = \alpha_9 \Delta BC_{t-1} + \alpha_{10} OI_t + \alpha_{11} TB_t + \alpha_{12} GDP_t + \alpha_{13} COM_t + \alpha_{14} DC_t + \varepsilon_t^5$, $\omega \sim N(0, \sigma^2)$.

Table 4 presents the results for NYSE banks. In a general way, Sargan statistics and autocorrelation tests do not indicate problem in the regressions. The results indicate that the coefficient on *OI* is negative and statistically significant. In other words, negative changes of *BC* can be explained by an increase in the opacity of banks. On average, the coefficients on *OI* that consider the 10 largest NYSE banks are greater than the coefficients found for the model "all banks". This result indicates that the effect of the transparency on the variation of the credit banks is greater when the largest banks are considered in the analysis. In regard to the control variables, the signs and statistical significance of the coefficients are in accordance with the assumptions presented in the previous sections.

The regressions concerning NASDAQ banks are in table 5. As observed through Sargan tests and both autocorrelation tests, there is no problem of autocorrelation or over-identification problem in all specifications. As observed for NYSE banks, the coefficient on *OI* is negative and statistically significant in all regressions. This result demonstrates the importance of *OI* in explaining variations in bank credit and may indicate its relevance even in the presence of CSS. Unlike the results observed for the NYSE banks, the coefficients on *OI* for the case of the largest NASDAQ banks are (on average) lower than observed for the model "all banks". Once again, with the exception of the coefficient on *COM* in the model "50 largest banks", the coefficients on control variables are in accordance with the hypothesis adopted in the previous sections.

To study more specifically the effect of opacity on bank credit in the presence of CSS for the period from first quarter 1995 to fourth quarter 2009, the methodology developed by Calvo (2009) to detect events of CSS is adopted. According to this view, the first step is the sum of credits supplied by all banks at period t and after this series is deflated by the U.S. Consumer Price Index. In this analysis, credit flow is the variation of bank credit between t and $t-1$. Hence, the variation of credit flow corresponds to the credit flow at t less credit flow at $t-1$ ($Ch(tQx)$). Assuming that $\mu(tQx)$ is the mean of the series $Ch(\bullet)$ from the first quarter 1995 to tQx and $\sigma(tQx)$ is the standard error, the CSS is a result of:

(13) $$Ch(tQx) - \mu(tQx) < -2\sigma(tQx).$$

Table 4

Efecct on bank credit (first difference) – NYSE (system GMM)

Regressors	NYSE – all banks						NYSE - 10 larget banks					
	Specification 1		Specification 2		Specification 3		Specification 1		Specification 2		Specification 3	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
ΔBC_{t-1}	-0.1038***	0.0135	-0.0702***	0.0057	-0.0896***	0.0109	-0.1718***	0.0024	-0.1711***	0.0034	-0.1902***	0.0066
OI_t	-0.0077***	0.0013	-0.0023***	0.0005	-0.0017*	0.0010	-0.0179***	0.0043	-0.0113**	0.0051	-0.0187***	0.0057
TB_t	0.0954***	0.0263	0.1021***	0.0049	0.0781***	0.0253	0.0480***	0.0047	0.0333***	0.0061	0.0090	0.0090
GDP_t			0.4344***	0.0121	0.2572***	0.0320			0.2872***	0.0082	0.1337***	0.0160
COM_t					0.0080*	0.0042					0.0099***	0.0009
DC_t	-0.0520	0.2206	0.8970***	0.0768	0.5681*	0.2975	-0.0139	0.0509	0.4996***	0.0326	0.3591***	0.0270
N. instruments	22		22		22		7		7		7	
Obs.	1619		1619		1619		316		316		316	
Sargan test	38.7183		31.8932		31.2098		43.1657		42.3828		42.9502	
(p-value)	0.27		0.47		0.46		1.00		1.00		1.00	
m1	-1.8027		-3.1280		-2.3865		-1.6060		-1.6475		-1.7719	
(p-value)	0.07		0.00		0.02		0.11		0.10		0.08	
m2	-1.1009		-0.8721		-1.0141		-0.4012		-0.4184		0.0442	
(p-value)	0.27		0.38		0.31		0.69		0.68		0.96	

Note: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1.

Table 5

Effect on bank credit (first difference) – NASDAQ (system GMM)

Regressors	NASDAQ – all banks						NASDAQ - 50 largest banks					
	Specification 1		Specification 2		Specification 3		Specification 1		Specification 2		Specification 3	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
ΔBC_{t-1}	-0.0091***	0.0003	-0.0153***	0.0006	-0.0320***	0.0009	-0.0477***	0.0144	-0.0365**	0.0145	-0.0310*	0.0173
OI_t	-0.1136***	0.0000	-0.0547***	0.0003	-0.0248***	0.0002	-0.0515***	0.0025	-0.0311***	0.0028	-0.0336***	0.0038
TB_t	0.1455***	0.0008	0.1288***	0.0011	0.1109***	0.0018	0.1688***	0.0006	0.1653***	0.0030	0.1669***	0.0051
GDP_t			0.3095***	0.0011	0.2357***	0.0017			0.4797***	0.0183	0.4946***	0.0232
COM_t					0.0079***	0.0001					-0.0012***	0.0007
DC_t	-0.4026***	0.0086	0.2064***	0.0126	0.1531***	0.0174	-0.1841***	0.0425	0.9313***	0.1023	0.9382*	0.1066
N. instruments	15		15		15		21		21		21	
Obs.	7606		7606		7606		1854		1854		1854	
Sargan test	232.8629		232.0582		229.0318		45.0332		43.3655		43.3489	
(p-value)	0.31		0.32		0.34		0.39		0.41		0.37	
m1	-2.0277		-1.9202		-1.8061		-2.0043		-2.6947		-2.7253	
(p-value)	0.04		0.05		0.07		0.05		0.01		0.01	
m2	-1.4234		-1.3841		-1.4700		-1.2399		-1.4680		-1.3673	
(p-value)	0.15		0.17		0.14		0.22		0.14		0.17	

Note: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1.

Following the framework adopted in the previous sections, figure 2 shows events of CSS for NYSE ("all banks" and "10 largest banks") and for NASDAQ ("all banks" and "50 largest banks"). The analysis concerning NYSE banks ("all banks") allows one to observe three events of CSS. The first (fourth quarter 1997 to second quarter of 1998) corresponds to the Asian crisis experienced in the late 1990s. The second (fourth quarter 2001) corresponds to the attacks of September 11, 2001. The third (first quarter 2009) is due to the subprime crisis. For the case of NASDAQ banks it is also possible to identify the events listed above. Moreover, the rise in U.S. interest rates between July 2004 and July 2006 may explain the events of CSS in the fourth quarter of 2004 and first quarter of 2006.[9]

With the intention of considering the events of CSS in the analysis presented in the section 4.2, a dummy variable (*DCSS*) is included in those models. Hence:

(14) $BC_t = \gamma_0 BC_{t-1} + \gamma_1 OI_t + \gamma_2 TB_t + \gamma_3 DC_t + \gamma_4 DCSS_t + \vartheta_t^0$;

(15) $BC_t = \gamma_5 BC_{t-1} + \gamma_6 OI_t + \gamma_7 TB_t + \gamma_8 GDP_t + \gamma_9 DC_t + \gamma_{10} DCSS_t + \vartheta_t^1$; and

(16) $BC_t = \gamma_{11} BC_{t-1} + \gamma_{12} OI_t + \gamma_{13} TB_t + \gamma_{14} GDP_t + \gamma_{15} COM_t + \gamma_{16} DC_t + \gamma_{17} DCSS_t + \vartheta_t^2$,

$\vartheta \sim N(0, \sigma^2)$.

Table 6 shows the results for NYSE banks. Sargan tests and autocorrelation tests indicate that the models are over-identified and there is no serial autocorrelation. The results indicate that even considering CSS the opacity index is relevant to bank credit in all specifications. The coefficients on *OI* are negative and statistically significant which, in turn, is in accordance with the idea that a lower opacity contributes to an increase in credit. This result is particularly relevant for the largest NYSE banks which present (on average) the greatest effect of *OI* on credit bank. As expected, the dummies for CSS are negative and statistically significant for all specifications.

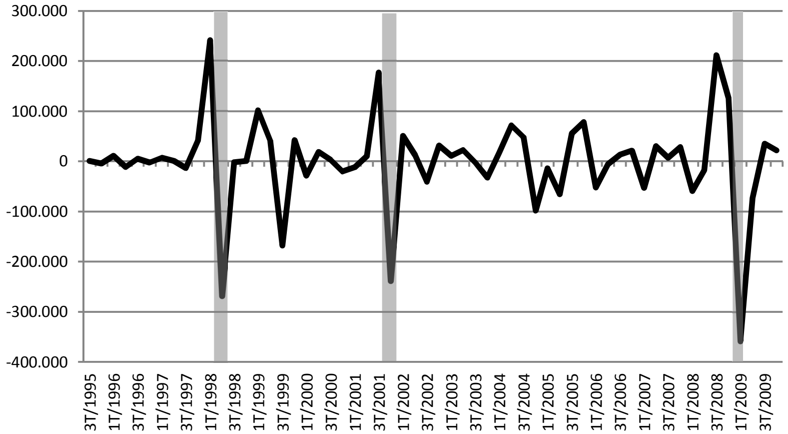
As observed in the previous sections, the results in table 6 reveal that the coefficients on BC_{t-1} are statistically significant and positive in all specifications. Furthermore, the control variables (*TB*, *GDP*, and *COM*), with the exception of the coefficients on *TB* and *GDP* in the specification 3 for "10 largest banks", all coefficients are statistically significant and the signs confirm the previously adopted hypotheses.

[9] These results are in agreement with those found by Calvo (2009).

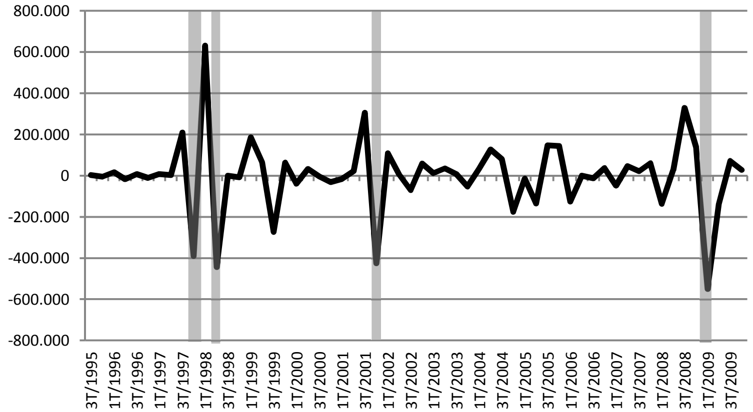
Figure 2

Credit Sudden Stops

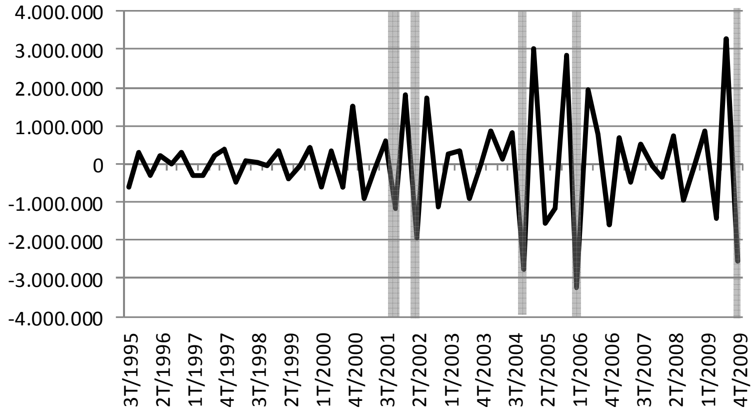
NYSE – all banks



NYSE – 10 largest banks



NASDAQ – all banks



NASDAQ – largest 50 banks

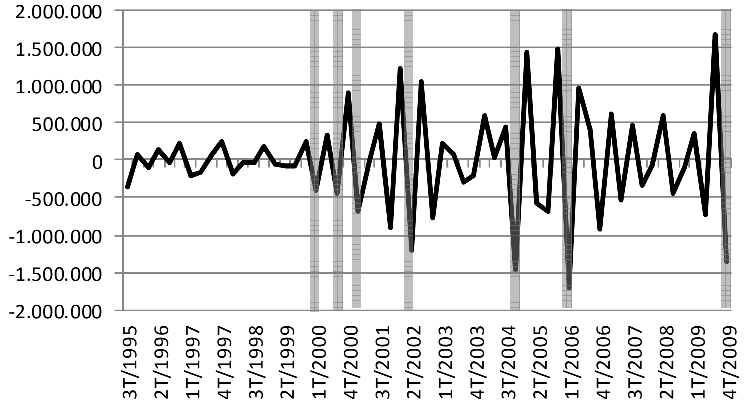


Table 6

Effect on bank credit with CSS – NYSE (system GMM)

Regressors	NYSE – all banks						NYSE - 10 largest banks					
	Specification 1		Specification 2		Specification 3		Specification 1		Specification 2		Specification 3	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
BC_{t-1}	0.9050***	0.0025	0.9299***	0.0015	0.9403***	0.0025	0.9855***	0.0022	0.9898***	0.0023	0.9955***	0.0032
OI_t	-0.0136***	0.0027	-0.0077***	0.0026	-0.0093**	0.0037	-0.0154***	0.0028	-0.0122***	0.0033	-0.0063*	0.0036
TB_t	0.1437***	0.0178	0.1242***	0.0132	0.1027***	0.0239	0.0623***	0.0155	0.0524***	0.0157	0.0260	0.0182
GDP_t			0.2128***	0.0123	0.1306***	0.0466			0.0869***	0.0298	0.0434	0.0292
COM_t					0.0060***	0.0023					0.0064***	0.0014
DC_t	0.1013***	0.0569	0.4822***	0.0678	0.3178**	0.1440	0.2262***	0.0659	0.3780***	0.0694	0.3517***	0.0704
$DCSS$	-0.5463***	0.2459	-0.3615*	0.1873	-0.5448*	0.3118	-1.3037***	0.0103	-1.2524***	0.0202	-1.2039***	0.0200
N. instruments	22		22		22		7		7		7	
Obs.	1619		1619		1619		316		316		316	
Sargan test	30.4810		30.9432		35.0361		22.4550		22.4602		22.2184	
(p-value)	0.59		0.47		0.28		0.99		0.98		0.98	
m1	-3.0376		-4.1336		-3.8332		-3.4707		-3.5288		-3.6319	
(p-value)	0.00		0.00		0.00		0.00		0.00		0.00	
m2	0.2736		0.0368		-0.0672		0.3489		0.3339		0.3124	
(p-value)	0.78		0.97		0.95		0.73		0.74		0.76	

Note: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1.

Table 7

Effect on bank credit with CSS – NASDAQ (system GMM)

Regressors	NASDAQ – all banks						NASDAQ - 50 largest banks					
	Specification 1		Specification 2		Specification 3		Specification 1		Specification 2		Specification 3	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
BC_{t-1}	0.9505***	0.0001	0.9679***	0.0001	0.9725***	0.0001	0.8899***	0.0075	0.9037***	0.0068	0.9022***	0.0096
OI_t	-0.1384***	0.0002	-0.0870***	0.0002	-0.0594***	0.0002	-0.0495***	0.0094	-0.0232***	0.0071	-0.0267**	0.0109
TB_t	0.1644***	0.0008	0.1458***	0.0005	0.1277***	0.0005	0.1956***	0.0078	0.1869***	0.0080	0.1903***	0.0087
GDP_t			0.2448***	0.0011	0.1914***	0.0015			0.4142***	0.0147	0.4285***	0.0183
COM_t					0.0062***	0.0001					-0.0010	0.0009
DC_t	-0.1970***	0.0100	0.2332***	0.0063	0.1806***	0.0093	0.2170**	0.0877	1.1119***	0.1393	1.1408***	0.1553
DCSS	-0.0836***	0.0062	-0.0165***	0.0047	-0.0178***	0.0049	-0.2834***	0.0246	-0.2425***	0.0271	-0.2399***	0.0280
N. instruments	15		15		15		20		20		20	
Obs.	7606		7606		7606		1854		1854		1854	
Sargan test	229.8886		231.4889		232.7176		45.0386		43.7624		43.7027	
(p-value)	0.34		0.32		0.27		0.35		0.36		0.32	
m1	-1.7371		-1.9574		-2.0434		-2.3835		-2.1890		-2.1443	
(p-value)	0.08		0.05		0.04		0.02		0.03		0.03	
m2	-1.1113		-1.2752		-1.3375		-0.2904		-0.5839		-0.5503	
(p-value)	0.27		0.20		0.18		0.77		0.56		0.58	

Note: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1.

Considering the case of the NASDAQ Banks (see table 7), Sargan test and autocorrelation tests assure the robustness of results. Furthermore, as expected from the theoretical perspective, the coefficients on *OI* are negative and statistically significant in all models. In short, this result shows the importance of *OI* to bank credit even in the presence of events CSS. The results for NASDAQ banks indicate that the effect of *OI* on bank credit is smaller to larger banks. The other indicators did not present significant difference in comparison with those observed for the previous estimations.

5. Concluding remarks

This article analyzed the effect caused by lack of transparency, based on NYSE banks and NASDAQ banks, on bank credit for the period from the first quarter 1995 to fourth quarter 2009. Hence, three indicators had a special role in this study: opacity index, bank credit, and events of credit sudden stop. In order to summarize the results obtained in sections 4.2 and 4.3, table 8 presents the effects on bank credit at period *t* from shocks of one standard deviation to the opacity index at *t-1*. With this objective, the coefficients on *OI* are considered in the three different analyses: (i) "effect on bank credit" (equation 7 to 9); (ii) "effect on bank credit – first difference" (equation 10 to 12); and (iii) "effect on bank credit with CSS" (equation 14 to 16).

Table 8

Effect of OI on bank credit

Analysis	Models	Stand. Dev.	Coefficient	Effect - *OI*
Effect on bank credit (Analysis 1)	**NYSE - all**	9.42	-0.0150	-0.1413
	NYSE - 10+	5.39	-0.0154	-0.0830
	NASDAQ – all	6.40	-0.0081	-0.0518
	NASDAQ - 50+	7.76	-0.0121	-0.0939
Effect on bank credit - first difference (Analysis 2)	**NYSE- all**	9.42	-0.0039	-0.0367
	NYSE - 10+	5.39	-0.0160	-0.0862
	NASDAQ- all	6.40	-0.0644	-0.4120
	NASDAQ - 50+	7.76	-0.0387	-0.3002
Effect on bank credit with CSS (Analysis 3)	**NYSE – all**	9.42	-0.0102	-0.0961
	NYSE - 10+	5.39	-0.0113	-0.0609
	NASDAQ – all	6.40	-0.0949	-0.6072
	NASDAQ - 50+	7.76	-0.0331	-0.2568

It is observed that a shock on opacity index, in the case of analysis 1, has the highest effect on the bank credit for the model which considers all NYSE banks. In other words, a shock on opacity index implies a decrease in bank credit around 14 basis points (b.p.). When the first difference of the bank credit is considered in the analysis the result indicates that the most relevant impact is observed for all NASDAQ banks. A shock on opacity index provokes a decrease in the variation of the bank credit of 41 b.p.. Finally, when the CSS is included in the analysis the model which considers all NASDAQ banks presents the highest impact on the decrease of bank credit (61 b.p.).

It is still noteworthy to highlight that in all models, as expected on theoretical grounds, the impact of opacity index is not negligible on bank credit. This result is very important for studies that look for tools for mitigating financial crisis. In short, bank transparency contributes to reduce uncertainty in the financial system and thus creates an environment conducive to amplifying credit without generating speculative bubbles.

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