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The Profitability of US Community Banks: A Cross-Sectional and Dynamic Panel Analysis

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ABSTRACT

This study compares 5,286 community banks operating in rural and metropolitan counties from 2000 through the end of 2013 on the variables attributing to bank profitability using pooled OLS, pooled time-series OLS, and dynamic panels methodologies. Following the SCP and competition-fragility literature one would expect a difference in the variables contributing to profitability. The size of the coefficients indicates that the variables contributing to profitability differ in magnitude when comparing community banks in metropolitan counties to those in rural counties. Both the pooled and time-series OLS models indicate that bank size contributes to profitability more in metropolitan areas.

KEYWORDS: community banking, structure-conduct-performance

INTRODUCTION

The US Banking industry in the US has undergone dramatic changes over the past 30 years as restrictions of both the geographic area of operation and the scope of financial services banks can offer have change dramatically. Until 1911, banks in the US were regulated by the states. Even after federal regulation a two-tiered banking system of both state and federally chartered banks existed and depression era federal regulations limited banks to whatever the state they operated in allowed in terms of geographic areas. The result was a large number of small banks serving communities across the nation. Beyond that, Great Depression era Glass-Steagall Act of 1933, limited the scope financial activities in which commercial banks could participate. Although an in depth discussion is beyond the scope of this paper, those limitations from the 1930s through the 1980s through various court decisions and legislative and regulatory changes. In the 1980s a series of legislative initiatives leading up to the Gramm-Leach-Bliley Act of 1999 eliminated most of the remaining limitations on the geographic scope of banks and restrictions on what services entities in the financial services sector could offer. What followed was a massive progression of acquisitions and mergers as commercial banks, investment banks, and insurance companies combined into comprehensive financial services firms.

In a quest to cover the nation or particular regions of it, publicly traded banks acquired banks across the nation with the vast majority, 87% of branches, being in metropolitan areas. This resulted in a 59% decrease in the number of bank charters and over 80% of all bank assets held by only 107 banks. The remaining 6,356 remaining small banks held only 14% of bank assets. Nonetheless, these small community banks play an important role in the US economy because they continue to provide the vast majority of funding to small businesses and small businesses continue employee the vast majority of people in the US. In addition, more of the US population is migrating to metropolitan areas and that is likely where community banks encounter the greatest competition from the massive nationwide and regional banks. Therefore, it is important to understand how deregulation has changed the competitive environment of community banking.

LITERATURE REVIEW

Structure-Conduct-Performance and Bank Deregulation

Due to the evolution of banking regulation in the US, the restrictions on geographic operating area resulted in most US banks being small banks with tight ties to the communities that operated in. Great Depression era legislation, the Glass-Steagall Act of 1933, also limited the scope of bank activities by prohibiting commercial banks from engaging in investment banking (Calomiris, 2010). The Douglas Amendment in 1956 allowed states to establish the guidelines under which banks from other states could do business; however, the banking industry remained highly regulated and the vast majority of US banks operated in single counties or metropolitan areas with only a few competitors. During this same timeframe, legislative activity in the area of anti-trust made inter-industry data available for researchers to analyze using cross-sectional approaches (e.g., Bain, 1951, 1956). These studies provided insight in to the relationship between competitor concentration in a particular industry, also referred to as the market structure, and profitability. The use of observable industry structure indicators, such as concentration ratios, to measure the degree of competition lead to the development of the structure-conduct-performance paradigm (SCP) (Schmalensee, 1982, 1985, 1989). From one point of view, in highly concentrated markets competitors can collude, implicitly or explicitly, to extract higher profits. In contrast, profits may be the result of efficiencies that result from economies of scale in plant, firm, and advertising efforts.

In the 1980s, there was a movement to enhance competition in the financial services industry. During the legislative process Stephen Friedman (1981), Securities and Exchange Commission Commissioner at the time, commented that in the future only ten large banks would cover the US. Federal Reserve researcher Alton Gilbert (1984) reviewed 45 SCP studies on the banking industry to examine the issues of collusion and efficiencies through achieving economies of scale. He found that the studies on the influence of market structure were highly variable, but did not seem to support that competition concentration leads to collusion in the banking industry and that single small banks do not appear to be more costly to operate than a branch of a large bank. Gilbert (1984) did caution that the studies reviewed did not provide a solid basis to generalize about large banks operating branches across the nation. As the result of a series of legislative actions from the Depository Institutions Deregulation and Monetary Controls Act (DIDMCA) of 1980 to the Gramm-Leach-Bliley Act of 1999, the US financial services industry was deregulated. It turns out that Stephen Friedman was wrong only about the number of banks blanketing the nation, as of 2014 it is 4 instead of 10; JP Morgan Chase, Bank of America, Citi Group, and Wells Fargo. At the end of 2011, only 107 banks held 80% of industry assets and federally insured bank and thrift charters fell from 17,901 in 1985 to 7,353 in 2011. However, despite the industry consolidation and increased competition, locally owned community banks have not disappeared. Despite only holding 14% of total bank assets, they are the most common FDIC insured institution and supply most of the credit to small businesses in the US (FDIC CBS, 2012).

Beyond deregulation, technology has dramatically changed the competitive environment of banking in the last 10 to 15 years. Internet banking has gone from a novel concept to a service that bank customers expect. More recently, smartphones have enabled mobile banking and the ability to take a photo of a check to deposit it combined with mobile electronic payments is quickly making visits to a physical bank a rare event. On the one hand technology can bring cost reductions that lead to greater efficiency; however, the initial capital investment and the need for highly skilled, therefore costly, support staff can put technology implementation out of the reach of small banks. Community banks in large metropolitan areas would arguably have a larger customer base and assets to cover technology implementation and support cost; however, those are the community banks most likely confronting the highest concentration of competition from the large nationwide and regional banks. This is because the large banks have focused on acquisitions in metropolitan areas while avoiding the small rural communities. Therefore, this study compares the factors contributing to community bank profitability on rural versus metropolitan areas.

Determinants of Community Bank Profitability

Studies examining bank profitability have mostly used the SCP paradigm focusing on market concentration and bank efficiency on concentration (e.g., Berger, 1995a; Smirlock, 1985). As discussed previously, the dispute lies in the underlying causation of market power or efficiency through economies of scale. However, regardless of the level of market concentration, community bank profits are related to exogenous economic conditions; however, when faced with favorable economic conditions managerial skill will result in some banks performing better than others (Kupiec & Lee, 2012). Although return on equity (ROE) and return on assets ROA are often used to measure firm profitability, the study of community banks brings an interesting problem because about one-third of small banks are Type-S corporations. Because Type-S corporations act as a pass-through entities that pay no income tax at the corporate level and pass the profits on to shareholders who pay income tax at the individual level, comparing ROA or ROE between Type-S and Type-C banks would be erroneous. Therefore, this study uses pre-tax ROA as a measure of profitability (FDIC variable ptxroa).

Traditionally, banks make profits by operating as financial intermediaries by paying interest on deposits and loaning those funds out at higher rates. As a result, the gross profit from interest comes from the difference in those rates, which is the net interest margin (FDIC variable NIMY). In highly competitive markets to attract depositors banks would offer higher interest rates; however, by the same reasoning, to attract good clients to lend to banks would have to offer attractive loan rates and the net interest margin would be lower in these markets. However, partly due to competition and partly due to deregulation, banks have turned to generating income through non-interest activities that range from fees on services to operations in the forward and futures markets (FDIC variable noniiay). As is the case in any business, operating expenses reduce the gross profits and in banking terminology these are non-interest expenses (FDIC variable nonixay); the more efficient a bank is the lower its relative non-interest expense. Efficiency can come through reaching economy of scale and bank asset size maybe used as a proxy (FDIC variable asset5).

Given that the interest income is the difference in the rates paid on deposits and the interest charged for loans and that higher riskier loans pay higher interest rates, banks can arguably increase profitability by taking on riskier loan portfolios. Because of competition for deposits, there is a lower limit of what a bank can pay and retain sufficient deposits to lend. This is the basis of the charter value or competition-fragility views (Hellmann, Murdock, & Stiglitz, 2000; Keeley, 1990). Because deposit insurance can act as a put option that limits bank shareholder losses to the capital invested, banks may take on more risk and maintain lower capital to asset ratios (CAR). While the literature is not conclusive (Canoy, van Dijk, Lemmen, de Mooij, & Weigand, 2001; Carletti & Hartmann, 2003), Berger (1995b) found that higher CAR was correlated with higher profits. One possible explanation is that higher CAR leads to lower insurance premiums and that results in higher profits. Under either argument CAR is an important factor when it comes to explaining bank profitability (FDIC variable eqv).

MODEL

The data comes from the FDIC quarterly Performance and Conditions Ratios reports. Because this report focuses only on community banks, the data is restricted to those banks that met the definition of community banks in the 2012 FDIC Community Banking Study that reported for the fourth quarter of 2012. The data is from individual banks and excludes bank holding companies. To avoid the issues related to ratios with De Novo banks, institutions that joined the FDIC after January 2, 1998 were not included. A dummy variable indicated whether the bank operated in a rural (0) or metropolitan (1) county. The data contains 296,098 observations from the quarterly FDIC Performance Reports from 5,286 unique community banks operating from 2000 through the end of 2013.

The methodology in this paper follows Goddard, Molyneux, and Wilson (2004). The content of the model is as follows:

$$\prod_{i,t} = f\,(\prod_{i,t-1}\ ,\ s_{i,t},\ o_{i,t}\ ,\ c_{i,t}\ d_{1,i}\,)$$

Where $\Pi i,t$ is the profit of the bank i in year t, as measured by pre-tax return on assets; s i,t is the natural logarithm of total assets average over the preceding five years; oi,t is the off balance sheet or non-interest income; ci,t is CAR; and d 1,i = 1 for metro and 0 for rural. The inclusion of s i,t captures any relationship between bank size and profitability. Following the SCP literature, a positive sign may indicate that large banks may benefit from economies of scale or scope or they may benefit from brand image. In the alternative, a negative sign may indicate that size results in diseconomies of scale.

Since deregulation began, banks have increased income via non-interest income generated through fees for services and various contingent liabilities such as letters of credit, and other non-traditional banking activities including operations in the forward and futures markets. In competitive markets, non-interest income may play an important role in profitability. CAR is a crude proxy for risk; however, the competition-frailty view argues that less CAR contributes to profitability while the lower deposit insurance premium view argues that higher CAR results in greater profitability. Nonetheless, the goal of this study is not to resolve these differences but to better understand the factors that contribute to bank profitability in community banks operating in rural and metropolitan areas.

The pooled cross-sectional time-series structure of the data set enables the estimation of several variants of the relationship summarized in (1).

Pooled cross-sectional time-series model, estimated using OLS

$$\prod_{i,t} = \alpha_1 + \alpha_2 \prod_{i,t-1} + \alpha\, s_{i,t} + \alpha\, o_{i,t} + \alpha\, c_{i,t} + \alpha\, d_{1,i} + u_{i,t} \qquad i = 1, \ldots\ldots N,\ t = 2 \ldots\ldots T \tag{2}$$

Cross-sectional model, estimated using OLS

$$\prod_{i,t} = \beta_1 + \beta\, s_{i,t} + \beta\, o_{i,t} + \beta\, c_{i,t} + \beta\, d_{1,i} + w_{i,t} \qquad i = 1, \ldots\ldots N \tag{3}$$

Dynamic panel model GMM

$$\prod_{i,t} = \Upsilon_1 + \Upsilon_2 \prod_{i,t-1} + \Upsilon\, s_{i,t} + \Upsilon\, o_{i,t} + \Upsilon\, c_{i,t} + \eta_i + v_{i,t} \qquad i = 1, \ldots\ldots N,\ t = 2 \ldots\ldots T \tag{4}$$

The pooled model, equation (2), is based on the assumption that cross-sectional variation in any independent variable has the same implication for profit variation over time in that variable for an independent bank. During the period from 2000 to 2013, there were major shocks that included a terrorist attack and a banking crisis that resulted in two recessions. Given that banking profits are correlated with economic expansion and recession (Kupiec & Lee, 2012), the use individual bank differences from yearly means of all banks in the sample removes the exogenous effects of the economic cycle; in other words, economy-normalized values. Estimating the equations using both the data as reported and differenced from yearly means for all community banks provides some ability to understand how economic expansion and contraction effects profitability in rural and metropolitan banks differently.

Results

Table 1 reports the summary data on the untransformed dependent and independent variables used in the empirical model. Table 1 reports the summary data for all community banks (observations = 296,098) and for community banks operating in the rural (observations = 160,142) and metropolitan (observations = 135,696) areas.

Table 1
Descriptive Statistics

All Banks							
	roaptx	asset5	noniiay	eqv	nimy	nonixay	observations
mean	1.358655	229266.6	0.809128	10.97072	3.987371	3.065103	296,098
sd	3.483859	428960.3	5.615186	3.809603	0.955995	3.807264	
min	-212.39	1055.25	-23.02	-1.69	-3.24	-0.23	
max	419.01	1.30E+07	1066.4	95.9	72.64	1099.33	
Rural							
mean	1.434388	146835.1	0.691578	11.07118	4.026	2.944052	160,402
sd	1.883635	205449.8	0.86468	3.568647	0.918214	1.136296	
min	-141.32	1055.25	-6.63	-0.62	0	0	
max	53.86	4511235	87.28	81.55	72.64	72.64	

Metro							
mean	1.269134	326706.2	0.94808	10.85198	3.941708	3.208193	135,696
sd	4.719703	578010.3	8.239063	4.072919	0.996888	5.483222	
min	-212.39	2816	-23.02	-1.69	-3.24	-0.23	
max	419.01	1.30E+07	1066.4	95.9	29.02	1099.33	

Pooled OLS Regressions

Tables 2 through 7 report the results of pooled OLS regressions for both the economy-normalized data which is the difference in the individual bank value and the mean for the year of all banks on for that variable.

Table 2. Pooled OLS All Banks Using Non-Economy-Normalized

Source	SS	df	MS
Model	2586444.01	5	517288.802
Residual	1007365.93	296092	3.40220585
Total	3593809.94	296097	12.1372724

Number of obs	= 296098
F(5,296092)	= .
Prob > F	= 0.0000
R-squared	= 0.7197
Adj R-squared	= 0.7197
Root MSE	= 1.8445

roaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnasset5	-.0525325	.0031807	-16.52	0.000	-.0587665	-.0462985
noniiay	.998067	.0012559	794.68	0.000	.9956054	1.000529
eqv	.0013112	.0009108	1.44	0.150	-.0004738	.0030963
nimy	.8185951	.0036912	221.77	0.000	.8113605	.8258297
nonixay	-1.002629	.0018636	-538.00	0.000	-1.006281	-.998976
_cons	.9590993	.0447775	21.42	0.000	.8713366	1.046862

Table 3. Pooled OLS All Banks Using Economy-Normalized

Source	SS	df	MS
Model	2583750.98	5	516750.195
Residual	878563.155	296092	2.96719653
Total	3462314.13	296097	11.6931753

Number of obs	= 296098
F(5,296092)	= .
Prob > F	= 0.0000
R-squared	= 0.7462
Adj R-squared	= 0.7462
Root MSE	= 1.7226

droaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dlnasset5	-.0428519	.0030309	-14.14	0.000	-.0487924	-.0369113
dnoniiay	.9984751	.0011749	849.87	0.000	.9961724	1.000778
deqv	.0042829	.000853	5.02	0.000	.002611	.0059549
dnimy	.8220789	.0035092	234.26	0.000	.815201	.8289569
dnonixay	-1.003457	.0017441	-575.34	0.000	-1.006876	-1.000039
_cons	-5.41e-06	.0031656	-0.00	0.999	-.0062099	.0061991

Table 4. Pooled OLS Rural Banks Using Non-Economy-Normalized

Source	SS	df	MS
Model	113453.59	5	22690.7181
Residual	455662.024	160396	2.84085653
Total	569115.614	160401	3.54808021

Number of obs	=	160402
F(5,160396)	=	7987.28
Prob > F	=	0.0000
R-squared	=	0.1994
Adj R-squared	=	0.1993
Root MSE	=	1.6855

roaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnasset5	-.0450983	.0045527	-9.91	0.000	-.0540215	-.0361751
noniiay	1.077926	.0073078	147.50	0.000	1.063603	1.092249
eqv	-.0027492	.0012271	-2.24	0.025	-.0051543	-.0003441
nimy	.9005445	.0056208	160.22	0.000	.8895278	.9115613
nonixay	-1.132732	.0064456	-175.74	0.000	-1.145365	-1.120099
_cons	.9422624	.0623413	15.11	0.000	.8200747	1.06445

Table 5. Pooled OLS Rural Banks Using Economy-Normalized

Source	SS	df	MS
Model	113154.893	5	22630.9786
Residual	363544.699	160396	2.26654467
Total	476699.592	160401	2.97192407

Number of obs	=	160402
F(5,160396)	=	9984.79
Prob > F	=	0.0000
R-squared	=	0.2374
Adj R-squared	=	0.2373
Root MSE	=	1.5055

droaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dlnasset5	-.0447315	.0041818	-10.70	0.000	-.0529277	-.0365354
dnoniiay	1.085784	.0065819	164.97	0.000	1.072884	1.098685
deqv	-.0001967	.0010996	-0.18	0.858	-.0023518	.0019584
dnimy	.9196494	.0051538	178.44	0.000	.909548	.9297508
dnonixay	-1.149914	.0058443	-196.76	0.000	-1.161369	-1.138459
_cons	.0220373	.003977	5.54	0.000	.0142424	.0298321

Table 6. Pooled OLS Metro Banks Using Non-Economy-Normalized

Source	SS	df	MS
Model	2472735.17	5	494547.035
Residual	549951.714	135690	4.05300106
Total	3022686.89	135695	22.2755952

Number of obs	=	135696
F(5,135690)	=	.
Prob > F	=	0.0000
R-squared	=	0.8181
Adj R-squared	=	0.8181
Root MSE	=	2.0132

roaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnasset5	-.0604381	.0049594	-12.19	0.000	-.0701585	-.0507178
noniiay	.9916712	.0014136	701.54	0.000	.9889007	.9944418
eqv	.0017462	.0013703	1.27	0.203	-.0009395	.004432
nimy	.7977294	.005632	141.64	0.000	.7866908	.8087681
nonixay	-.9910865	.0021221	-467.03	0.000	-.9952458	-.9869273
_cons	1.071039	.0709305	15.10	0.000	.932016	1.210061

Table 7. Pooled OLS Metro Banks Using Economy-Normalized

Source	SS	df	MS
Model	2470699.04	5	494139.808
Residual	512765.941	135690	3.77895159
Total	2983464.98	135695	21.9865506

Number of obs	135696
F(5,135690)	.
Prob > F	0.0000
R-squared	0.8281
Adj R-squared	0.8281
Root MSE	1.944

droaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dlnasset5	-.0412878	.0048799	-8.46	0.000	-.0508524	-.0317232
dnoniiay	.9913288	.0013664	725.51	0.000	.9886507	.9940069
deqv	.0044963	.001328	3.39	0.001	.0018934	.0070992
dnimy	.7958965	.0055364	143.76	0.000	.7850452	.8067478
dnonixay	-.9904214	.0020519	-482.70	0.000	-.994443	-.9863998
_cons	-.0414837	.0055142	-7.52	0.000	-.0522915	-.0306759

From the pooled OLS analysis from both the economy-normalize and non-economy-normalized data the negative coefficient for bank size (asset5) is negative. This provides some support for the position that large banks may encounter diseconomies of scale. Kupiec and Lee (2012) found a curvilinear relationship between size and profitability in community banks where banks as small as $300 million in assets achieved a significant proportion of the gain in profits while banks over $1 billion in assets were less profitable. As expected, the coefficient for non-interest expense is negative in all tables. The fact that CAR (eqv) varies in the level of significance across the different analyses is interesting and need for further investigation. It is noteworthy that there were changes in capital requirements after the 2008 financial crisis.

Pooled Time Series OLS Regressions

Tables 8 through 13 report the results of pooled time-series OLS regressions for both the economy-normalized data which is the difference in the individual bank value and the mean for the year of all banks on for that variable. Because the data is quarterly, the dependent variable, pre-tax ROA, is lagged by 4 observations to capture the profit from one year before.

Table 8. Pooled TS OLS All Banks Using Non-Economy-Normalized

```
Fixed-effects (within) regression               Number of obs      =    264808
Group variable: crossid                         Number of groups   =      5466

R-sq:  within  = 0.1913                         Obs per group: min =        17
       between = 0.9837                                        avg =      48.4
       overall = 0.6838                                        max =        52

                                                F(6,259336)        =  10222.39
corr(u_i, Xb)  = 0.0752                         Prob > F           =    0.0000
```

roaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
roaptx						
L4.	-.0151202	.001825	-8.28	0.000	-.0186972	-.0115432
lnasset5	-.2956692	.0128646	-22.98	0.000	-.3208835	-.2704548
noniiay	1.016689	.0051139	198.81	0.000	1.006666	1.026713
eqv	.0239564	.0021096	11.36	0.000	.0198216	.0280912
nimy	.8786408	.0068121	128.98	0.000	.8652892	.8919924
nonixay	-1.079463	.0053617	-201.33	0.000	-1.089972	-1.068954
_cons	3.559793	.161227	22.08	0.000	3.243793	3.875794
sigma_u	.5451846					
sigma_e	1.8953757					
rho	.07641415	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(5465, 259336) =     2.57        Prob > F = 0.0000
```

Table 9. Pooled TS OLS All Banks Using Economy-Normalized

```
Fixed-effects (within) regression               Number of obs      =    264808
Group variable: crossid                         Number of groups   =      5466

R-sq:  within  = 0.2077                         Obs per group: min =        17
       between = 0.9858                                        avg =      48.4
       overall = 0.7145                                        max =        52

                                                F(6,259336)        =  11331.89
corr(u_i, Xb)  = 0.0764                         Prob > F           =    0.0000
```

droaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
droaptx						
L4.	-.0014562	.0018147	-0.80	0.422	-.0050131	.0021006
dlnasset5	-.2532024	.0167308	-15.13	0.000	-.2859942	-.2204105
dnoniiay	1.00999	.0047955	210.61	0.000	1.000591	1.01939
deqv	.0263796	.0019936	13.23	0.000	.0224722	.030287
dnimy	.9175164	.0065621	139.82	0.000	.9046549	.930378
dnonixay	-1.076489	.0050965	-211.22	0.000	-1.086478	-1.0665
_cons	-.0057685	.0034263	-1.68	0.092	-.0124839	.0009469
sigma_u	.50932716					
sigma_e	1.7628287					
rho	.07704656	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(5465, 259336) =     2.74        Prob > F = 0.0000
```

Table 10. Pooled TS OLS Rural Banks Using Non-Economy-Normalized

Fixed-effects (within) regression		Number of obs =	142943
Group variable: crossid		Number of groups =	3106
R-sq: within = 0.1137		Obs per group: min =	1
between = 0.6879		avg =	46.0
overall = 0.1770		max =	52
		F(6,139831) =	2989.01
corr(u_i, Xb) = -0.1443		Prob > F =	0.0000

roaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
roaptx						
L4.	-.0286746	.0025348	-11.31	0.000	-.0336429	-.0237063
lnasset5	-.2600908	.0179843	-14.46	0.000	-.2953396	-.224842
noniiay	1.177087	.0108638	108.35	0.000	1.155794	1.19838
eqv	.010226	.0029607	3.45	0.001	.0044231	.016029
nimy	.9447741	.009168	103.05	0.000	.9268051	.9627431
nonixay	-1.21727	.0105515	-115.36	0.000	-1.23795	-1.196589
_cons	3.302526	.2191399	15.07	0.000	2.873016	3.732036
sigma_u	.45151986					
sigma_e	1.7541192					
rho	.0621403	(fraction of variance due to u_i)				

F test that all u_i=0: F(3105, 139831) = 2.13 Prob > F = 0.0000

Table 11. Pooled TS OLS Rural Banks Using Economy-Normalized

Fixed-effects (within) regression		Number of obs =	142943
Group variable: crossid		Number of groups =	3106
R-sq: within = 0.1349		Obs per group: min =	1
between = 0.6349		avg =	46.0
overall = 0.1937		max =	52
		F(6,139831) =	3633.01
corr(u_i, Xb) = -0.2824		Prob > F =	0.0000

droaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
droaptx						
L4.	-.0086361	.0025089	-3.44	0.001	-.0135536	-.0037187
dlnasset5	-.4066864	.023388	-17.39	0.000	-.4525265	-.3608462
dnoniiay	1.194264	.0098972	120.67	0.000	1.174866	1.213662
deqv	.0136587	.0026671	5.12	0.000	.0084312	.0188861
dnimy	.9976664	.008516	117.15	0.000	.9809752	1.014358
dnonixay	-1.256684	.0097787	-128.51	0.000	-1.27585	-1.237518
_cons	-.0843095	.0077981	-10.81	0.000	-.0995937	-.0690254
sigma_u	.51602911					
sigma_e	1.5597466					
rho	.09865752	(fraction of variance due to u_i)				

F test that all u_i=0: F(3105, 139831) = 2.39 Prob > F = 0.0000

Table 12. Pooled TS OLS Metro Banks Using Non-Economy-Normalized

```
Fixed-effects (within) regression               Number of obs      =    121865
Group variable: crossid                         Number of groups   =      2652

R-sq:  within  = 0.2468                         Obs per group: min =         1
       between = 0.9868                                        avg =      46.0
       overall = 0.7889                                        max =        52

                                                F(6,119207)        =   6508.77
corr(u_i, Xb)  = 0.2695                         Prob > F           =    0.0000
```

roaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
roaptx						
L4.	-.0059829	.0026497	-2.26	0.024	-.0111762	-.0007896
lnasset5	-.3870837	.0204479	-18.93	0.000	-.4271612	-.3470063
noniiay	.9792774	.0063348	154.59	0.000	.9668613	.9916934
eqv	.0349243	.0031389	11.13	0.000	.028772	.0410765
nimy	.8714233	.011354	76.75	0.000	.8491697	.8936768
nonixay	-1.054804	.0069426	-151.93	0.000	-1.068411	-1.041196
_cons	4.574221	.2637499	17.34	0.000	4.057276	5.091167
sigma_u	.77265					
sigma_e	2.0447255					
rho	.12494804	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(2651, 119207) =     2.90        Prob > F = 0.0000
```

Table 13. Pooled TS OLS Metro Banks Using Economy-Normalized

```
Fixed-effects (within) regression               Number of obs      =    121865
Group variable: crossid                         Number of groups   =      2652

R-sq:  within  = 0.2525                         Obs per group: min =         1
       between = 0.9906                                        avg =      46.0
       overall = 0.8054                                        max =        52

                                                F(6,119207)        =   6710.78
corr(u_i, Xb)  = 0.3202                         Prob > F           =    0.0000
```

droaptx	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
droaptx						
L4.	.0017847	.0026506	0.67	0.501	-.0034105	.0069799
dlnasset5	-.219934	.0270817	-8.12	0.000	-.2730137	-.1668543
dnoniiay	.972894	.0061332	158.63	0.000	.9608731	.9849149
deqv	.0339648	.0030848	11.01	0.000	.0279186	.0400111
dnimy	.9223176	.0113704	81.12	0.000	.9000318	.9446034
dnonixay	-1.039375	.0067974	-152.91	0.000	-1.052698	-1.026053
_cons	.025413	.0107307	2.37	0.018	.004381	.0464449
sigma_u	.67401676					
sigma_e	1.9707322					
rho	.10472332	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(2651, 119207) =     2.95        Prob > F = 0.0000
```

A review of the time-series OLS indicates that CAR differs from the results in the pooled cross-sectional regressions. In the time-series regressions, CAR (eqv) is positive and significant across all regressions. An interesting result is that lagged pre-tax ROA is negative when significant and is worthy of further investigation although size of the coefficient is relatively small. Otherwise, the signs of the coefficients are the same as in the cross-sectional OLS regressions with size (asset5) and non-interest expense being (nonixay) negative.

Dynamic Panel Estimation

The null hypothesis of the Sargan test that the over-identifying restrictions are valid were rejected for both the non-economy-normalized and economy-normalized panel regressions; therefore, they are not valid. The Arellano-Bond test for zero autocorrelation in first-differenced errors revealed evidence of misspecification for the non-economy-normalized panel regressions. However, there was no evidence of misspecification in the economy-normalized regressions. Despite the results of the Sargan test, the results of the economy-normalized regressions are provided here.

Table 14. Dynamic Panel All Banks Using Economy-Normalized Data

```
Arellano-Bond dynamic panel-data estimation  Number of obs      =    249338
Group variable: crossid                      Number of groups   =      5466
Time variable: timeid
                                             Obs per group:  min =        16
                                                             avg =  45.61617
                                                             max =        51

Number of instruments =   1.5e+03            Wald chi2(9)       =   2444.07
                                             Prob > chi2        =    0.0000
One-step results
                                 (Std. Err. adjusted for clustering on crossid)
```

droaptx	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
droaptx						
L1.	.3973775	.0441071	9.01	0.000	.3109292	.4838258
L2.	-.0175836	.0152226	-1.16	0.248	-.0474193	.0122521
L3.	-.1011649	.0191132	-5.29	0.000	-.1386261	-.0637036
L4.	.0369237	.0118291	3.12	0.002	.013739	.0601083
dlnasset5	-2.720921	.222671	-12.22	0.000	-3.157348	-2.284494
dnoniiay	.8255317	.051451	16.05	0.000	.7246896	.9263738
deqv	.0777918	.0186109	4.18	0.000	.0413152	.1142685
dnimy	.7787569	.0465123	16.74	0.000	.6875944	.8699194
dnonixay	-.8508638	.068657	-12.39	0.000	-.985429	-.7162986
_cons	.0321022	.0397568	0.81	0.419	-.0458197	.1100241

```
Instruments for differenced equation
        GMM-type: L(2/.).droaptx
        Standard: D.dlnasset5 D.dnoniiay D.deqv D.dnimy D.dnonixay
Instruments for level equation
        Standard: _cons
```

Table 15. Dynamic Panel Rural Banks Using Economy-Normalized

```
Arellano-Bond dynamic panel-data estimation  Number of obs      =    134391
Group variable: crossid                      Number of groups   =      3103
Time variable: timeid
                                             Obs per group:   min =      1
                                                              avg = 43.31002
                                                              max =     51

Number of instruments =    1.5e+03           Wald chi2(9)       =  52572.28
                                             Prob > chi2        =    0.0000
One-step results
```

droaptx	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
droaptx						
L1.	.4498633	.002912	154.49	0.000	.4441559	.4555707
L2.	-.0310608	.0029281	-10.61	0.000	-.0367997	-.0253219
L3.	-.1364222	.0027547	-49.52	0.000	-.1418214	-.1310231
L4.	.0647087	.002365	27.36	0.000	.0600733	.069344
dlnasset5	-3.173354	.075241	-42.18	0.000	-3.320823	-3.025884
dnoniiay	1.065877	.0126253	84.42	0.000	1.041132	1.090622
deqv	.0288549	.0055402	5.21	0.000	.0179963	.0397135
dnimy	.7833973	.0138901	56.40	0.000	.7561731	.8106214
dnonixay	-1.117461	.0127266	-87.81	0.000	-1.142405	-1.092517
_cons	-.8499601	.0209723	-40.53	0.000	-.891065	-.8088553

```
Instruments for differenced equation
        GMM-type: L(2/.).droaptx
        Standard: D.dlnasset5 D.dnoniiay D.deqv D.dnimy D.dnonixay
Instruments for level equation
        Standard: _cons
```

Table 16. Dynamic Panel Metro Banks Using Economy-Normalized

```
Arellano-Bond dynamic panel-data estimation  Number of obs      =    114947
Group variable: crossid                      Number of groups   =      2652
Time variable: timeid
                                             Obs per group:   min =      1
                                                              avg = 43.34351
                                                              max =     51

Number of instruments =    1.5e+03           Wald chi2(9)       =   1468.22
                                             Prob > chi2        =    0.0000
One-step results
                                  (Std. Err. adjusted for clustering on crossid)
```

droaptx	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
droaptx						
L1.	.3685604	.062088	5.94	0.000	.2468702	.4902506
L2.	-.0129432	.0175742	-0.74	0.461	-.0473881	.0215017
L3.	-.0845967	.0237472	-3.56	0.000	-.1311403	-.038053
L4.	.0199218	.0136042	1.46	0.143	-.0067419	.0465855
dlnasset5	-1.644153	.3033744	-5.42	0.000	-2.238756	-1.04955
dnoniiay	.8151457	.0397175	20.52	0.000	.7373007	.8929906
deqv	.102721	.0309129	3.32	0.001	.0421327	.1633092
dnimy	.9003749	.0895391	10.06	0.000	.7248815	1.075868
dnonixay	-.8179056	.0532217	-15.37	0.000	-.9222183	-.7135929
_cons	.5602436	.1056296	5.30	0.000	.3532133	.7672738

```
Instruments for differenced equation
        GMM-type: L(2/.).droaptx
        Standard: D.dlnasset5 D.dnoniiay D.deqv D.dnimy D.dnonixay
Instruments for level equation
        Standard: _cons
```

Conclusion

The goal of this study is to compare community banks operating in rural and metropolitan counties on the variables attributing to bank profitability using pooled OLS, pooled time-series OLS, and dynamic panels methodologies. Following the SCP and competition-fragility literature and given that community banks operating in metropolitan areas are facing direct competition from massive nationwide and regional banks whereas community banks are not to a great extent, one would expect a difference in the variables contributing to profitability. This study is exploratory in nature in that the purpose is to provide informative insight into areas in need of further research.

Overall, the three methodologies are more alike than different in that the signs of the coefficients are alike across all three methodologies. The size of the coefficients indicates that the variables contributing to profitability differ in magnitude when comparing community banks in metropolitan counties to those in rural counties. Both the pooled and time-series OLS models indicate that bank size contributes to profitability more in metropolitan areas. One could argue that in a rural community with few banks that size is not as important when it comes to attracting and retaining customers. In the results from the dynamic panel analysis, metropolitan banks have a smaller size coefficient than rural banks; however, we must view these results with caution given the results of the Sargan test.

The results across all three methodologies provide some interesting insight into net interest margins, non-interest income, and non-interest expenses. Traditionally, the majority of bank profit comes from the difference in the rate paid for deposits and the rates charged for loans. In both the pooled OLS and pooled time-series OLS models net-interest margins contribute less to profitability in metropolitan banks. This would conform to the competition-fragility argument that competition in the banking sector leads to lower net interest margins. One might expect that banks in metropolitan areas might have more opportunities to profit from non-interest fee income; however, the results from the pooled OLS, pooled time-series OLS, and dynamic panel models indicate that non-interest income contributes less to profitability in metropolitan banks. One possibility might be that metropolitan banks compete with massive nationwide and regional banks and as a result have to compete by offering free or lower cost services whereas the SCP paradigm indicates that small banks in rural communities have a greater ability to collude on fees such as checking, overdraft, letters of credit, and charges for other services. Non-interest expense is negative in all results as expected. The results from the pooled OLS, pooled time-series OLS, and dynamic panel models indicate that non-interest expense has less of an impact on profits in metropolitan banks. Given the higher real estate and labor prices in metropolitan areas one might expect non-interest expense to have more of a negative impact on profits in big cities than small towns. However, it may be possible that efficiencies achieve though economies of scale in metropolitan banks may result in non-interest expenses being less of a factor. In the results from the dynamic panel analysis, metropolitan banks have a larger net interest margin coefficient than rural banks; however, we must view these results with caution given the results of the Sargan test.

Finally, the coefficient for equity was small but positive and significant across all methodologies, except cross-sectional OLS by type, with the coefficient being larger for metropolitan banks. However, future research needs to examine this variable before and after the financial crisis because there were regulatory changes that required increases in CAR after the crisis. It would be interesting to examine the difference in CAR between rural and metropolitan banks prior to the regulatory changes. Given the wide fluctuation in economic conditions over the period of this study all studies were run economy-normalized data where the individual bank numbers for each variable were subtracted for the year mean for all banks. This did not lead to any changes in the signs of coefficients; however, it is noteworthy that only the economy-normalized dataset passed the Arellano-Bond test for zero autocorrelation in first-differenced errors. However, both data samples failed to pass the Sargan test and as a result, one must view the dynamic panel results with caution.

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