Does diversification affect the quality of loan portfolio?Panel Granger-causality evidence from US banks

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Abstract:

This paper investigates the direction of causality between bank business model and the quality of loan portfolio using a large sample of US banks. We employ the panel causality testing approach, developed by Dumitrescu and Hurlin (2012), and new technique of optimal lag selection of Hans et al (2017). Empirical results show that there is evidence of two-way causality between diversification and non-performing loans.

Keywords: Bank diversification, Non-performing loan, Panel Granger-causality

JEL Classification Codes : G21, G28, G34, G38

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1. Introduction

Bank plays an important role in the economy when serving as a channel through which disruption in its smooth functioning may lead to negative impacts on the real economy (Tran et al. (2019)). In the aftermath of the global financial crisis (GFC) with the failure of a large number of banks around the world and the consequent economic recession in many countries, many criticized the dark side of functional diversification. Banking deregulation since early 1970s that enables the *casino-style gambling* on Wall Street, allowing banks to move toward highly volatile and complex non-traditional banking activities. Regulators since then are moving toward structural changes in banking regulation, including the scope of bank business model (Gambacorta and van Rixtel (2013)). This demonstrates these non-traditional banking activities lead to higher riskiness in banks. In line with this view, these financial institutions need to turn back to their traditional activities.

However, whether from the theoretical or empirical perspectives, the question on the effects of diversification on the quality of bank loan portfolio remain a conflicting debate among scholars. On the one hand, under the perspective of the modern portfolio theory (Markowitz (1952)), an incorporation of different activities will reduce the total risk of bank, thanks to the generated co-insurance effect (Brewer (1989), DeYoung and Roland (2001), Gandhi, Kiefer, and Plazzi (2016)). As bank reduce the share of interest incomes over the net operating incomes, banks earn more non-interest incomes and at the same time experience less interest risk and credit risk. Furthermore, Diamond (1984) shows that in the absence of conflicts between borrowers and banks, banks that engage in different activities may improve the credibility in their loan-making decisions and in their borrowers' monitoring by overcoming information asymmetry between depositors and borrowers (Tran et al. (2019)). Different studies support this argument such as Eisenbeis and Kwast (1991), Boyd, Chang, and Smith (1998), DeYoung and Torna (2013) for US banks sample or Elsas, Hackethal, and Holzhäuser (2010), Sanya and Wolfe (2011) with an international sample.

One the other hand, some may argue that by moving toward non-traditional banking activities, banks may experience a decrease of the quality of their loan portfolio. Diversification may lead to an intensified agency problem due to the increased size and consequently bank opaqueness, leading to discretionary decisions to undertake value-decreasing investments (Berger and Ofek, 1995). Stiroh (2004) and Stiroh and Rumble (2006) find banks may benefit from diversification gains, but these gains are quickly offset by increased exposure to non-interest activities. De Jonghe (2010) documents the increased tail beta of diversified European banks, particularly during times of turmoil. Recently, Tran et al. (2019) provide an update assessment of the effects of diversification on the non-performing loans of banks, and show that the loan portfolio quality of banks decreases with the moving toward non-traditional banking activities, and these findings are partially explained by the agency problems.

Although there exist a large literature examining the effects of bank business model to bank risk, to the best of our limited knowledge, most studies only focus on a unidirectional causality running from the diversification to bank risk. However, some may argue that high risk appetite banks may choose to engage into non-traditional banking activities which are considered riskier, leading to self-selection bias (Tran et al. (2019)). Surprisingly, this causal direction is usually ignored in earlier studies. Our study aims to fulfill this gap, by providing an investigation on the possibility of a two-way causality between bank business model and the quality of loan portfolio. Earlier works usually impose various assumptions during the estimation process such as slope homogeneity or cross-sectional independence, and do not deal with causality in a systematic fashion, which may lead to incorrect causal inferences (Bai and Kao (2006)), and consequently conflicting research results depending on the time periods and sample selection. Some studies employ GMM method to control for the problem of endogeneity arising from the dependent and independent variables, however, GMM method is still under the assumption of slope homogeneity.

To circumvent this challenge, we use Granger causality techniques on panel data. The standard causality test defined by Granger (1969) widely applied in the empirical literature of financial development. Due to the characteristic of our panel data, we use more specifically the Granger non-causality test for panel data models extended by Dumitrescu and Hurlin (2012). This method requires stationary data and can be used in case of cross-sectional dependency. Moreover, we apply to new technique of optimal lag selection extended by Han et al (2017) for robustness result.

Following prior literature (Zhang et al. (2016), Louzis, Vouldis, and Metaxas (2012), Stiroh and Rumble (2006), Tran et al. (2019), Tran, Hassan, and Houston (2019)), we measure banks' diversification using the ratio of non-interest incomes over net operating incomes (NIII) and use the ratio of non-performing loans (NPL) as a proxy of the quality of bank' loan portfolio. We document that there is evidence of diversification Granger-causing non-performing loans, and also evidence of non-performing loans Granger-causing diversification.

Our study contributes to the existing literature in different ways. First, unlike previous studies, we employ a novel technique - the Granger causality techniques on panel data. This approach is novel to the banking literature, and has advantages to compare with techniques usually employed in prior literature. Since it does not assume the homogeneity of the panel data which is difficult to satisfy in a panel data, the test for Granger-causality can be performed on each individual panel member separately. However, since contemporaneous correlation is allowed across banks, this approach makes possible to exploit the extra information provided by the panel data setting. To the best of our limited knowledge, there is no attempt to incorporate the hypothesis of cross-sectional dependence in the literature on the diversification and bank risk profile. In this study, we also choose the optimal lag for dynamic panel data developed by Han et al (2017). This methodology corrects the sensitive result of Dumitrescu and Hurlin (2012) with the different lag chosen. Second, we demonstrate there are two-way causality between bank business model and the quality of loan portfolio. Finally, to correct the potential endogeneity concern, we investigate the dynamic OLS (DOLS) developed by Kao and Chang (2000), the estimation confirms our hypothesis.

The remainder of the paper is organized as follows. Section 2 provides the technical issues related to the Granger non-causality on panel data methodology. Section 3 provides empirical results. Section 4 concludes our study.

2. Data, variables, and methodology

To shed light our research question, we use a large sample of US bank holding companies (BHCs) with assets from $150 million and over. The data range covers the period of 2003:Q2 to 2013:Q4. All banks with incomplete or missing (quarter) data are excluded. We also exclude all banks with negative or nonexistent outstanding loans or deposits. To reduce the effects of outliners, we winsorized all variables at 1% level on their distribution's top and bottom.

Our variables of interest are the diversification which is measured by the ratio of non-interest incomes over net operating incomes (NII) (Stiroh and Rumble (2006), Tran et al. (2019), Tran, Hassan, and Houston (2019)) and the quality of bank's loan portfolio as measured by the ratio of non-performing loans (NPL) (Zhang et al. (2016), Louzis, Vouldis, and Metaxas (2012), Tran, Hassan, and Houston (2019)).

The test of Granger non-causality of Dumitrescu and Hurlin (2012) requires on heterogeneous panel data with fixed effects and stationary variables. Moreover, they extend the standard causality test in the panel data that allow for the presence of cross-sectional dependence. The Granger non-causality relationship between the diversification and non-performing loan is estimated as follow:

$$NPLR_{it} = \alpha_{i1} + \sum_{k=1}^{K} \beta_{i1}^{(k)} NPLR_{i,t-k} + \sum_{k=1}^{K} \gamma_{i1}^{(k)} NONR_{i,t-k} + \varepsilon_{it} \quad (1)$$

$$NONR_{it} = \alpha_{i1} + \sum_{k=1}^{K} \beta_{i1}^{(k)} NONR_{i,t-k} + \sum_{k=1}^{K} \gamma_{i1}^{(k)} NPLR_{i,t-k} + \varepsilon_{it}$$

where NPLis non-performing loan ratio; NII is non-interest income over the net operating income. α_{i1} is individual effects. i = 1,...,N and t = 1,...,T is cross-section unit and time period of the panel data. K is the lag order identical for all cross-section units of the panel.

Dumitrescu and Hurlin (2012) propose to test the homogeneous non-causality (HNC) hypothesis that is the homogeneous non causality hypothesis from x to y. A rejection of the null hypothesis, indicating that there is a causality relationship from *x* to *y* for at least one cross-section unit. The HNC Wald statistic associated with this test is computed by the average of individual Wald statistic:

$$NW_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T} \tag{2}$$

Then, Z_{HNC} and $\tilde{Z}_{HNC}$ statistics are calculated to test the HNC test. The Z_{HNC} is used for large N and T samples, $Z_{HNC} = \sqrt{\frac{N}{2K}} * \left(W_{N,T}^{HNC} - K\right)$; whereas the approximated value $\tilde{Z}_{HNC}$ is applied for finite T samples, $\tilde{Z}_{HNC} = \sqrt{\frac{N}{2K}\frac{T-2K-5}{T-K-3}} * \frac{T-2K-3}{T-2K-1} * (W_{N,T}^{HNC} - K)$

However, Dumitrescu and Hurlin (2012) did not present the methodology finding optimal lag in the HNC estimation. Hence, it leads the sensitive result with lag selection. Generally, the best model is chosen by minimizing of Akaike information or Bayesian information criteria (BIC). However, Stone (1979) proved the inconsistent of BIC due to the presence of incidental parameter whereas Moon et al. (2007) demonstrated that these criteria information are inconsistent in dynamic panel models. Han et al. (2017) proposed new information criteria to choose optimal lag in dynamic panel which is called the Modify Bayesian information criteria (MBIC).[2] Therefore, we apply the latter extension in this study.

The MBIC is computed based on an autoregressive model *AR(k)*:

$$y_{it} = \sum_{s=1}^{K} \rho_s y_{i,t-s} + \varepsilon_{it} \tag{3}$$

[2] Refer to Tran, Phi, and Diaw (2017) for more details.

$$MBIC(K) = \ln(\hat{\sigma}_k) + K\frac{\ln(\sqrt{N}(N-K))}{\sqrt{N}(N-K)} \tag{4}$$

where

$$\hat{\sigma}_k^2 = \frac{1}{N(t-K)}\sum_{i=1}^{N}\sum_{t=k+1}^{T}\hat{\sigma}_{k,it}^2 \tag{5}$$

$\hat{\sigma}_{k,it}^2 = y_{it} - \hat{\beta}_k X'_{k,it}; X_{k,it} = (y_{it-1}, \dots, y_{it-k}); \beta_k = (\rho_1, \dots, \rho_k)'$

For robustness and control for the problem of endogeneity, we estimate the long run relationship between NPL and NII by Dynamic OLS (DOLS) regression thanks to its outperforming over other models.[3] DOLS is relevant to OLS and FMOLS because it allows us to correct the standard pooled OLS for serial correlation and potential endogeneity.

The DOLS estimator requires the lead and lag in order to obtain unbiased results (Kao and Chang, 2000), and following fixed effect panel regression in general:

$$y_{it} = \alpha_i + \beta x_{it} + u_{it}$$

where y_{it} is a matrix 1x1, β is a kx1 vector of the slope parameters, α_i is the fixed effects, and u_{it} are disturbance terms. x_{it} is assumed to be a matrix kx1 integrated processes of order one for all i, where:

$$x_{it} = x_{it-1} + \varepsilon_{\ it}$$

Then, the DOLS estimator will take the following form:

$$y_{it} = \alpha_i + \beta x_{it} + \sum \gamma_{ij}\,\Delta\, x_{it+j}\ + u_{it}$$

where γ_{it} is the coefficient of lead and lag. In this paper, we use Akaike information criterion for determining the optimal lead and lag. And in our estimation, *x, y* are represented by NII and NPL respectively.

[3] Some estimation for panel long-run relationship such as dynamic fixed effect (DFE), mean group (MG) and pooled mean group (PMG) proposed by Pesaran and Smith (1995) and Pesaran et al. (1999), fully modified OLS (FMOLS) or DOLS

3.Empirical Results

3.1 Preliminary tests

In this section, we verify some preliminary tests including the homogeneity panel data, the presence of cross-sectional dependence, panel unit root. After having validation of these tests, we will find the optimal lag by using MBIC, then we will test the HNC non-causality relationship of banking business model and quality of loan portfolio.

First, we apply Hsiao (2003) approach to perform the heterogeneous test for panel data. The null hypothesis is homogeneity panel data against the alternative hypothesis of heterogeneous panel data. Recall that a homogeneous panel data model is a model in which all parameters including constant and slope coefficients are common. Hence, there are three cases for testing homogeneity panel data such as slopes and intercepts simultaneously homogeneous, slopes are the same, and intercepts are the same. The results are shown in the Table 1, indicating that we reject the null hypothesis of homogeneity panel data the panel data at the 1% level for the three cases. These results confirm our panel data is heterogeneity significantly at the 1% level.

Second, we verify the presence of cross-sectional dependence in our panel data by applying Pesaran's CD test (Pesaran, 2004). The null hypothesis is no cross-sectional dependence. The results in Table 2 show that we reject the null hypothesis of no-cross sectional dependence, confirming that the presence of cross-sectional dependence of the panel data

Third, we perform a series panel unit root tests introduced by LLC, IPS and ADF.[4] The null hypothesis is that the series contains a unit root. The panel unit root tests are shown in Table 3 for both variables in level. Both variables are stationary at the 1% level.

3.2 Main results

In this section, we provide the optimal lag for each regression, then we perform the HNC non-causality tests between banking business model and quality of loan portfolio in aggregated level, and in cross-section.

In order to find the optimal lag, we choose four lags as the lag maximum due to the suggestion of Dumitrescu and Hurlin (2012) who demonstrate that the lag order K must satisfy the condition of the size T-K must be larger than $5 + 2*K$. We compute MBIC for each lag, and the minimum MBIC corresponds the optimal lag. Results in Table 4 suggest that one lag is the optimal lag selection for two-way causality.

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[4] LLC, IPS and ADF tests represent by panel unit root test of Levin, Lin and Chu; Im, Pesaran and Shin; Maddala and Wu

Thanks to presence of cross-sectional dependence, we apply the bootstrap simulation with 1000 replication to create the criteria values of Z_{HNC}, $\tilde{Z}_{HNC}$ and P-value for HNC test. The HNC non-causality relationship results are reported in Table 5. The results show that the banking business model (NII) and the quality of loan portfolio (NPLR) do Granger-cause in two way for at least one cross-section unit (bank). Therefore, we continue to investigate the causality relationship in each cross-section unit, and present in Table 6. We document that there is also two-way causality for 29 banks. This result confirms at least the causality in cross-section. However, different from these 29 banks, there are also some banks that exits the one-way causality between NII and NPL.

For the control the endogeneity, our estimation using DOLS are performed in Table 8. Before regression, we verify the existence of cointegration by using Westerlund test that take into account the presence of cross-section dependence. The null hypothesis of no cointegration. The results of Westerlund tests are shown in Table 7. It shows that 3/4 tests reject the null hypothesis of no cointegration. Thus, there is cointegration between NPL and NII, suggesting that we can estimate for the long run estimation of between NPL and NII.

Table 8 presents that the coefficients of NII and NPL are negative and significantly at the 5% level. This point suggests that there is evidence of diversification Granger-causing the decreased quality of loan portfolio on the one hand, and on the other hand, evidence of non-performing loans Granger-causing diversification.

4.Conclusion

The question on the relationship between bank business model and their loan portfolio quality has long remained an important issue of debate in the banking literature, especially after the global financial crisis where many blame the casino-style gambling of Wall Street. We examine the direction of causality among these variables in question for a long period from 2003 to 2013 for a large sample of US banks. Our novel point is to employ the recently proposed panel causality testing approach which takes into account cross-sectional dependence across banks. The method used in this study is the recently proposed panel causality testing approach which takes into account cross-sectional dependence across banks. The empirical findings suggest the two-way direction of causality between diversification and non-performing loans.

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Table 1: Homogeneity panel data

Null hypothesis:	F-statistic
Slopes and intercepts simultaneously homogeneous	8.950***
Slopes are the same	3.336***
Intercepts are the same	18.164***

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 2: Cross sectional independence

Pesaran's test of cross sectional independence	**Pesaran's statistic**
NPL NII	840.114***[0.0000]

Notes: P-value is in brackets, ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 3: Panel unit root

Test	NPL	NII
Levin, Lin & Chu t*	-7.66189***	-44.6275***
Im, Pesaran and Shin W-stat	-6.28489***	-50.6070***
ADF - Fisher Chi-square (Maddala &Wu (1999)	1032.55***	4569.09***

Notes: optimal lag is chosen by Schwarz information criterion ; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 4: Optimal lag based on Hans et al. (2017)

Lag	NII → NPLR	NPL → NII
1	-3.866	7.339
2	-3.847	7.370
3	-3.823	7.401
4	-3.801	7.434

Notes: Bold means the optimal lag corresponding the minimum of MBIC

Table 5: Granger non-causality test for panel data

Null hypothesis of HNC hypothesis	Wald statistics W_HNC	Z_{HNC}	$\tilde{Z}_{HNC}$
NII does not Granger-cause NPL	1.8809***[0.002]	12.348	10.552
NPL does not Granger-cause NII	2.7235***[0.000]	24.159	21.307

Notes: We use 1000 bootstrap replications. P-value computed using 1000 bootstrap replications in brackets. For the null hypothesis of NII does not Granger-cause NPLR, 95% critical value of Z_{HNC} and $\tilde{Z}_{HNC}$ are 7.6967 and 6.3179 respectively; and for the null hypothesis of NPL does not Granger-cause NII, 95% critical value of Z_{HNC} and $\tilde{Z}_{HNC}$ are 8.4798 and 7.0309. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 6: Granger-causality in each cross-section unit (bank)

No.	id	NII → NPL Wald statistic	NPL → NII Wald statistic	No.	id	NII → NPL Wald statistic	NPL → NII Wald statistic
1	1020180	0.0702	1.897	41	1064728	3.8062*	4.8585**
2	1021682	0.0686	2.2958	42	1066209	8.2881***	7.5990***
3	1023239	0.1222	0.3643	43	1066414	0.5996	0.0001
4	1025309	0.6887	5.2988**	44	1066713	1.3292	3.0395*
5	1025541	4.5890**	0.0471	45	1068025	0.0441	0.1143
6	1026801	1.1782	4.0425**	46	1068191	0.1471	0.1226
7	1027004	5.7078**	0.3496	47	1069778	5.2476**	6.3293**
8	1027518	6.1251**	0.6431	48	1070345	5.3577**	0.0222
9	1028533	0.5767	2.0532	49	1070448	0.8887	0.0209
10	1029334	0.637	0.0404	50	1070569	0.0047	1.0955
11	1029464	0.4638	1.5222	51	1070756	0.0597	1.1762
12	1030170	5.8986**	12.6735***	52	1070765	0.0939	5.7757**
13	1030947	2.6961	0.4597	53	1070831	0.7815	0.8109
14	1031449	1.5114	0.8004	54	1071191	0.1909	7.8575***
15	1037003	0.2423	3.2880*	55	1071276	4.5532**	2.8493*
16	1039502	5.6777**	1.7987	56	1071397	2.551	4.6481**
17	1048812	1.7243	2.6487	57	1071454	1.6405	0.4881
18	1048894	4.5936**	0.0591	58	1073757	0.522	0.3906
19	1049341	6.5453**	0.5815	59	1074156	19.1133***	8.5898***
20	1050646	0.7314	2.8049*	60	1075612	1.0708	20.0880***
21	1050712	0.1093	3.6702*	61	1075694	0.6454	17.4596***
22	1050909	2.3504	0.0775	62	1076002	3.2131*	2.3587
23	1051465	0.7008	0.5052	63	1076262	0.1026	0.0463
24	1051979	3.7679*	1.8542	64	1076431	6.5710**	1.5623
25	1052220	4.3422**	0.0161	65	1076600	1.8505	6.3180**
26	1053272	0.1235	0.1479	66	1076619	0.0074	3.8491**
27	1053496	0.3943	4.4482**	67	1076673	0.1421	4.3485**
28	1053580	3.1711*	7.6192***	68	1079562	0.8647	14.9966***
29	1054091	0.0709	3.5468*	69	1080139	7.1939***	0.2448

30	1054514	1.8157	0.178	70	1081239	0.3414	1.8745
31	1055007	1.1518	1.7212	71	1081314	2.3313	0.3628
32	1055155	0.0127	2.3403	72	1081538	1.9244	0.1736
33	1056161	0.4289	0.165	73	1081613	0.0355	1.3102
34	1057588	1.0456	0.1361	74	1082067	6.8403***	5.8887**
35	1060627	0.0008	7.9542***	75	1082777	1.4866	1.0889
36	1061679	2.3094	7.0495***	76	1083475	4.5174**	1.3812
37	1062621	0.0046	5.8056**	77	1083783	0.8368	1.934
38	1063552	0.0021	0.0906	78	1085170	7.5883***	8.7049***
39	1064429	0.0459	0.0039	79	1085255	0.0022	0.1863
40	1064652	2.1432	4.3320**	80	1085509	0.8018	1.0987

No.	id	NII → NPL Wald statistic	NPL → NII Wald statistic	No.	id	NII → NPL Wald statistic	NPL → NII Wald statistic
81	1085572	0.176	0.085	121	1109599	0.4011	0.1535
82	1086168	1.4632	2.0282	122	1109991	0.1752	15.7886***
83	1086270	2.4351	1.9719	123	1115349	0.2171	0.1515
84	1086533	0.0764	8.0990***	124	1115385	0.5359	10.9615***
85	1086654	2.4092	1.5377	125	1117026	4.6931**	5.9940**
86	1086748	3.0866*	2.1286	126	1117213	5.7657**	3.9382**
87	1090987	0.0081	0.0001	127	1117316	1.2677	0.2871
88	1094314	0.767	0.5938	128	1117464	0.1768	1.0596
89	1094640	0.0018	1.4594	129	1117491	3.0378*	0.0397
90	1094828	2.7247*	6.1355**	130	1118238	6.0340**	2.5644
91	1095254	0.964	1.6889	131	1118265	0.0444	2.0521
92	1095674	1.0525	14.2981***	132	1118340	0.0847	0.0799
93	1096505	1.4237	0.1866	133	1118368	2.7535*	1.9372
94	1097025	0.4018	1.4572	134	1118434	7.6901***	0.7661
95	1097089	0.2211	2.6542	135	1118797	1.2469	3.1361*
96	1097173	5.7817**	7.5430***	136	1118854	0.0355	0.2816
97	1097182	0.9929	0.0329	137	1119383	15.1920***	1.2977
98	1097306	0.0009	6.1496**	138	1119404	0.0005	1.9172
99	1097566	0.3556	2.7402*	139	1119495	0.5579	4.2101**
100	1097771	0.0139	0.0336	140	1119794	3.1019*	0.3715
101	1098303	0.2759	5.6216**	141	1120754	1.8255	6.0560**
102	1098620	0.0371	1.6958	142	1121229	3.9131**	0.791
103	1098732	0.3941	3.5576*	143	1123193	0.079	2.5929
104	1098796	0.21	1.7675	144	1123915	3.9495**	0.2211
105	1099382	0.0122	0.0499	145	1123933	1.0907	0.1952
106	1099917	6.2231**	1.8671	146	1124060	0.032	0.2191
107	1100813	1.3534	0.0018	147	1125843	6.8641***	0.2075
108	1102312	3.4289*	8.3907***	148	1126354	6.4559**	2.3615
109	1102367	0.0408	0.0887	149	1127146	0.3105	4.0005**
110	1102581	1.9275	0.8221	150	1128358	0.9018	5.3534**

111	1103766	2.2158	9.4637***	151	1128769	0.0059	0.2737
112	1103878	0.0636	3.1498*	152	1129533	1.1614	0.2381
113	1104923	0.0016	0.2902	153	1130098	1.1641	1.9835
114	1107522	0.9573	0.4804	154	1130584	5.5788**	0.9735
115	1108163	0.2705	9.0649***	155	1130931	3.9438**	0.028
116	1108350	1.5829	0.0744	156	1131077	0.0031	0.0052
117	1108707	0.1299	4.7179**	157	1131750	0.0119	3.3419*
118	1109094	0.0009	0.0158	158	1131787	0.4404	0.8015
119	1109290	0.6512	2.9021*	159	1132104	1.858	0.7528
120	1109496	0.155	0.0063	160	1132672	2.8993*	0.7812

No.	id	NII → NPL Wald statistic	NPL → NII Wald statistic	No.	id	NII → NPL Wald statistic	NPL → NII Wald statistic
161	1133174	0.3044	0.1843	201	1200692	0.2755	2.0849
162	1133503	1.086	1.4019	202	1201112	6.0039**	0.3086
163	1133781	0.5785	1.1216	203	1201457	2.2603	0.3778
164	1133932	0.0529	2.4389	204	1201925	11.5039***	0.1353
165	1134498	1.6992	1.001	205	1201934	1.2651	1.6197
166	1134630	0.8354	1.772	206	1202052	2.7270*	4.8651**
167	1134694	0.0019	1.7298	207	1202258	0.0935	1.8754
168	1135002	0.9198	5.3925**	208	1202762	0.6429	0.6957
169	1135048	0.112	0.1938	209	1203509	1.1856	1.1912
170	1135374	0.7074	0.1592	210	1203714	0.0855	15.268***
171	1135404	0.1433	4.5757**	211	1203778	0.1019	0.686
172	1135516	3.4352*	3.9866**	212	1203974	0.5896	1.7916
173	1135824	1.7648	0.0848	213	1204177	0.0403	2.5621
174	1136009	3.2944*	3.8051*	214	1204560	0.1675	3.6562*
175	1136803	2.5692	14.5159***	215	1204627	0.0222	5.4201**
176	1137453	0.2632	2.5982	216	1204814	0.4576	2.6292
177	1137770	1.4074	2.4251	217	1205026	1.8553	2.7378
178	1138450	0.0017	2.9376*	218	1205183	9.9205***	6.1244**
179	1138919	4.1044**	2.6785	219	1206546	6.9833***	0.7746
180	1139242	0.6442	0.5224	220	1206591	0.6197	0.4274
181	1139363	0.0001	9.4238***	221	1206760	0.1854	2.2733
182	1139532	0.3215	0.5023	222	1206911	0.0001	1.0502
183	1139925	0.0031	4.1124**	223	1207132	0.6573	3.0961*
184	1140127	0.7603	5.9200**	224	1207431	0.1961	3.6927*
185	1140239	0.9758	0.0475	225	1208009	0.4004	1.1147
186	1140323	0.0107	0.0018	226	1208120	0.3305	0.962
187	1140994	0.8031	0.4835	227	1208184	1.753	0.0124
188	1141348	1.1895	6.8424***	228	1208513	0.3316	0.0456
189	1141487	0.0434	0.5697	229	1208531	0.1451	0.2319
190	1141647	0.0213	0.7526	230	1208559	11.6909***	3.2221*
191	1142242	7.9211***	26.9073***	231	1208595	0.0091	3.0560*
192	1142336	0.9779	0.4196	232	1209042	0.8262	1.8802
193	1142475	0.0008	1.1017	233	1209109	3.8148*	0.8857

194	1143623	2.8869*	0.0044	234	1209145	6.6399**	1.4484
195	1199611	1.2215	0.1699	235	1209181	2.9729*	2.4361
196	1199844	1.0294	0.2666	236	1209248	0.482	1.2851
197	1199974	0.005	1.6851	237	1209426	0.1405	0.1366
198	1200124	1.0991	3.5847*	238	1210066	0.515	9.3365***
199	1200311	0.3011	0.2568	239	1210589	0.8315	4.2781**
200	1200348	0.1634	0.9128	240	1245228	0.1853	4.7164**

No.	id	NII → NPL Wald statistic	NPL → NII Wald statistic	No.	id	NII → NPL Wald statistic	NPL → NII Wald statistic
241	1245291	2.0766	0.0015	281	1842421	13.0770***	0.7652
242	1245385	0.2453	8.6369***	282	1843080	0.4752	16.3388***
243	1245705	4.8023**	4.1900**	283	1848003	0.0922	4.5133**
244	1246252	3.14	4.0813**	284	1860863	0.1309	1.0791
245	1246467	0.1062	0.0066	285	1862036	1.0069	2.8938*
246	1246533	3.6817*	0.1719	286	1883693	4.6870**	0.0311
247	1247428	3.0633*	0.0143	287	1885307	4.1840**	7.4272***
248	1247576	0.3316	0.8278	288	1917600	0.7013	0.536
249	1247679	3.1149*	3.9484**	289	1947045	0.0342	1.0261
250	1247987	4.1150**	0.0057	290	1951350	7.2644***	0.7696
251	1248032	0.6429	0.0301	291	1951770	0.6087	4.5232**
252	1248078	0.4854	3.8950**	292	1966671	0.036	1.7037
253	1248153	0.0157	4.0384**	293	1971693	0.0727	0.4962
254	1248304	7.2026***	0.7717	294	1978713	0.2856	0.5538
255	1248845	2.8338*	2.3227	295	1988646	0.0543	2.0041
256	1248939	0.0041	0.0136	296	1995523	1.4034	0.9797
257	1249002	4.8108**	0.1824	297	2007647	0.6353	1.5452
258	1249039	0.958	4.5150**	298	2012315	0.0482	9.8222***
259	1249712	0.006	0.7246	299	2033226	0.808	0.9903
260	1249918	0.8966	7.0061***	300	2040288	0.8371	1.0884
261	1250437	0.1508	2.4081	301	2052777	0.0084	1.6561
262	1250473	0.0488	0.938	302	2066868	0.563	6.2260**
263	1401109	0.0021	0.0013	303	2067007	1.0612	0.0009
264	1404687	0.0846	0.9507	304	2078816	6.7813***	1.0709
265	1416523	0.9077	7.9503***	305	2088329	0.0633	0.0471
266	1417333	0.2074	0.1048	306	2107707	0.1843	3.0679*
267	1426755	0.0459	0.061	307	2124795	2.1216	0.6313
268	1427275	4.8211**	3.3386*	308	2126977	2.2035	0.3242
269	1471849	0.6714	0.1122	309	2128917	0.0634	2.7201*
270	1471960	22.7016***	0.004	310	2149622	0.0109	9.8182***
271	1478017	3.4490*	0.7077	311	2158156	2.8415*	0.0089
272	1490701	9.9324***	5.6157**	312	2166124	0.2696	0.0077
273	1491360	0.3356	2.2664	313	2169871	1.5398	0.6597

274	1491409	2.4105	0.9392	314	2176413	1.305	13.7860***
275	1493654	1.1191	0.0227	315	2181426	10.5689***	0.0041
276	1823345	1.2722	0.0163	316	2217503	1.1034	11.8555***
277	1823608	0.3058	1.4136	317	2233950	0.0049	0.2662
278	1832048	0.7489	1.4431	318	2253529	0.2933	0.5849
279	1833997	0.6993	4.1072**	319	2256539	5.2371**	0
280	1838974	0.0931	0.184	320	2260406	4.3981**	1.4208

No.	id	NII → NPL Wald statistic	NPL → NII Wald statistic	No.	id	NII → NPL Wald statistic	NPL → NII Wald statistic
321	2291624	1.9212	2.9338*	358	2728157	2.6371	0.0891
322	2291914	6.5131**	7.2277***	359	2734064	1.7493	6.9017***
323	2294812	1.6895	0.0225	360	2734233	2.5281	9.0851***
324	2297701	0.0057	0.1856	361	2743235	1.0123	2.7399*
325	2303910	0.2386	4.3592**	362	2745604	0.4807	6.8278***
326	2314327	1.1785	3.0047*	363	2747644	1.5484	1.2873
327	2320618	0.4507	0.067	364	2748995	0.2847	2.0914
328	2325350	0.0863	0.6323	365	2759900	2.3431	4.7130**
329	2336806	2.9634*	6.4654**	366	2781910	0.0149	5.6675**
330	2337401	1.569	0.3138	367	2787118	0.2552	10.6482***
331	2339133	0.055	3.2857*	368	2809560	0.2606	0.3806
332	2349815	0.4734	5.6700**	369	2810285	0.1833	0.2014
333	2352226	0.5373	2.1875	370	2818245	2.7042	3.3897*
334	2352280	1.1199	0.0178	371	2849799	4.4080**	0.9201
335	2356073	0.8241	0.0482	372	2856377	0.1109	9.3976***
336	2367921	0.0001	2.1325	373	2858773	1.8207	0.0043
337	2389941	2.9794*	8.2608***	374	2858951	1.7974	0.4
338	2454380	0.9938	0.2396	375	2868129	14.2874***	2.2628
339	2467689	2.5108	0.0029	376	2868950	1.8687	0.0637
340	2482196	0.0509	0.079	377	2869733	0.7813	1.2872
341	2497462	0.0377	0.0522	378	2900261	0.52	11.8197***
342	2502049	0.89	6.9459***	379	2907822	2.1348	0.3893
343	2507790	0.0138	1.605	380	2925657	2.9975*	18.6665***
344	2533100	0.7083	0.032	381	2935142	0.8298	4.2556**
345	2557405	0.5851	3.4553*	382	2942702	1.1009	1.9615
346	2560263	0.1126	3.2992*	383	2961879	6.5894**	0.438
347	2568102	0.3129	5.8898**	384	2976396	0.0204	0.1768
348	2582827	2.3702	14.0266***	385	3012554	0.5017	1.0065
349	2592714	1.5582	1.8943	386	3015975	0.2308	2.0965
350	2618388	2.3961	7.0105***	387	3025385	0.0187	0.963
351	2626691	0.777	0.0084	388	3030307	1.2643	0.01
352	2634490	5.4145**	0.0019	389	3047743	14.2185***	1.2809
353	2634696	1.2402	0.3438	390	3098576	0.4143	0.0003

354	2652104	0.4207	3.4002*	391	3103603	0.3442	0
355	2682996	0.0384	0.0118	392	3109904	0.8285	0.0002
356	2706735	0.0471	2.5069	393	3150997	9.2079***	2.2264
357	2721112	4.4114**	0.5432				

Table 7: Cointegration test: Westerlund test

Statistic	Value	Z-value	P-value
Gt	-1.330	-6.737	0.000
Ga	-4.046	-1.062	0.144
Pt	-148.493	-118.549	0.000
Pa	-36.137	-240.408	0.000

Table 8: Dynamic OLS estimation

Variable	Coefficient	Variable	Coefficient
NPL	-2.161*(0.921)	NII	-0.001**(0.000)
R-squared	0.178	R-squared	0.328

Notes: standard error is shown in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.