The Impact of Credit Rating Changes on U.S. Banks

Nicholas Apergis [a], James E. Payne [b], Chris Tsoumas [c]

[a,c] University of Piraeus, Greece
[b] University of South Florida, USA

This study examines the impact of credit rating upgrades and downgrades on six comprehensive banks' asset classes, profitability, leverage and size using data from the call reports and Bloomberg over the period 1989 to 2008. The findings indicate that in the one year horizon after the rating change, an upgrade yields an increase in net loans and profitability, while a downgrade yields an increase in loss allowance and other real estate owned. Turning to the two year horizon, upgraded banks continue to exhibit higher profitability and an increase in size. On the other hand, downgraded banks continue to increase their loss provisions, while their liquidity position improves. Surprisingly though, there is an increase in their leverage and size. In summary, the results, confirmed by a number of robustness checks, suggest that a downgrade has a lasting and relatively more severe impact on banks than an upgrade; however, downgraded

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1. Introduction

The main objective of banks is the processing of risk and information (Greenbaum and Thakor, 2007). The uniqueness of their business and essential role in the economy underscores the importance of monitoring banks' risks and supervision of behavior. Other intermediaries, such as credit rating agencies help resolve, at least in part, the problem of asymmetric information that plagues lending relationships. The rationale for credit ratings is based on the achievement of economies of scale in information production about credit risk and address agency problems (Gonzalez et al., 2004). The latter yields the extensive employment of ratings in asset management rules, as well as in banks' supervision and government regulations on financial institutions (Tang, 2009).

In the Basel II Capital Accord, emphasis is placed on credit ratings and market discipline – one of the three pillars on which bank prudential supervision is based. This pillar is designed to employ market participants as disciplinary devices through increased disclosure and transparency. Market discipline incorporates two distinct notions: market monitoring and market influence (Bliss and Flannery, 2002). The first refers to the investors' ability to evaluate a bank's true value, while the second examines how changes in market prices affect managers' actions to offset adverse changes in the bank's financial condition. Apart from market discipline however, banks also face regulatory discipline (Billett et al. 1998). Nevertheless, as Berger et al. (2000) point out, credit rating agencies and bank supervisors have similar incentives, as they are both concerned with default risk, and provide evidence that information produced by one of these two groups is subsequently incorporated into the other's assessment. Thus, the impact of credit rating changes on banks may stem from their role as a corporate device mechanism as in the case of non-financial firms (Kisgen, 2006; Tang, 2009). Alternatively, this line of inquiry may also stem from the joint outcome of both market discipline triggered by a credit rating change and regulatory discipline – at least for downgraded banks, given the complementary role supervisors and market participants have in the governance of financial institutions (Berger et al., 2000).

Therefore, to test whether the use of credit rating agencies on this governance scheme is effective, one should isolate the impact of credit rating changes on banks from the contemporaneous effect of possible regulatory actions. We examine whether the banks in our sample that received a rating change also faced an enforcement action adopted by U.S. banking supervisory authorities. We do so in this study using data on bank enforcement actions from the FDIC, OCC, and FRB for the period examined.

In particular, the study investigates the impact of upgrades and downgrades on six comprehensive banks' asset classes, profitability, leverage and size in one and two year horizon after the rating change. For this, the financial account variables employed in Flannery et al. (2004) with data from the annual call reports and changes in the S&P long term issuer credit rating from Bloomberg for the 1989 to 2008 period are used. As in Kang and Liu (2009), the difference-in-differences econometric approach, properly modified to take into account Bertrand et al.'s (2004) critique is implemented. The basic model is estimated using Heckman's two-step estimation method which addresses the issues of endogeneity and sample selection bias.

Our results show that in the one year horizon after a rating change an upgrade results in an increase in net loans and profitability. A downgrade, however, results in an increase in loss allowance and other real estate owned, providing evidence of the effort by downgraded banks to reduce their loan portfolio risk and cleanse bad loans. Turning to the two year horizon, upgraded banks continue to exhibit higher profitability and increase in size, while downgraded banks continue to increase their loss provisions, while improving their liquidity position. Surprisingly though, there is evidence of an increase in their leverage and size. In summary, the findings, confirmed by a number of robustness checks, suggest that a downgrade has a lasting and relatively more severe impact on banks than an upgrade; yet, downgraded banks do not seem to effectively reduce their appetite for risk over a longer horizon.

Section 2 provides a brief review of the literature on the market discipline of banks and on the role of credit ratings. Section 3 describes the data with the econometric methodology presented in Section 4. Section 5 discusses the empirical results. Concluding remarks are given in Section 6.

2. Brief Literature Review

2.1. Market Discipline on Banks

There is a relatively large empirical literature with respect to the market discipline of banks. The literature focuses on the market monitoring component of banks' risks, providing mixed evidence of its effectiveness. For example, in the light of the recent financial turmoil, a possible systematic market failure in such monitoring has been put forth as a possible explanation (Flannery, 2008). On the contrary, Palvia and Patro (2010) provide evidence that markets can indeed monitor banks effectively, reinforcing the role of market discipline as a supervisory mechanism. However, when it comes to market influence on banks' decisions, to the best of our knowledge, only Bliss and Flannery (2002) examine this issue. They employ a large set of managerial action variables and stock and bond returns for the period 1986 to 1998 to investigate the role of market participants on the governance of bank holding companies. Their results do not provide strong evidence that either stock or bond investors regularly influence managerial actions, although they find patterns consistent with market influence. Nevertheless, as Rajan (2001) argues, the result of market influence is hard to identify empirically.

Opaqueness, an inherent characteristic of banks, may alter market discipline and justifies bank regulation to mitigate the difficulty of bank assets' valuation. Conceptually, opaqueness is based on information asymmetry and is closely related to Knightian uncertainty more than to risk (Morgan, 2002). Incomplete disclosure of information, the uncertain quality and credibility of the disclosures, as well as the inherent complexity of the banking business and/or the ability of managers to rapidly transform assets may result in imprecise knowledge by the investors about the underlying profitability and risks of the firm (Myers and Rajan, 1998).

2.2. The Role of the Credit Ratings

The role of credit rating agencies has increased considerably during recent years. However, there is an unsettled debate about credit ratings' impact in the literature. On the positive side, Graham and Harvey (2001) show that credit ratings are more important in affecting a firm's funding policy than factors suggested by theories of capital structure. Along this front, Faulkender and Petersen (2006) reveal that firms which issue rated bonds are more leveraged. Kisgen (2006, 2009) finds that firms close to a rating upgrade or downgrade issue less debt than equity relative to firms without a rating change. Tang (2009) also documents that credit ratings significantly affect firms' access to credit markets. Others, however, question the importance of credit ratings as providers of information. For example, Brealey and Myers (2003) argue that credit rating agencies reflect as much about market participants' opinion about a firm's financial condition as providing new information.

The consequences of rating changes on the valuation of stock and bonds have been extensively examined. For example, Hand et al. (1992) show that only rating downgrades have a negative impact on stock and bond prices, while upgrades' information is incorporated into prices prior to the announcement. Ederington and Goh (1998) reveal that downgrades cause negative equity returns and analysts' earning forecast revisions. Brooks et al. (2004) confirm that rating changes have the same impact on countries' market returns as in the case of firms. Jorion et al. (2005) explore the effect of the Fair Disclosure (FD) Regulation in the US, which prohibited the selective, non-public disclosure of information by firms to favored investment analysts excluding credit rating agencies, to find that the informational effect on stock prices of downgrades and upgrades is much larger in the post-FD period.

In an effort to tie together the empirical findings, as well as to provide a comprehensive explanation for the increased role of credit ratings, Boot et al. (2006) develop a theoretical model to show that credit ratings coordinate investors' beliefs. As they argue, credit ratings have a real value and impact through their monitoring role, especially in the credit watch procedure, and the significance of the ratings for institutional investors' decisions. However, Boot et al. (2006) point out that market participants' increased reliance on credit rating agencies might discourage other monitoring mechanisms and fuel an excessive dependence on them.

More recently, Kuang and Qin (2009) document the role and significance of credit ratings on firms' managerial actions to find that credit ratings act as delegated monitors and deter managers' risk taking incentives. In accordance with this finding, Kang and Liu (2009) provide evidence on the positive impact of rating changes on managers' incentives. They show that credit ratings play a disciplinary role on managers' actions and help reduce agency conflicts, in combination with other corporate governance mechanisms.

3. Data Description

Data comes from Bloomberg and the call reports.[1] Bloomberg provides data for commercial banks' and bank holding companies' credit ratings. The call reports provide financial data for all commercial banks and bank holding companies that are regulated by the Federal Reserve System, the Federal Deposit Insurance Corporation, and the Comptroller of the Currency.

The Standard and Poor's long term issuer credit rating, for which data is available for 370 financial entities over the period 1989 to 2009 is used. This initial credit rating sample includes 4,043 firm-year observations. We convert the letter long term issuer credit rating at the end of each year to a numerical scale as AAA=1, AA+=2,…,D=22, thus higher numbers correspond to lower ratings. The 370 financial entities contained in the initial credit rating sample are then matched with those included in the annual call reports. This matching process yields 295 entities, from which 201 are commercial banks and 94 bank holding companies. From the annual call reports data ten financial account variables are calculated denoted as X_1 to X_{10} for each banking firm.[2] Table 1 presents the financial account variables employed in the analysis.

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[1]Reports of Condition and Income are available on line at
http://www.chicagofed.org/webpages/banking/financial_institution_reports/index.cfm.

[2] Adapted from Flannery et al. (2004).

Table 1
Financial Account Variables' Definition

Symbol	Definition
X_1	(Total loans and leases, gross –Allowance plus excess allowance for loan and lease losses + Customers' liabilities on outstanding acceptances) / Total assets
X_2	Allowance plus excess allowance for loan and lease losses / Total assets
X_3	Trading assets, total / Total assets
X_4	Other real estate owned / Total assets
X_5	(Book value of bank premises and fixed assets + Investments in unconsolidated subsidiaries + Intangible assets + Other assets) / Total assets
X_6	(Cash and balances due + Total investment securities + Interbank balances + Federal funds sold and securities purchased under agreement to resell) / Total Assets
X_7	Net income / Total assets
X_8	Total non interest income / Total assets
X_9	Total liabilities / Book value of equity
X_{10}	Log (Total assets)

Source: Call reports and authors' calculations

As Table 1 documents six of the financial account variables measure the asset composition of each bank at the end of each year. X_1 refers to net loans; X_2 to loan loss allowance, a variable indicative of the quality of each banking firm's loan portfolio; X_3 to trading assets, which proxies for the size of its trading portfolio; while X_4 refers to other real estate owned which measures real estate taken in settlement of problem loans plus real estate investments, other than bank premises. X_5 refers to the sum of bank's premises and fixed assets, investments in unconsolidated subsidiaries and intangible assets. This variable measures the more opaque assets, i.e., assets that investors cannot value very accurately (Flannery et al., 2004). X_6 refers to the more transparent assets, i.e., assets that are more easily valued, and includes the sum of cash and balances due, total investment securities, interbank balances, and federal funds sold and securities purchased under agreement to resell. The remaining four variables pertain to banks' profitability, leverage and size. More specifically, X_7 and X_8 refer to net income and total non-interest income, respectively. These two profitability measures could be viewed as less discretionary as the other financial account variables employed in the analysis; however, it is important in our opinion to examine the impact of rating changes on banks' profitability. All the above variables are scaled by total assets. Due to this scaling, the difference in economic size of the banking firms in the sample does not drive the results, nor does it affect their interpretation. Finally, X_9 measures total liabilities scaled by the book value of equity; and X_{10} is the log of total assets. Surely, a change in several of these variables may not be a direct result of bank managerial actions in response to a credit rating change, but rather a reflection of the deteriorating/improving performance of the bank related indirectly to a rating change.

The call reports sample contains 6,019 firm-year observations on the ten financial account variables used, from which 4,154 pertain to commercial banks and the remaining 1,865 on bank holding companies. Finally, the two samples, the initial credit rating sample and the call reports sample are merged. This merged sample includes 2,895 firm-year observations for which both financial and credit ratings data are available with 1,848 observations on commercial banks and 1,047 on bank holding companies.

To examine the impact of credit rating changes on banks' financial account variables the difference-in-differences (henceforth, DD) technique following Kang and Liu (2009) is employed. Each bank that has a rating that changed at year *t*, relative to its value at *t*-1, is defined as a 'treated' bank. Hence, the event date for the 'treatment' as *t* is identified. Then, for every 'treated' bank in the sample all 'untreated' banks are identified that satisfy the following three criteria, in order to properly function as candidate controls for the 'treated' bank: (1) the 'untreated' bank must have the same rating as the 'treated' bank at *t*-1, i.e., one year before the event date; (2) its rating remained unchanged for one year after *t*, i.e., until *t*+1; and (3) for each 'treated' commercial bank or bank holding company, a commercial bank or bank holding company that satisfy criteria (1) and (2) is distinguished as a candidate control. This procedure identifies several 'untreated' banks that could serve as controls for each 'treated' bank. Then, in the case of every financial account variable for each 'treated' bank, we calculate the average value of the respective variable for all available control banks, i.e., we construct an 'average' control bank for each 'treated' bank.

For each bank, both 'treated' and control, the changes for the X_1 *to* X_{10} variables for the *t*-1 to *t*+1 period, defined as DDX_1 to DDX_{10} are calculated. These variables are the focus of the examination of the changes in banks' asset composition, profitability, leverage and size after a credit rating change. To facilitate the econometric analysis, the respective changes for the *t*-1 to *t* period, denoted as DX_i, i =1,.., 10, as well as the value of each variable at *t*-1, denoted as X_ilag1, i =1,.., 10 are also employed.

The final working dataset contains 289 pairs of firm-year observations matched with their controls which cover the 1989 to 2008 period. However, a symmetric impact of a credit rating upgrade or downgrade on banks' decision making and performance is a rather strong assumption. Credit rating agencies evaluate a bank's financial condition on behalf of its debt-holders, and thus, an upgrade is highly unlikely to impact banks' decision making in an analogous way as a downgrade. Furthermore, credit rating changes cause different reactions in money and capital markets, e.g., a decrease (increase) of a bank's risk premium in the case of an upgrade (downgrade), which, in turn, is more likely to impact the bank's asset-liability management and profitability unevenly. Thus, the analysis is performed separately to the two samples of upgraded and downgraded banks matched with their controls. The results confirm the highly heterogeneous impact of a credit rating change on upgraded and downgraded banks' decision making and performance. Hence, the final working dataset is split to construct two samples: one containing 158 pairs of firm-year observations for upgraded banks, and one containing 131 pairs for downgraded banks.

Furthermore, to mitigate concerns regarding the contemporaneous effect of possible regulatory actions, i.e., the regulatory discipline effect, we examined whether the banks in our final working dataset also faced an enforcement action imposed by the FDIC, OCC, and FRB for the period examined. This examination yielded only ten banks with an enforcement action imposed within two years around the rating change: five of them concerned upgraded banks and five downgraded banks. We included these banks in the sample given concerns about degrees of freedom and since they represent a very small fraction of the sample size. However, the results remain the same when we excluded these banks from the analysis.

4. Econometric Methodology

As already mentioned, to explore the impact of credit rating changes on banks' asset composition, profitability, leverage and size, the difference-in-difference (DD) estimation method is employed. This method has become widely used as a tool to examine the causal effect of a 'treatment' event, usually measured by a dummy variable, on a variable of interest that accounts for the characteristics and/or the behavior of the 'treated' group, i.e., the group that is exposed to this event.

For this, the change in the variable of interest before and after the event for the 'treated' group is compared to the change of the same variable for an 'untreated' or control group over the same period. The main econometric issue with the DD estimation method is the omitted variable bias, or selection bias, which stems from the possible heterogeneity between the 'treated' and control group for reasons other than the 'treatment' event. This bias is possibly present in the case of non-experimental or observational data. Econometric techniques, such as instrumental variables regression, are routinely used to deal with the problem of missing or unknown controls. The DD estimation method has several appealing characteristics, such as simplicity and the potential to deal with endogeneity issues, and flexibility to be used in a panel or repeated cross-section regression framework with group and time fixed effects, where the time dimension of the panel usually covers several periods.

However, as Bertrand et al. (2004) point out, in a panel regression framework where multiple observations are used in the time dimension for the event variable, the significance of the change is overstated due to the presence of serial correlation and the inconsistency in the resulting standard error of the estimate associated with the event effect. This correlation problem is inherent in the construction of the event variable, which consists of a series of zeros for the pre-event period, followed by a series of ones. To bypass the serial correlation problem, Bertrand et al. (2004) suggest the use of a single observation in the post-event period t+1, instead of multi-year post-treatment observations, and focusing on the average change in the variable of interest for this observation at t+1 relative to the benchmark year t-1. Furthermore, the endogeneity of the credit rating change variable could be a serious problem which is not easily tackled in the usually employed panel regression framework.

Following Bertrand et al.'s (2004) suggestions, we employ the change for the variables of interest at t+1 relative to their values at t-1 for the 'treated' and control banks. The omitted variable bias is dealt with by calculating an 'average' control bank for each 'treated' bank, as mentioned in the previous section. Because there are many factors that could affect a bank's asset composition, as well as its profitability, leverage and size, the changes in X_1 to X_{10} variables lagged once, i.e., for the period from t-2 to t, defined as $DDX_i lag1$, for i=1,…,10, are used as covariates. The inclusion in the model of the change in the dependent variable for the t-1 to t period, DX_i, and its' value at t-1, $X_i lag1$, as well as of variables other than the dependent variable at t-1, i.e., $X_j lag1$ for $j \neq i$, in some cases, is also suggested by the Ramsey's RESET specification test and the Schwartz and Akaike information criteria. To save space, the results of these tests are not reported but are available upon request. Thus, the basic model for the one year horizon after the rating change is formulated as:

$$DDX_i = \alpha_i + \beta_i CRDUM + \sum_{k=1}^{10} \gamma_k DDX_k lag1 + \delta_i DX_i + \varepsilon_i X_i lag1 + \sum_{j \neq i} \zeta_j X_j lag1 + u_i \tag{1}$$

where k takes the values from 1 to 10, spanning the ten financial account variables examined. *CRDUM* is a dummy variable that takes the values of 1 and 0 for the 'treated' and control banks, respectively.[3] The focus is on the sign and significance of the estimated parameter β_i. A positive (negative) and significant β_i indicates an increase (decrease) of the relevant variable of interest for the 'treated' group relative to the control group. To reduce the effect of possible outliers on the estimated coefficients of interest, a trimming procedure on the 99.7% confidence interval (i.e., removal of the outliers that lie outside three standard deviations from the mean) is performed for the two samples of upgraded and downgraded banks with respect to all variables employed. However, the results are essentially the same when we include these outliers.

[3] With this approach, we do not account for the possible nonlinear effect of the credit rating level of the 'treated' bank before a rating change occurs. In other words, a downgrade from AA+ to A, for example, may not be as relevant as a downgrade from BBB to BBB-. Instead, we obtain estimates of the mean impact of a rating change on the dependent variable across the rating ladder.

Formulated in this way, the above model adequately captures the complex dynamics among banks' different asset classes, profitability and leverage; hence, it abstracts from the need of explicitly modeling the banks' decision making and ever-changing environment. More importantly, the change specification in equation (1) cancels out any fixed bank-specific effects that could drive the results. Furthermore, equation (1), together with the structure of the dataset of matched pairs of 'treated' and control banks, allows for time-invariant unobservable differences between them.

To further address the potential selection bias problem and the endogeneity of the *CRDUM* variable, the above model is estimated using Heckman's two-step estimation method in the two samples of upgraded and downgraded banks. The cluster robust standard errors method is used to deal with heteroskedasticity problems. Thus, in the first stage regression, *CRDUM* is estimated using the following probit model:

$$\Pr(CRDUM = 1 \left| X, \beta \right.) = \Phi(X'\beta) \tag{2}$$

where X is a vector containing the explanatory variables employed in equation (1) and a set of instruments, Z, that are correlated with *CRDUM* and uncorrelated with the disturbance term in equation (1). Φ is the standard normal cumulative distribution function. The set of instruments includes seven variables: the change of the log assets from t-1 to t, DX_{10}; loss allowance to total assets at t-1, X_2lag1; the sum of bank's premises and fixed assets, investments in unconsolidated subsidiaries and intangible assets to total assets at t-1, X_5lag1; the sum of cash and balances due, total investment securities, interbank balances, and federal funds sold and securities purchased under agreement to resell to total assets at t-1, X_6lag1; net income to total assets at t-1, X_7lag1; log assets at t-1, $X_{10}lag1$; and S&P's long term issuer credit rating at t-1, *CRlag1*.

The rationale for the use of these instrumental variables can be traced to their intuitive relationship with a credit rating change. Specifically, the change in the (log) of total assets, DX_{10}, and the level of this variable at t-1, $X_{10}lag$, proxy for the risk-taking behavior of banks (Flannery and Nikolova, 2004), as well as for bank's portfolio diversification capabilities, economies of scale and scope as well as access to capital markets. Loan loss allowance to total assets at t-1, X_2lag1 provides a proxy for the credit quality of a bank's loan portfolio. The sum of bank's premises and fixed assets, investments in unconsolidated subsidiaries and intangible assets to total assets at t-1, X_5lag1, and the sum of cash and balances due, total investment securities, interbank balances, and federal funds sold and securities purchased under agreement to resell to total assets at t-1, X_6lag1, proxy for the ability to absorb potential losses in their portfolios and for their level of liquidity. Finally, net income to total assets at t-1, X_7lag1, is a measure of the capability of a bank's asset portfolio to generate profits and thus, of its quality, while the lagged value of the bank's long term issuer credit rating is a proxy for the bank's overall credit quality and is expected to have a positive relationship with the probability of a downgrade. Here, it must be stressed that the same seven instruments are employed in equation (2) for both samples of upgraded and downgraded banks along with their controls. The correct econometric specification of the model in equation (2) is tested by the use of the likelihood ratio and the Hosmer–Lemeshow goodness-of-fit tests. The Hosmer–Lemeshow statistic must fail to reject the null for the model to have an acceptable match between predicted and observed probabilities. Again, to save space, the results of these tests are not reported here but are available upon request.[4]

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[4] To gain confidence with respect to the results, the analysis is repeated by employing the two stage least squares (TSLS) estimation technique in the above model. Specifically, the first stage regression (2) is estimated with OLS, i.e., a linear probability model is employed for the CRDUM variable. The over-identifying restrictions test, which fails to reject the null at the 5% confidence level for all 10 dependent variables, is performed yielding essentially the same results. As an additional robustness check, following Kang and Liu's (2009) approach, the impact of credit rating changes on banks' characteristics is examined using a model which abstracts from the need of instruments for the estimation. Specifically, the dataset is restructured by splitting each variable employed to form two distinct series: one comprising of the values for the 'treated' banks and one for their controls. Then the following model is estimated with OLS:

$$DDX_i = \alpha_i + \beta_i CNTRDDX_i + \sum_{k=1}^{10} \gamma_k DDX_k lag1 + \delta_i DX_i + \varepsilon_i Xlag1_i + \sum_{j \neq i} \zeta_j X_j lag1 + u_i$$

The impact of a credit rating change on upgraded and downgraded banks is further examined for a two year horizon after the change. Thus, the variable denoted as *$DDX_i av2$, i=1,..,10* is calculated as the average value of the respective X_i variable at t+1 and t+2, minus its value at t-1, as in Kang and Liu (2009). Due to missing data at t+2 for some banks, these longer horizon samples include 126 pairs that refer to upgraded banks matched with their controls and 94 pairs to downgraded banks. *$DDX_i av2$* is used as the dependent variable, while the covariates *$DDX_i av2lag1$, i=1,.., 10* are defined as the average value of the respective X_i variable at t+1 and t, minus its value at t-2. The Ramsey's RESET specification test and the Schwartz and Akaike information criteria are performed yielding the basic model as follows:

$$DDX_i av2 = \alpha_i + \beta_i CRDUM + \sum_{k=1}^{10} \gamma_k DDX_k av2lag1 + \delta_i DDX_i + \sum_{j \neq i} \zeta_j X_j lag1 + \varepsilon_i \tag{3}$$

The Heckman two-step estimation method is undertaken in equation (3), as well as the TSLS method described in footnote [4].

5. Results

The results are reported in Tables 2 to 5. All tables have the same structure. The first row shows the dependent variables, i.e., the ten financial account variables examined, while the other rows report the estimated coefficients of the explanatory variables, the number of observations and the Wald statistic. The last two rows in Tables 2 to 5 report the pseudo-R2 and the likelihood ratio statistics from the first stage regression estimated from equation (2). The coefficients of interest are highlighted in grey.

To make sense of the huge amount of information generated by the empirical analysis, the focus is on the following issues: First, whether the coefficient of the *CRDUM* variable in equation (1) is significant, as well as the sign is positive or negative in relation to the financial account variables for upgraded and downgraded banks. Second, whether the financial account variables that are significant in the one year horizon are the same with those in the two year horizon, i.e., whether a rating change has a lasting impact on banks.

5.1. Upgraded Banks: One Year Horizon

As Table 2 documents, for the change in net loans to total assets, *DDX1*, the *CRDUM* variable is positive and significant at the 10% level. This indicates that upgraded banks expand net credit more than their controls. Other significant explanatory variables are the change in net loans for the *t-1* to *t* period, *DX1*, and the level of net loans at *t-1*, *X1lag1*, with a positive and negative sign, respectively. Additionally, the change from t-2 to t in log assets, *DDX10lag1* and the values at *t-1* of *X5* and *X10* which measure fixed assets and subsidiaries and the size of banks are significant, all with a negative sign. The Wald statistic is 391.94 and highly significant, while the statistics for the first stage regression indicate that the instruments employed for the *CRDUM* variable are satisfactory.

For the change in loss allowance to total assets, *DDX2*, the coefficient of *CRDUM* is negative and significant at the 1% level. This result indicates that upgraded banks reduce their provisions, a strategy which may be the outcome of a more prudent credit expansion policy, or, equally as plausible, of a less conservative and more optimistic management of risk. As before, lagged changes and values of loss allowance, profitability and size are significant in explaining the variation of the dependent variable.

Lastly, the only other dependent variable for which *CRDUM* is significant at the 1% level with a

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where $CNTRDDX_i$ is the change in the variable of interest for the control banks and DDX_i is the relevant change for the 'treated' banks. Here, the coefficient of interest is α_i. The inclusion of the $CNTRDDX_i$ variable in the above equation takes into account factors that may affect the 'treated' bank's decisions and performance, irrespective of its rating change. To economize on space, these results, which are in full accordance with the Heckman's two-step estimation method results , are available upon request.

positive sign, is the change in net income to total assets, *DDX7*. This result suggests that upgraded banks are becoming more profitable than their pairs. In the present analysis, we do not examine where this increased profitability originates but leave this for future research. The changes from t-2 to t of loss allowance, *DDX2lag1*, trading assets, *DDX3lag1*, and fixed assets, *DDX5 lag1*, are also significant with mixed signs, indicating that changes in banks' asset composition affect its profitability in a rather complicated way. The lagged changes and the value at t-1 of net income also play their role, as indicated by the significance of *DDX7 lag1*, *DX7* and *X7 lag1*, coupled with the values at *t-1* of loss allowance, *X2 lag1*, liquidity, *X6lag1*, and *size*, *X10lag1*.

5.2. Downgraded Banks: One Year Horizon

For the sample of downgraded banks, the results of Table 3 indicate that when the change in loss allowance, *DDX2*, is employed as the dependent variable, *CRDUM* is significant with a positive sign. Thus, a downward revision of a bank's credit rating seems to act as a disciplinary mechanism that forces bank managers to reduce their loan portfolio risk. Alternatively, it could also be the outcome of asset quality deterioration caused by the downgrading. Specifically, a downgraded bank faces increased borrowing costs and/or deteriorated reputation which serves as an incentive for the banks to take more risks in lending. The relatively large number of the other explanatory variables that are significant for this model suggests that for the increase in loss allowance for downgraded banks, their asset composition, profitability, leverage and size are taken into account. *CRDUM* is also significant and positive for the change in other real estate owned, *DDX4*. As previous mentioned, this variable measures real estate taken in settlement of problematic loans plus real estate investments other than bank premises. As such, this finding indicates that downgraded banks make an effort to cleanse their portfolio of bad loans.

5.3. Upgraded Banks: Two Year Horizon

Turning to the two years horizon after the rating change, the results of the Heckman's two-step estimation method for the sample of upgraded banks are summarized in Table 4. Upgraded banks continue to have increased profitability relatively to their pairs over a two years horizon after the rating change, since *CRDUM* is significant with a positive sign. The same holds for the change in log assets. Upgraded banks are increasing in size.

5.4. Downgraded Banks: Two Year Horizon

As far as downgraded banks, Table 5 reports that several financial account variables increases are in order after the downgrade. In the loss allowance equation, *DDX2*, the coefficients for the *CRDUM* variable in equation (1) is positive and significant. In the liquidity equation, *DDX6*, the coefficient for the *CRDUM* variable is also significant. This is possibly the result of a more precautionary policy by the downgraded bank in terms of liquidity, rather than a change in its lending activity, as suggested by the insignificant results for the total loans equation, *DDX1*. This could be achieved either through higher case balances and/or a higher level of investment securities held in the bank's portfolio which points to a change in the bank's asset management. Certainly, a more detailed analysis is needed, which is beyond the scope of this study to investigate the forces which drive the increased liquidity position of downgraded banks. In the leverage and size equation, *DDX9* and *DDX10*, respectively, the relevant coefficients are positive and significant as well. The statistical significance of the respective coefficients for these variables is lower in the Heckman's two-step estimation method, i.e., significance at the 10% level, than in the OLS approach described in footnote 4, i.e., significance at the 1% level. However, this should be attributed to the less precise estimate of the instrumental variable approach. This finding is surprising, since both leverage and size point to a more risky institution. Rationally, a downgrade should lead to the opposite result. A possible explanation is that in the long run a downgrade provides incentives for banks to incur greater risks in an effort to improve their rating quality. To put it differently, it seems that a downgrade disciplines banks only in the short term.

Table 2
Upgraded Banks – One Year Horizon – Heckman's Two-Step Estimation Method

	DDX_1	DDX_2	DDX_3	DDX_4	DDX_5	DDX_6	DDX_7	DDX_8	DDX_9	DDX_{10}
C	0.119***	-0.008***	0.0001	0.0004***	-0.013*	0.016	0.011***	0.025***	1.789***	0.029
CRDUM	0.016*	-0.003***	0.004	-0.0001	-0.004	-0.006	0.004***	-0.001	-0.019	0.006
DDX_1lag1	0.003	0.002	-0.060	0.0003	0.016	-0.365***	-0.004	-0.028	0.102	0.250***
DDX_2lag1	0.110	-0.205***	-0.532*	-0.008	-0.075	0.793	0.181***	0.072	6.885	2.410***
DDX_3lag1	-0.089	0.010	-0.736***	-0.0001	0.014	0.326***	-0.028***	-0.044	-0.068	0.117
DDX_4lag1	-0.601	0.117	1.017*	0.030	0.679***	-1.458	0.023	-0.267	-58.017**	-1.526
DDX_5lag1	-0.005	-0.004	0.251***	-0.005*	0.043	-0.594***	-0.044***	-0.050	8.628*	0.099
DDX_6lag1	-0.063	0.002	-0.020	-0.001	-0.016	-0.151	-0.002	-0.012	4.642**	0.239***
DDX_7lag1	0.711	-0.143***	0.725***	-0.016	0.284**	-1.421***	-0.143**	-0.332**	35.339**	-0.011
DDX_8lag1	-0.221	-0.009	-0.114	0.012***	-0.055	0.514*	0.035	0.087	3.110	-0.063
DDX_9lag1	0.001	0.0001	0.0004	0.0002	0.0004	-0.003	-0.0001	-0.0003	0.046	0.0008
$DDX_{10}lag1$	-0.052*	-0.0001	0.003	0.0003	0.004	0.125***	-0.001	0.009	-0.514	0.147***
DX_i,	0.838***	1.330***	1.514***	0.841***		0.791***	0.767***	1.068***	0.664***	1.046***
X_ilag1	-0.072***	0.003	-0.032	-0.271***		-0.137***	-0.314***	-0.004	-0.185***	-0.003
X_2lag1							0.217***			
X_5lag1	-0.170*									0.523***
X_6lag1							0.010***			
X_7lag1		0.093***								
X10lag1	-0.009**	0.001***			0.003***		-0.002***	-0.003***		
Obs.	308	310	316	304	300	316	306	316	316	316
Wald stat.	391.940	321.470	151.970	675.080	280.180	323.200	446.530	257.240	405.780	453.790
Pseudo-R^2	0.331	0.307	0.329	0.314	0.310	0.326	0.325	0.321	0.324	0.321
LR stat.	141.330	132.010	144.090	132.240	129.070	142.940	138.000	140.800	142.050	140.800

Notes: Sample period: 1989-2008. X_1-X_{10} as defined in Table 1. DDX_i: Change in variable X_i between t-1 and t+1. *CRDUM*: Dummy variable that takes the values of 1 and 0 for the 'treated' and control banks, respectively. DDX_ilag1: Change in variable X_i between t-2 and t.. DX_i: Change in variable X_i between t-1 and t. X_ilag1: Value of variable X_i at t-1. One (*), two (**) and three (***) asterisks denote significance at respectively the 10%, 5% and 1% level. The last two rows report statistics from the first stage probit regression model for *CRDUM*. Sources: Call reports, Bloomberg and authors' calculation

Table 3
Downgraded Banks – One Year Horizon – Heckman's Two-Step Estimation Method

	DDX_1	DDX_2	DDX_3	DDX_4	DDX_5	DDX_6	DDX_7	DDX_8	DDX_9	DDX_{10}
C	0.133***	-0.0003	0.002	0.008***	-0.019**	0.036**	-0.002	0.001	0.452	0.083**
CRDUM	0.023	0.004**	-0.002	0.002**	-0.002	-0.025	0.003	0.003	-0.279	-0.028
DDX_1lag1	0.055	-0.007	0.027*	-0.0002	0.005	-0.113*	0.012	0.009	-0.513	0.142***
DDX_2lag1	-1.202***	-0.256**	-0.005	-0.062***	0.307***	0.782	-0.206***	-0.062	-32.245***	-0.822*
DDX_3lag1	0.102	-0.033**	0.214***	-0.001	0.017	-0.014	0.030	0.005	-2.103	0.008
DDX_4lag1	0.169	0.139	-0.372	-0.220***	0.017	-0.355	0.060	0.014	15.459	-1.930**
DDX_5lag1	-0.089	0.074***	0.099	-0.017*	0.037	-0.460*	-0.017	0.037	-6.478	-0.264
DDX_6lag1	-0.076	-0.017**	0.089***	-0.006*	-0.001	0.040	0.007	0.010	-3.367*	0.095
DDX_7lag1	0.544	-0.192***	-0.152	-0.079***	0.358***	-0.934	-0.340***	-0.249***	-10.800	-0.219
DDX_8lag1	-0.139	-0.067***	-0.094*	0.015*	0.038	-0.102	0.114***	0.111	-0.815	0.090
DDX_9lag1	0.005**	-0.001***	0.0002	0.0001	0.002***	-0.004	-0.0006*	0.0004	-0.178**	0.002
$DDX_{10}lag1$	-0.037	0.017***	0.004	-0.001	0.006	0.048	-0.003	-0.001	2.129**	-0.016
DX_i,	0.728***	1.273***	0.585***	1.274***	0.686***	0.475***	0.982***	0.706***	0.832***	1.060***
X_ilag1	-0.083***	-0.178***	-0.117***	-0.268***	-0.118***	-0.106***	-0.133*	-0.056	-0.082***	-0.005
X_2lag1							0.108*			
X_6lag1				-0.007***						
$X_{10}lag1$	-0.014***			-0.0009***	0.004***					
Obs.	254	246	262	262	254	256	262	248	262	254
Wald stat.	238.430	528.910	388.800	430.300	185.070	157.840	291.520	292.380	283.510	434.230
Pseudo-R^2	0.251	0.259	0.256	0.249	0.253	0.280	0.249	0.323	0.258	0.276
LR stat.	88.450	88.460	93.090	90.420	88.990	99.280	90.310	110.940	93.580	97.120

Notes: Sample period: 1989-2008. . X_1-X_{10} as defined in Table 1. DDX_i: Change in variable X_i between t-1 and t+1. *CRDUM*: Dummy variable that takes the values of 1 and 0 for the 'treated' and control banks, respectively. DDX_ilag1: Change in variable X_i between t-2 and t. DX_i: Change in variable X_i between t-1 and t. X_ilag1: Value of variable X_i at t-1. One (*), two (**) and three (***) asterisks denote significance at respectively the 10%, 5% and 1% level. The last two rows report statistics from the first stage probit regression model for *CRDUM*. Sources: Call reports, Bloomberg and authors' calculations.

Table 4.
Upgraded Banks – Two Year Horizon – Heckman's Two-Step Estimation Method

	DDX_1av2	*DDX_2av2*	*DDX_3av2*	*DDX_4av2*	*DDX_5av2*	*DDX_6av2*	*DDX_7av2*	*DDX_8av2*	*DDX_9av2*	*$DDX_{10}av2$*
C	-0.002	-0.00002	-0.003**	0.00004	0.002*	0.004	0.003***	0.003***	0.173	0.013**
CRDUM	-0.001	-0.001	0.002	-0.0002	0.0003	-0.004	0.001*	0.0003	-0.066	0.030***
$DDX_1av2lag1$	0.133*	0.001	-0.017	-0.001	0.001	-0.167***	0.010*	0.010*	1.880	-0.106
$DDX_2av2lag1$	0.313	-0.908***	0.079	0.033**	-0.282	0.577	0.070	-0.157***	19.588	1.038
$DDX_3av2lag1$	0.033	0.015**	-0.151**	-0.001	-0.051*	-0.022	-0.001	0.002	4.375**	-0.233*
$DDX_4av2lag1$	-0.799	0.499***	0.537	-0.021	-0.171	0.359	-0.177	0.178*	-13.008	-0.518
$DDX_5av2lag1$	0.101	-0.036***	-0.065	-0.008**	-0.007	-0.225**	-0.011	-0.007	8.197***	-0.041
$DDX_6av2lag1$	0.044	-0.007	-0.005	-0.003**	0.001	-0.108	0.015***	0.011*	-1.115	-0.064
$DDX_7av2lag1$	0.470	0.052	0.308*	0.0001	-0.588***	0.291	-0.319***	-0.215***	44.423***	2.421***
$DDX_8av2lag1$	-0.120	-0.057***	0.048	0.006	0.176***	-0.222	-0.026	-0.084	-10.495**	-0.022
$DDX_9av2lag1$	-0.0008	-0.0002	-0.002***	0.00006**	-0.001*	0.0002	0.0001	0.0002	-0.017	0.003**
$DDX_{10}av2lag1$	0.008	0.001	0.031***	0.002***	-0.009	0.026	0.003	-0.0002	1.375**	0.070
DDX_i,	0.932***	1.562***	1.138***	1.072***	0.866***	0.913***	1.009***	1.131***	0.950***	0.953***
X_2lag1									-19.562***	
X_3lag1							-0.007*	-0.01***		
X_6lag1									-1.708***	
X_7lag1		0.052**				-0.497**	-0.306***	-0.252***	19.978***	
Obs.	252	248	252	252	252	244	252	244	252	252
Wald stat.	3559.830	442.950	3161.130	3139.070	1004.510	1337.660	1483.570	2086.050	2481.110	1617.780
Pseudo-R^2	0.305	0.305	0.303	0.306	0.304	0.311	0.361	0.331	0.303	0.304
LR stat.	106.470	99.830	105.960	106.980	106.240	105.210	126.170	111.890	105.880	106.030

Notes: Sample period: 1989-2007. . X_1-X_{10} as defined in Table 1. *DDX_iav2*: Change in variable X_i between *t*-1 and its average value for the *t*+1 to *t*+2 period. *CRDUM*: Dummy variable that takes the values of 1 and 0 for the 'treated' and control banks, respectively. *$DDX_iav2lag1$:* Change in variable X_i between *t*-2 and its average value for the *t* to *t*+1 period. *DDX_i*: Change in variable X_i between *t-11* and *t*+1. *X_ilag1*: Value of variable X_i at *t*-1. One (*), two (**) and three (***) asterisks denote significance at respectively the 10%, 5% and 1% level. The last two rows report statistics from the first stage probit regression model for *CRDUM*. Sources: Call reports, Bloomberg and authors' calculations.

Table 5
Downgraded Banks – Two Year Horizon – Heckman's Two-Step Estimation Method

	DDX_1av2	DDX_2av2	DDX_3av2	DDX_4av2	DDX_5av2	DDX_6av2	DDX_7av2	DDX_8av2	DDX_9av2	$DDX_{10}av2$
C	-0.001	-0.002***	0.001	0.0003**	0.002	0.013*	0.001**	-0.00004	2.213***	0.0004
CRDUM	-0.010	0.001***	-0.001	-0.0001	-0.003	0.012*	0.0003	0.0003	0.389*	0.016*
$DDX_1av2lag1$	-0.010	0.003	0.055***	0.003**	0.034***	0.133***	0.009***	0.016***	0.844	-0.155**
$DDX_2av2lag1$	-1.545***	-0.132*	0.096	0.001	0.258***	0.505	0.145***	-0.084	-26.344***	-1.144*
$DDX_3av2lag1$	-0.231*	0.0001	0.731***	-0.0001	-0.023	0.239*	0.010	0.012	-4.057	0.039
$DDX_4av2lag1$	-0.145	0.020	0.195	-0.133**	0.140	0.679	0.107**	0.297***	-8.006	-1.519
$DDX_5av2lag1$	-0.400***	0.001	0.083**	0.005	-0.236*	0.383***	-0.004	0.043**	10.716**	-0.707***
$DDX_6av2lag1$	-0.046	0.001	0.057***	0.003**	0.033***	0.096	0.004	0.010*	-0.445	-0.068
$DDX_7av2lag1$	-1.161***	-0.047	0.277**	-0.013	-0.010	1.074**	0.211***	-0.145**	4.245	1.253
$DDX_8av2lag1$	1.016***	0.042***	-0.178***	-0.003	0.160**	-0.669***	0.028	0.264**	-6.917	0.349
$DDX_9av2lag1$	-0.002	0.0001	-0.0001	0.0001**	-0.0005	0.005***	-0.0001	-0.0001	-0.289***	-0.003
$DDX_{10}av2lag1$	0.077***	0.001	-0.002	-0.001	0.002	-0.108***	0.005*	0.006	-0.158	-0.359***
DDX_i,	0.851***	0.942***	0.283***	0.892***	0.998***	0.914***	0.648***	0.660***	1.104***	1.327***
X_ilag1		0.006***	-0.089***	-0.176***		-0.047**	-0.136***		-0.171***	
X_2lag1		-0.162***							-16.98***	
X_5lag1									-6.243***	
X_7lag1										1.039**
Obs.	188	182	188	188	188	184	184	182	182	182
Wald stat.	1660.120	2801.560	2221.900	4546.470	1015.800	1786.460	1141.920	656.680	1371.270	1471.410
Pseudo-R^2	0.327	0.422	0.333	0.339	0.374	0.345	0.461	0.343	0.319	0.374
LR stat.	85.280	106.580	86.840	88.260	97.570	87.950	107.360	86.640	80.580	94.280

Notes: Sample period: 1989-2007. DDX_iav2: Change in variable X_i between t-1 and its average value for the t+1 to t+2 period for the 'treated' banks. *CRDUM*: Dummy variable that takes the values of 1 and 0 for the 'treated' and control banks, respectively. $DDX_iav2lag1$: Change in variable X_i between t-2 and its average value for the t to t+1 period for the 'treated' banks. DDX_i: Change in variable X_i between t-1 and t+1 for the 'treated' banks. X_ilag1: Value of variable X_i at t-1 for the 'treated' banks. One (*), two (**) and three (***) asterisks denote significance at respectively the 10%, 5% and 1% level. The last two rows report statistics from the first stage probit regression model for *CRDUM*. Sources: Call reports, Bloomberg and authors' calculations.

6. Concluding Remarks

This study examines credit ratings' impact on banks. Specifically, the study investigates the impact of upgrades and downgrades on six comprehensive banks' asset classes, profitability, leverage and size for one and two years' horizon after the rating change. The results indicate that in the one year horizon after a rating change an upgrade results in an increase in net loans and profitability. This finding probably reflects a decrease in the price of wholesale funding, combined with increased loan market shares for these banks. A downgrade, however, results in an increase in loss allowance and other real estate owned, providing evidence that downgraded banks attempt to reduce their loan portfolio risk and cleanse bad loans.

Turning to the two year horizon after a rating change, upgraded banks continue to exhibit higher profitability and increase in size. The latter is evidence of an increase in risk taking behavior (Flannery and Nikolova, 2004). Downgraded banks continue to increase their loss provisions, while they improve their liquidity position. Surprisingly though, there is evidence for an increase in their leverage and size, confirmed by a number of robustness checks.. In summary, the findings suggest that a downgrade has a lasting and relatively more severe impact on banks than an upgrade; yet, downgraded banks do not seem to effectively reduce their appetite for risk over a longer horizon.

The above evidence corroborates that credit ratings do serve as corporate governance devices and impact banks' asset and liability management. To put it differently, credit ratings have real economic decision-making consequences for banks, as Kisgen (2006) and Tang (2009) argue when examining non-financial firms. It seems, however, that the role of credit rating agencies, as an integral part of banks' prudential supervision through market discipline, is overstated over a longer horizon. The findings point to the increased role for supervisors' responsibility in deterring banks' risk taking behavior – especially for downgraded banks – and evaluating the banks' performance towards the goal of a sound financial system. The optimal mix between rating agencies and supervisory authorities' roles in the context of an improved regulation and supervision schemes remains an open question.

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