Multiple credit ratings and liquidity creation

George Kladakis, Lei Chen, Sotorios K. Bellos

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Abstract

We examine the relationship between multiple credit rating purchases by banks and liquidity creation using a diverse sample of 486 banks from 71 countries. We show that liquidity creation is negatively associated with the number of ratings purchased by the bank, and that capital can positively moderate this relationship, allowing banks that obtain more ratings to create more liquidity.

Keywords: banks, rating agencies, multiple credit ratings, liquidity creation

JEL: G21, G24, G28

1. Introduction

Credit Rating Agencies (CRAs) act as information intermediaries by rating the ability of issuers of debt securities to meet their payment obligations as well as issuers' likelihood of default. Banks rely significantly on CRAs for the assessment of their creditworthiness and have been required by regulatory frameworks to obtain investment-grade ratings from multiple CRAs. However, CRAs have received substantial criticism for inflating the ratings of complex instruments, such as Mortgage Backed Securities (MBSs) and Collateralized Debt Obligations (CDOs) during the financial crisis of 2007-2009. It is also argued that competition among CRAs may encourage rating shopping (e.g. Bolton et al., 2012).

The ongoing debate about the effectiveness of multiple CRAs motivates academic researchers to investigate the effects of multiple credit ratings and the business models of CRAs (e.g. Bongaerts et al., 2012; Sangiorgi and Spatt, 2017). Adding to the growing literature in this area, we investigate whether purchasing multiple credit ratings impedes or enhances liquidity creation, which is one of banks' main functions in the economy.

Banks' unique intermediation skills allow them to provide liquidity to both borrowers and depositors through funding illiquid loans with liquid deposits (Bryant, 1980; Diamond and Dybvig, 1983). Literature has documented that the liquidity creation function of banks is an important driver of real economic output (Berger and Sedunov, 2017). Yet, higher levels of liquidity creation are associated with greater liquidity risk as financing illiquid loans with liquid deposits makes banks vulnerable to runs (Diamond and Dybvig, 1983; Leiva and Mendizábal, 2019), and liquidity risk is an important bank risk factor in CRAs' assessment models.

There are three hypotheses attempting to explain theoretically why firms seek to obtain multiple credit ratings and they are not mutually exclusive. First, the information production hypothesis suggests that firms purchase multiple ratings to reduce information asymmetries. When a CRA provides an additional rating that agrees with the existing rating by another CRA, investors are likely to be more confident about the creditworthiness of the issuer (e.g. Morkoetter et al., 2017; Drago and Galo, 2018). Second, the rating shopping hypothesis argues that issuers may apply for multiple ratings and opt to disclose only the favourable ones. Such a behaviour of issuers received significant attention during the financial crisis of 2007-2009 (e.g. Skreta and Veldkamp, 2009; Sangiorgi and Spatt, 2017). Finally, the regulatory certification hypothesis suggests that firms purchase additional ratings to comply with the regulations that require certain types of assets to be rated as investment-grade (e.g. Brister et al., 1994; Bongaerts et al., 2012). For instance, the ratings-based approach (RBA) of Basel II requires risk weights to be differentially assigned based on the external rating grade.

We posit that liquidity creation is negatively associated with the number of ratings purchased by the bank and that this relationship might be theoretically explained through the three aforementioned hypotheses. First, in terms of information production, should banks opt to buy more ratings to reduce information asymmetries, they may reduce their liquidity creation levels to become less opaque in the eyes of CRAs. As holding more opaque types of assets can increase rating disagreements (e.g. Morgan, 2002; Iannotta, 2006; Kladakis et al., 2020), illiquid loans with long maturity and opaque corporate borrowers can also deteriorate the agreement levels of bank credit ratings. Second, liquidity creation is highly associated with liquidity risk, which is an important determinant of bank credit ratings. Should rating shopping be associated with banks' need for a better rating, banks may reduce their liquidity creation levels in order to obtain their desired rating grade. Finally, Brister et al. (1994) show that the dichotomy of investment grade and high-yield securities by regulation can create inefficiencies in the market such as the overpricing of investment grade assets and crowding investment away from high-yield assets. Therefore, such legal constraints may discourage or restrict banks from diversifying their portfolio with illiquid assets, thus limiting banks' capacity to create liquidity.[1] Our empirical findings support our expectations that multiple credit ratings and liquidity creation are negatively associated. We also show that bank capitalization can mitigate the negative relationship between multiple credit ratings and liquidity creation, suggesting that the rating shopping hypothesis might prevail.

The remainder of the paper is structured as follows: Section 2 describes our data and key variables; Section 3 outlines our regression framework; Section 4 presents our empirical results; Section 5 presents our robustness tests; and Section 6 concludes and discusses the policy implications of our findings.

2. Data and Key Variables

We investigate the relationship between multiple credit ratings and liquidity creation with a diverse sample of 486 banks[2] from 71 countries[3] mainly from Europe and Asia-Pacific, over the period of 2005-2018. We obtain annual bank-level data from the S&P Global Market Intelligence (S&P GMI) database and macroeconomic data from the International Monetary Fund (IMF). The S&P GMI database provides a rich sample of long-term Issuer Credit Ratings (ICR) assigned by the Big 3 credit rating agencies (S&P, Moody's and Fitch). This allows us to create our key independent variable for multiple credit ratings (MULT) which takes the ordinal values of 1 to 3, depending on how many ratings have been assigned to each bank. We exclude all banks that have not been assigned at least one rating as it is a common practice in the literature that studies multiple

[1] Duan et al. (2021) show that banks with lower efficiency create less liquidity.
[2] We use all companies classified as banks by the S&P GMI database which are mainly commercial, savings and mortgage banks.
[3] Table 1 presents the number of banks per country available in the sample.

credit ratings (e.g. Drago and Galo, 2018; Goergen et al., 2021). Figure 1 presents the evolution of multiple credit ratings over time and shows that on average banks purchase more credit ratings after the financial crisis, possibly due to regulatory certification which supports the selection of the sample period.

<Insert Table 1 & Figure 1 Here>

To construct our liquidity creation measures, we follow the method developed by Berger and Bouwman (2009). The Berger-Bouwman method consists of three steps. First, we classify all balance sheet items as liquid, semi-liquid or illiquid. Second, we assign to illiquid assets and liquid liabilities a weight of 0.5 and to liquid assets, illiquid liabilities and equity we assign a weight of -0.5. Any balance sheet items classified as semi-liquid receive a 0 weight and are not included in the calculation. In our two main liquidity creation measures (LC1 and LC2) we use long-term loans as illiquid loans, while we use two types of liquid deposits: short-term deposits (in LC1) and transactional and savings deposits (in LC2). Thus, in our baseline regressions, we use two liquidity creation measures which we normalize by total assets.[4]

3. Regression Framework

Because the number of ratings purchased by banks in our sample is largely time-invariant, the fixed-effects estimator might not serve the purpose of our investigation. Instead, looking into the between dimension is more appropriate and can capture the potential long-run effects of purchasing multiple credit ratings (e.g. Mergaerts and Vennet, 2016). We use the between- and random-[5] effects estimators[6] (henceforth BE and RE, respectively) that deal better with variables

[4] We assign a weight of 0.5 to long-term loans, fixed assets, intangible assets, other assets, short-term deposits (or transaction and savings deposits) and trading liabilities, while we assign a weight of -0.5 to cash, total securities, trading assets, subordinated debt, other liabilities and equity.

[5] Following the literature, we use the random effects maximum likelihood estimator (e.g. Wang et al., 2020).

[6] We are aware that the results of these specifications cannot imply causality and we are careful with our interpretation of the results.

that do not vary significantly over time. To further support the selection of these estimators, we conduct the Hausman test which suggests the use of random- over fixed-effects. We therefore construct the following econometric specifications:

$$\boldsymbol{BE}: \overline{Liquidity\ Creation}_i = \alpha_0 + \beta_1 \overline{MULT}_i + \sum_{j=1}^{7} \beta_j\ \overline{Bank\ Control}_i + \sum_{j=1}^{2} \beta_j\ \overline{Country\ Control}_c + \mu_c + \varepsilon_i \quad (1)$$

$$\boldsymbol{RE}: Liquidity\ Creation_{i,t} = \alpha_0 + \beta_1 MULT_{i,t-1} + + \sum_{j=1}^{7} \beta_j\ Bank\ Control_{i,t-1} + \sum_{j=1}^{2} \beta_j\ Country\ Control_{c,t-1} + \lambda_t + \mu_c + \varepsilon_{i,t} \quad (2)$$

where Liquidity Creation is one of our measures of liquidity creation and MULT is our multiple credit ratings variable, calculated as described in Section 2. We also include 7 bank-level and 2 country-level control variables that are commonly used in the liquidity creation literature (e.g. Berger and Bouwman, 2009; Distinguin et al., 2013; Fungacova et al., 2017). More specifically, we use the equity to assets ratio (EQRAT), loan loss reserves (LLR), return on average assets (ROAA), managerial quality[7] (MQ), natural logarithm of the ZSCORE[8] (LNZSCORE), bank size (SIZE), natural logarithm of the bank's age in years (AGE), real GDP growth (GDPG) and unemployment rate (UNEMP).[9] μ_c, λ_t and $\varepsilon_{i,t}$ are the country dummies, year dummies and error term respectively. The descriptive statistics of all variables used in our regressions are presented in Table 2.

<Insert Table 2 Here>

4. Results

Our baseline results are presented in Table 3. In Columns (1) to (4), we regress our liquidity creation measures (LC1 and LC2) on the multiple credit ratings variable (MULT) using the BE

[7] MQ is calculated as the ratio of operating expenses to operating income.
[8] ZSCORE is calculated as the sum of EQRAT and ROAA divided by the standard deviation of ROAA.
[9] GDPG and UNEMP refer to the home country of each bank.

and RE estimators. In Columns (5) to (8), we report the same regressions but add the bank- and country-level control variables. The results are consistent with our expectations. The coefficient of MULT is negative and highly significant at the 1% level in almost all regressions, indicating a strong negative relationship between multiple credit ratings and liquidity creation. As expected, in the BE results, purchasing an additional rating is associated with creating less liquidity by 4.2%, while in the RE results where one-year lags are used, the same figure is ranging between 0.7% and 1.6% depending on the liquidity creation measure. In both cases, the results are economically significant.

<Insert Table 3 Here>

5. Robustness Tests

We conduct five robustness tests. The results of these tests are presented in Tables 4 and 5. First, we use two alternative liquidity creation measures by replacing long-term loans with corporate loans[10] (Berger and Bouwman, 2009) (Table 4, Columns (1) and (2)). Second, we use an alternative multiple credit ratings variable by replacing MULT with MULT-D (Table 4, Columns (3) and (4)). MULT-D is a dummy variable that equals 0 if the bank has purchased one rating and equals 1 if the bank has purchased more ratings. Third, we remove from the sample the weaker banks that either have average problem loans higher than the 75th percentile[11] in our sample or have received a high-yield rating by at least one CRA (Table 4, Columns (5) and (6)). As Bongaerts et al. (2012) argue, if the regulatory certification role of CRAs holds, the weaker issuers

[10] Compared to LC1 and LC2, LC3 and LC4 use corporate loans instead of long-term loans to measure illiquid loans on the asset side of the balance sheet. On the liability side, short-term deposits are used in LC1 and LC3, while transactional and savings deposits are used in LC2 and LC4 as measures of liquid deposits. The sample banks included in these regressions are slightly different than that in the other regressions where LC1 and LC2 have been used as liquidity creation measures.

[11] The average problem loans variable is constructed as the bank-specific average of the best available in the following order: 1) Non-Performing Loans, 2) Gross Impaired Loans, 3) Net Impaired Loans, 4) Other Problem Loans (of unknown categorization), normalized by Net Total Loans.

will be in greater need of additional ratings. Overall, in the first three tests, our initial results presented in Table 3 are confirmed as the coefficients of MULT and MULT-D remain negative and highly significant at either the 1% or 5% level, except for the coefficient of MULT-D in Column (4) which is negative but not significant.

Fourth, we test for potential endogeneity between our multiple credit ratings variables and LC1 and LC2 using the Hausman-Taylor (HT) estimator (Hausman and Taylor, 1981). We chose the HT estimator because our MULT and MULT-D variables are largely time-invariant. HT uses instrumental variables under the assumption that some of the independent variables are correlated with the individual random effects but none of the independent variables are correlated with the error term.[12] Therefore, the estimator can handle possible endogeneity in our regressions by using a set of internally constructed instruments. We also report the Sargan-Hansen test of overidentifying restrictions to evaluate the validity of instruments used and the null hypothesis is not rejected in all regressions, suggesting that the excluded instruments are uncorrelated with the error term and thus rightly excluded from the estimations. For the purposes of the estimator, the MULT and MULT-D variables are transformed into completely time-invariant by calculating the bank-level average and along with the other bank-specific control variables are treated as endogenous. Following the liquidity creation literature, country-specific control variables (e.g. Distinguin et al., 2013), Age[13] (e.g. Fungacova et al., 2017) and the time dummies are treated as exogenous. The results presented in Columns (7) to (10) of Table 4 confirm our baseline findings.

<Insert Table 4 Here>

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[12] The HT has been previously used in many studies that faced similar problems with endogenous time-invariant explanatory variables (e.g. Tennant and Sutherland, 2014; Alraheb et al., 2019).

[13] As the estimator requires one exogenous time-invariant variable, Age is transformed into time-invariant by calculating the bank-level average.

Finally, although the three hypotheses (i.e. information production, rating shopping and regulatory certification) all indicate towards a negative relationship between multiple credit ratings and liquidity creation, they focus on different motives of purchasing multiple credit ratings. If banks are motivated for rating shopping to obtain their desired rating grade, they may reduce their liquidity creation as creating liquidity is associated with liquidity risk which is an important determinant of bank credit ratings. In such a scenario, banks with higher level of capital may be more confident about their risk bearing capacity and have less incentive to reduce their liquidity creation. Therefore, we introduce an interaction term between MULT and EQRAT to test the moderating role of bank capital in the relationship between multiple credit ratings and liquidity creation, and the results are presented in Table 5. We observe that the coefficient of MULT remains negative and highly significant in almost all the regressions, while the coefficient of the interaction term is positive and significant in six of the eight regressions. These findings show that bank capitalization can mitigate the negative relationship between multiple credit ratings and liquidity creation and provide some evidence on the rating shopping hypothesis as the potential explanation of this relationship. Previous studies have shown that banks with a stronger capital structure have higher levels of risk-bearing capacity, especially for large banks that are high liquidity creators (e.g. Berger and Bouwman, 2009). While banks contract their liquidity creation levels to improve their credit profile and obtain their favourable rating, reduced insolvency risk through holding more capital may make banks more confident about their perceived creditworthiness by CRAs and increase their capacity to create liquidity.

<Insert Table 5 Here>

6. Conclusions and Policy Implications

We examine the relationship between multiple credit ratings purchases by banks and liquidity creation. Consistent with our theoretical predictions, we show that they are negatively associated. This finding has important policy implications. Credit ratings are used in various ways by financial, legal and regulatory entities, and their institutional and regulatory importance motivates firms to purchase multiple credit ratings (Bongaerts et al., 2012). Although regulators have been aware of some potential adverse effects of reliance on credit ratings, such as distorting the information production and investment decision-making processes (Bongaerts et al., 2012), how rating shopping could affect the functions of banks has not been well explored. Our study reveals that multiple credit ratings purchases are likely to impede banks' capacity to create liquidity in the economy, indicating further the importance of reducing the reliance of regulations on credit ratings.

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Table 1
Number of banks per country

Country	N. of Banks	Country	N. of Banks
Italy	35	Australia	5
Russia	25	Bulgaria	5
China	22	Cyprus	4
United Kingdom	18	Slovakia	4
Spain	18	Belgium	4
Hong Kong	16	Czech Republic	4
Austria	15	Lithuania	4
France	14	Georgia	4
Germany	14	Kuwait	3
Brazil	14	Singapore	3
Turkey	14	Sweden	3
Poland	13	Belarus	3
Saudi Arabia	12	Colombia	3
Vietnam	12	Thailand	3
Malaysia	11	Mongolia	3
Netherlands	10	Azerbaijan	3
South Korea	10	Slovenia	2
Indonesia	10	Iceland	2
Portugal	9	Egypt	2
Nigeria	9	Morocco	2
Canada	8	Sri Lanka	2
Greece	8	Brunei	2
Ireland	7	Costa Rica	2
South Africa	7	Croatia	1
Chile	7	Bahrain	1
Romania	7	Malta	1
Kazakhstan	7	Hungary	1
Luxembourg	6	Ecuador	1
Denmark	6	Norway	1
Peru	6	Switzerland	1
Ukraine	6	Mexico	1
New Zealand	6	Jordan	1
Israel	5	Dominican Republic	1
Philippines	5	Venezuela	1
Panama	5	Latvia	1
Finland	5	Total	486

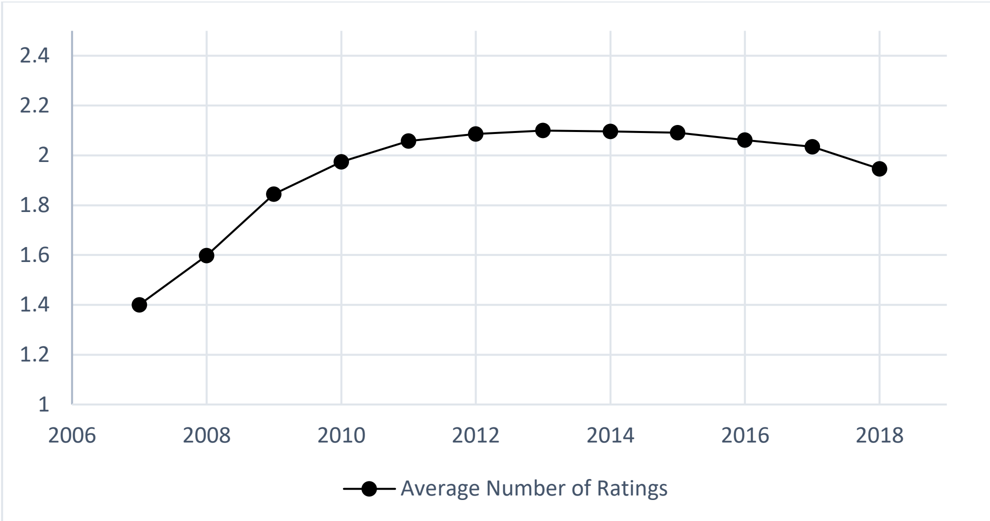

Fig. 1. Average number of ratings purchased by banks per year.
The figure presents the three-year moving average of the average number of ratings purchased by banks. Only banks with at least one rating available are included.

Table 2
Descriptive Statistics

	Obs.	Mean	Median	Std. Dev.	5th Perc.	95th Perc.
LC1	2,509	0.243	0.261	0.187	-0.109	0.505
LC2	2,509	0.133	0.128	0.173	-0.165	0.402
LC3	2,437	0.217	0.238	0.167	-0.113	0.450
LC4	2,437	0.098	0.107	0.138	-0.148	0.306
MULT	2,509	2.013	2.000	0.827	1.000	3.000
MULT-D	2,509	0.665	1.000	0.472	0.000	1.000
EQRAT	2,509	0.084	0.078	0.038	0.032	0.156
LLR	2,509	0.035	0.024	0.041	0.003	0.102
ROAA	2,509	0.008	0.008	0.012	-0.007	0.024
MQ	2,509	0.560	0.546	0.217	0.311	0.843
LNZSCORE	2,509	2.911	3.093	1.068	1.060	4.164
SIZE	2,509	2.297	2.000	0.750	1.000	3.000
AGE	2,509	3.867	3.951	1.072	2.197	5.252
GDPG	2,509	0.026	0.024	0.035	-0.037	0.079
UNEMP	2,509	0.075	0.065	0.045	0.031	0.172

This table presents the descriptive statistics of all variables used in the regressions. The values for all variables except for LC3 and LC4 are based on their common sample used in the between-effects regressions. The values for LC3 and LC4 are based on a slightly different common sample with the independent variables. LC1, LC2, LC3 and LC4 are the liquidity creation measures, MULT and MULT-D are the multiple credit ratings variables, EQRAT is the equity ratio, LLR is the ratio of total loan loss reserves to total loans and leases, ROAA is the return on average assets, MQ is the cost to income ratio, LNZSCORE is the natural logarithm of the ZSCORE, SIZE is the bank size class (1 = small, 2 = medium, 3 = large), AGE is the natural logarithm of the bank's age in years, GDPG is the real GDP growth and UNEMP is the unemployment rate.

Table 3
Between- and random-effects estimations for the relationship between multiple credit ratings and liquidity creation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LC1	LC2	LC1	LC2	LC1	LC2	LC1	LC2
MULT	-0.034***	-0.030***	-0.017***	-0.009**	-0.042***	-0.042***	-0.016***	-0.007**
	(0.012)	(0.011)	(0.004)	(0.003)	(0.014)	(0.014)	(0.004)	(0.003)
EQRAT					-0.230	-0.278	0.017	0.019
					(0.347)	(0.338)	(0.126)	(0.114)
LLR					0.143	-0.127	-0.557***	-0.528***
					(0.409)	(0.398)	(0.082)	(0.073)
ROAA					-0.445	-0.103	-0.869***	-0.780***
					(1.308)	(1.275)	(0.275)	(0.246)
MQ					0.023	0.012	-0.006	0.001
					(0.065)	(0.064)	(0.009)	(0.008)
LNZSCORE					0.014	0.012	0.018***	0.021***
					(0.010)	(0.010)	(0.007)	(0.006)
SIZE					0.015	0.022	-0.004	0.000
					(0.017)	(0.017)	(0.014)	(0.014)
AGE					0.009	0.009	0.002	0.005
					(0.008)	(0.008)	(0.007)	(0.006)
GDPG					-0.146	-0.123	0.487***	0.467***
					(0.623)	(0.607)	(0.075)	(0.066)
UNEMP					-1.055	-0.740	-0.053	-0.097
					(0.750)	(0.731)	(0.087)	(0.077)
CONSTANT	0.526***	0.358***	0.495***	0.313***	0.494***	0.324***	0.414***	0.197**
	(0.081)	(0.079)	(0.084)	(0.081)	(0.121)	(0.117)	(0.092)	(0.089)
Year Dummies	NO	NO	YES	YES	NO	NO	YES	YES
Country Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	2,509	2,509	2,066	2,066	2,509	2,509	2,066	2,066
N. of Banks	413	413	352	352	413	413	352	352
R2 Between	0.387	0.343			0.400	0.359		
Pseudo R2			0.055	0.058			0.082	0.091
Method	BE	BE	RE	RE	BE	BE	RE	RE

This table reports between- and random-effects estimator results. The sample ranges from 2005 to 2018. The dependent variable is liquidity creation denoted as LC1 or LC2. The main independent variable MULT stands for multiple credit ratings. EQRAT is the equity ratio, LLR is the ratio of total loan loss reserves to total loans and leases, ROAA is the return on average assets, MQ is the cost to income ratio, LNZSCORE is the natural logarithm of the ZSCORE, SIZE is the bank size class (1 = small, 2 = medium, 3 = large), AGE is the natural logarithm of the bank's age in years, GDPG is the real GDP growth and UNEMP is the unemployment rate. In the RE regressions, independent variables are used in their one-year lagged form. Standard errors are reported in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 4
Robustness Tests

	(1) LC3	(2) LC4	(3) LC1	(4) LC2	(5) LC1	(6) LC2	(7) LC1	(8) LC2	(9) LC1	(10) LC2
MULT	-0.011***	-0.006**			-0.025***	-0.013***	-0.112*	-0.140**		
	(0.004)	(0.003)			(0.005)	(0.004)	(0.066)	(0.067)		
MULT-D			-0.017***	-0.006					-0.201**	-0.274***
			(0.006)	(0.005)					(0.093)	(0.088)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country Dummies	YES	YES	YES	YES	YES	YES	NO	NO	NO	NO
Obs.	2,008	2,008	2,066	2,066	1,445	1,445	2,509	2,509	2,509	2,509
N. of Banks	335	335	352	352	245	245	413	413	413	413
Pseudo R2	0.093	0.071	0.080	0.090	0.105	0.104				
Sargan-Hansen P-Value							0.337	0.507	0.397	0.547
Method	RE	RE	RE	RE	RE	RE	HT	HT	HT	HT

This table reports random-effects and Hausman-Taylor estimator results. The sample ranges from 2005 to 2018. The dependent variable is liquidity creation denoted as LC1, LC2, LC3 or LC4. The main independent variables are MULT and MULT-D that stand for multiple credit ratings. The same control variables are used as in Table 3. In the RE regressions, independent variables are used in their one-year lagged form. In Columns (5) and (6), banks with more than 7.5% in average problem loans or rated as high-yield have been removed. Standard errors are reported in parentheses (robust standard errors clustered at the country level for the HT regressions). *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 5
The moderating role of bank capital in the relationship between multiple credit ratings and liquidity creation

	(1) LC1	(2) LC2	(3) LC1	(4) LC2	(5) LC3	(6) LC4	(7) LC3	(8) LC4
MULT	-0.103***	-0.088***	-0.017**	-0.020***	-0.058**	-0.052**	-0.010	-0.020***
	(0.031)	(0.030)	(0.007)	(0.006)	(0.028)	(0.025)	(0.007)	(0.006)
MULT*EQRAT	0.759**	0.557*	0.019	0.159**	0.544**	0.473*	-0.001	0.154**
	(0.333)	(0.325)	(0.074)	(0.065)	(0.273)	(0.250)	(0.073)	(0.061)
EQRAT	-1.416**	-1.149*	-0.015	-0.248	-1.164**	-0.945**	0.139	-0.177
	(0.624)	(0.610)	(0.176)	(0.158)	(0.496)	(0.454)	(0.171)	(0.145)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	NO	NO	YES	YES	NO	NO	YES	YES
Country Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	2,509	2,509	2,066	2,066	2,437	2,437	2,008	2,008
N. of Banks	413	413	352	352	402	402	335	335
R2 Between	0.409	0.365			0.499	0.417		
Pseudo R2			0.082	0.092			0.093	0.072
Method	BE	BE	RE	RE	BE	BE	RE	RE

This table reports between- and random-effects estimator results. The sample ranges from 2005 to 2018. The dependent variable is liquidity creation denoted as LC1 or LC2. The main independent variable MULT stands for multiple credit ratings. The same control variables are used as in Table 3. In the RE regressions, independent variables are used in their one-year lagged form. Standard errors are reported in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.