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Bank risk, business diversification, systemic designation and bank valuation

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Abstract

We study the relationship between bank value and bank risk (credit and liquidity risks), business diversification, and systemic designation using a multilevel econometric technique applied on a panel annual data comprising 576 commercial banks from 75 countries during the 2014–2019 period. This technique is employed to cope with inference issues because of nested data structure and to obtain generalizable insights from the heterogeneity pattern. We find that better credit and liquidity risk measures positively affect bank value. Nevertheless, both risk measures vary significantly from the second level (country) effect. Lastly, we find that systemic designation adversely affects bank value—a piece of evidence of possible weaning off "too big to fail" perception among investors.

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1. Introduction

Bank valuation is unique due to its business model, which deals with liquidity provision, information processing, and asset transformation (Greenbaum, Thakor and Boot, 2019). To asses this uniqueness, we employ three most common relative valuation measures: price to book, price to earnings and Tobin's Q. In this paper we investigate three most important drivers to bank valuation namely bank risk, business diversification and systemic designation. We focus on liquidity and credit risks as the two most prominent risks (Altunbas, Binici and Gambacorta, 2018). Banks create value by providing liquidity to their customer that should be balanced with its risk. The market reacts positively to better liquidity (Jones, Lee and Yeager, 2013 and Bogdanova, Fender and Takáts, 2018).

The impact of deteriorating credit risk measure is detrimental to bank value if perceived as a miscalculation by the bank (Calomiris and Nissim, 2014 and Niu, 2016). On the other hand, Elliot, Hanna and Shaw (1991) and Liu, Ryan and Wahlen (1997) argue that the positive relationship of credit risk measure with market valuation is caused by signaling i.e., anticipative credit risk management. Bushman and Williams (2012), Elnahass, Izzeldin and Abdelsalam (2014) and Guerry and Wallmeier (2017) provided empirical support for this notion.

Venturing into non-conventional business is beneficial for a bank from perspective of diversification (Freixas and Rochet, 2008, page 137) as empirically confirmed by Calomiris and Nissim (2014) and Fang et al. (2014). Nevertheless, in a condition of asymmetric information, bank expansion to non-traditional business could be perceived as risky. Huizinga and Laeven (2012) and Jones, Lee and Yeager (2013), Guerry and Wallmeier (2017), provide empirical support for this hypothesis.

Major regulatory reforms post the 2008 global crisis has launched policies aiming at reducing perception of "too big to fail" (also known as systemic institution) through instruments such as bail-in protocol, loss-absorbing equities, and living wills (Bongini, Nieri and Pelagatti, 2015). Systematic designation is given to a financial institution by supervisory authorities based on certain criteria such as size, interconnectedness, substitutability and complexity (see BCBS, 2011 for further details). Being designated as systemic could be very costly, and hence, value reducing. Studies by Bongini, Nieri and Pelagatti, (2015) and Bogdanova, Fender and Takáts (2018) supported this this notion.

Our main study main contribution is to obtain a widest possible generalizable empirical result. Therefore, we use an extensive coverage of cross-country data. A key challenge of this study is the bank's nested (multi-level) data structure. As emphasized by Rabe-Hesketh and Skrondal (2013), empirical design that ignore possible substantial variability of regressor by imposing non nested structure could yield biased inference because of incorrectly estimated variance. Analyzing the level structure of variability of regressors itself can decompose estimated relationship into the "core" and "variability" component. The ability to obtain the "core" relationship is critical and is directly correlated with the generalization principle of empirical science.

2. Material and Method

Our panel dataset comprises 576 commercial banks from 75 countries with annual data frequency from 2014–2019 (3,096 bank year observations). We obtain bank level financial information and G_SIFI designation from the Bank Focus database.

We use the following linear relationship as the baseline model:

$$MVAL_{ijt} = \alpha_0 + \alpha_1 LIQ\_RISK_{ijt} + \alpha_2 CRED\_RISK_{ijt} + \alpha_3 DIVER_{ijt} + \alpha_4 CAP_{ijt} + \alpha_5 ASSET_{ijt} + \alpha_6 PROFIT_{ijt} + \alpha_7 D\_GSIFI_{ijt} + \varepsilon_{ijt} \quad (1)$$

where

- Index i, j and t denote bank, country and time respectively
- $MVAL_{it}$ is the dependent variable, a measure of bank i valuation at time t. We use Tobin's Q (TOB) as the main proxy, calculated as the market value of equity divided by its asset book value. PB and PE are also used for robustness checks.
- LIQ_RISK_{it} is a measure of a bank's liquidity risk, calculated as liquid assets (sum of cash, central bank placement, and net interbank placement) at time t divided by total assets (LIQ) at time t.
- $CRED\_RISK_{it}$ is a measure of a bank's credit risk; we use the ratio of loan loss reserve to NPL (LLRNPL). As an alternative proxy, we employ the ratio of NPL to total equity (NPLTE).
- $DIVER_{it}$ is a measure of the extent of bank i business that has diversified from conventional (net interest margin based) practice and is proxied by the weighted average of non-interest share of revenue and off-balance sheet to total assets at time t. The weight is the inverse of the standard deviation of each variable. A higher value indicates that bank business has become more diversified.
- CAP_{it} is a measure of bank i capital buffer and is calculated as total equity divided by total assets at time t (EQTA).
- $ASSET_{it}$ is a proxy of bank i size (measured as log of total assets; AST_L at time t).
- $PROFIT_{it}$ is a measure of a bank i profitability. We use return on equity (ROE) calculated as net profit divided by total equity at time t.
- D_GSIFI_{it} is a dummy variable to indicate the G-SIFI designation of the bank (D_GSIFI=1 if the bank is G-SIFI and 0 otherwise). The designation is given by national banking authority.

In setting up multilevel regression specification, we follow Peugh's (2010) procedure. Here, we further decompose the residual term ε_{ijt} in equation 1 to control unobserved heterogeneity that arise from bank (first level; i), country (second level; j) and year (time series unit; t). We assume constant residual component for the first level, (fixed effect; indexed by *i* for a bank) and allow for random residual component for the second level (the country, indexed by *j*). That is the residual becomes

$$\varepsilon_{ijt} = u_i + v_j + w_{ijt} \quad (2)$$

Where u_i is residual component from bank (estimated by fixed effect method); v_j is residual component from country effect (estimated by random effect method) and w_{ijt} is left over (idiosyncratic) residual component that assumed to be pure independent and identically distributed.

Aligning with our research objective we allow for possible random variation in regression slopes only for the variable of interest: LIQ_RISK, CRED_RISK, and DIVER. That is estimated beta's (the slope of the variables of interest) are in the form of

$$\beta_{kj} = \widetilde{\beta_k} + \mu_j \quad (3)$$

Where $\widetilde{\beta_k}$ is the estimated slope of variable of interest k from first level (bank level fixed effect) and μ_{kj} is the standard deviation of the slope from second level (estimated from country level random effect). From equation 2 and 3, multilevel regression estimation yields not only the parameter of variables of interest but also its variation due to country level heterogeneity. Lastly, we control possible variation due to time (year effect =2014, …, 2019) using dummy variables.

The Likelihood Ratio (LR) test and intra-class correlation are used to verify whether the multilevel regression as a better specification compared to single level linear model. We also estimate Equation 1 using standard (single level) fixed effect, random effect and ordinary least squares for a robustness check. Standard error in all regression is estimated using country cluster method to mitigate heteroscedasticity.

4. Results and Discussions

From preliminary descriptive statistic and correlation analysis (table 1 and table 2), we could see that all variables are reasonably well behaved. We also don't observe data features that might adversely affect our empirical modeling.

Regression result is presented in Table 3. Better risk measures: higher liquidity and greater loan loss reserves are positively associated with higher valuation (Tobin's Q). The estimated coefficient of liquidity risk is aligned with results found by Jones, Lee and Yeager (2013) and Bogdanova, Fender and Takáts (2018). Our finding on credit risk coefficient is more consistent with studies from Bushman and Williams (2012), Elnahass, Izzeldin and Abdelsalam (2014), and Guerry and Wallmeier (2017) among others. Similar results are also obtained when we change the market valuation proxy with PB (model 2) and PE (model 3). However, the assertion of a better credit risk measure is positively associated with market valuation is not supported by the data when we use PB and PE as alternative proxies. The coefficient of BUS_DIV is not statistically significant across specifications, suggesting very low or no association of business diversification on market valuation in our cross-country study. As expected, the hypothesis of market valuation discount from G-SIFI designation is well supported by our empirical study.

Significant slope variation is present for LIQ and LLRNP. The standard deviation of LIQ slope is estimated to be 0.182 (in Tobin's Q regression), which is almost twice its mean estimate. Using PB and PE, we also obtain the ratio of standard deviation to mean (coefficient of variation-CV) in the range of 1.97–2.45. The CV of the slope is somewhat lower for LLRNPL (approximately 1.122) for Tobin's Q regression. When we replace the proxy with PB, the ratio increases to 4.363 and becomes insignificant in PE regression. Aligned with the mean estimate, the standard deviation of the BUS_DIV slope is not significant.

Significance result of LR test shows that multilevel specification is better than single level specification. Nevertheless, intraclass correlation indicates that multilevel specification is more appropriate for model 1 (TOB valuation proxy) and model 2 (PB valuation proxy) due to their considerable large value (>0.2). Model 3 (PE valuation proxy) perhaps is not much improved using multilevel specification due to low intra class correlation. We perform a robustness check through the sequential inclusion of variables of interest and replacing LLRNPL with NPLTE. The findings outlined before remain largely unaltered[1].

[1] To save space the result is not reported, but it is available upon request.

Table 1. Descriptive Statistics

	TOB	PB	PE	LIQ	LLRNPL	NPLTE	BUS_DIV	EQTA	AST_L	ROE
Mean	0.691	1.762	18.474	0.132	3.159	0.355	0.292	0.208	17.427	0.124
Median	0.123	0.998	11.502	0.105	0.836	0.152	0.255	0.113	17.613	0.118
Standard Dev.	14.369	14.551	41.174	0.116	52.921	0.929	0.186	0.263	4.157	0.283
Percentille 1	0.004	0.027	0.585	0.001	0.131	0.002	0.045	0.041	9.307	-0.329
Percentille 99	1.855	6.089	185.404	0.619	14.065	3.454	0.998	1.000	27.125	0.470
Min	0.000	-9.062	0.056	0.000	0.025	-0.009	0.012	-0.120	8.080	-3.159
Max	488.155	488.999	869.443	0.836	2210.769	32.088	2.163	1.000	27.979	12.728
Obs	3082	3082	2887	3096	2452	2470	2273	3096	3096	3096

Table 2. Correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) TOB	1.000									
(2) PB	0.418	1.000								
(3) PE	0.316	0.225	1.000							
(4) LIQ	-0.113	0.076	-0.032	1.000						
(5) LLRNPL	0.143	0.142	0.021	-0.112	1.000					
(6) NPLTE	-0.158	-0.151	-0.013	0.147	-0.205	1.000				
(7) BUS_DIV	0.036	0.030	-0.093	0.156	-0.057	-0.041	1.000			
(8) EQTA	0.781	-0.057	0.182	-0.192	-0.003	-0.116	0.032	1.000		
(9) AST_L	-0.466	0.020	-0.111	0.264	-0.170	-0.011	0.019	-0.578	1.000	
(10) ROE	-0.013	0.115	-0.221	0.042	0.023	-0.155	0.058	-0.082	0.073	1.000

Table 3. Regression Results

This table reports the baseline regression estimation results (coefficients, standard error and significance level) with the dependent variable of TOB (model 1), PB (Model 2) and PE (model 3) using Multilevel Econometric Model. Standard errors are calculated using heteroscedasticity robust cluster standard error. Model 4, 5 and 6 present regression with dependent variable TOB estimated using FE, RE and OLS respectively. Significance level denotes by ***, **, and * for 1%, 5%, and 10% respectively.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LIQ	0.091**	0.808**	25.060**	0.085	0.045	0.007
	(0.046)	(0.397)	(10.220)	(0.069)	(0.051)	(0.045)
LLRNPL	0.013***	0.104	0.031	0.002	0.004**	0.011***
	(0.005)	(0.078)	(0.255)	(0.002)	(0.002)	(0.002)
BUS_DIV	-0.002	0.036	-6.554	0.002	-0.013	-0.013
	(0.014)	(0.219)	(4.169)	(0.016)	(0.015)	(0.011)
EQTA	0.785***	-1.643***	41.48***	0.848**	0.752***	0.890***
	(0.048)	(0.324)	(10.500)	(0.372)	(0.239)	(0.144)
AST_L	0.001	0.031***	-0.649***	-0.011	0.002	0.003***
	(0.001)	(0.009)	(0.241)	(0.013)	(0.002)	(0.001)
ROE	0.131***	1.371***	-91.991***	-0.037	0.011	0.174***
	(0.018)	(0.115)	(5.675)	(0.045)	(0.050)	(0.049)
D_GSIFI	-0.042***	-0.477***	-1.875		-0.047***	-0.032***
	(0.012)	(0.079)	(2.553)		(0.011)	(0.008)
Constant	0.014	0.820***	36.27***	0.228	0.044	-0.026
	(0.025)	(0.196)	(5.135)	(0.245)	(0.048)	(0.028)
sd(LIQ)	0.182	1.987	49.400			
sd(LLRNPL)	0.014	0.454	0.000			
sd(BUS_DIV)	0.000	1.013	10.633			
sd(_cons)	0.053	0.567	5.013			
Year Fixed Effect	Yes	Yes	Yes	No	No	No
Bank Fixed Effect	Yes	Yes	Yes	Yes	No	No
Observations	2134	2134	2011	2134	2134	2134
R-squared				0.050	0.217	0.259
Chi Square	448.600***	272.990***	331.130***			
Wald Test				9.680***		
Breusch Pagan					1085.480***	
Hausman					69.340***	
LR Test	467.290***	845.030***	218.950***			
Intra-Class Correlation	0.283	0.543	0.078			

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

5. Conclusion

This research has fairly met its objective. We found the risk measures to be fairly good explanatory variables for bank valuation as a "core relationship". The spatial (country level) effect on the slope is significant for liquidity and credit risk measures. On the other hand, diversification is not statistically significant in influencing market valuation. Strong empirical support was also found for the existence of valuation discounts because of the G-SIFI designation.

Our study has several profound policy implications. First, banks must seriously handle its risk management. Second, there is evidence of the weaning off "too big to fail" perception among investors that should be a welcome development for banking regulation. Third, communication and coordination among country regulators should be intensified, at least for G-SIFI banks to avoid regulatory arbitrage.

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