US COMMUNITY BANK PROFITABILITY: A CROSS-SECTIONAL AND DYNAMIC PANEL ANALYSIS OF RURAL AND METROPOLITAN BANKS

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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 contributing 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; however, on average, rural banks have higher return on assets, higher net interest margins, and higher non-interest income. These findings provide some support for the competition-fragility argument that more competition in banking, as seen in metropolitan areas, leads to lower net interest margins. Arguably, the higher net interest margins and contribution of non-interest income to profits in the concentrated rural bank markets supports the structure-conduct-performance paradigm that when few competitors exist in a market, they are more likely to collude, implicitly or explicitly, to extract higher profits. The findings of this study indicate that community banks are not a homogenous group and highlight the importance of segregating rural and metropolitan banks when examining the US community banking industry.

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 changed dramatically. Until 1911, states regulated banks in the US. 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 diminished from the 1930s to 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 to 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 and examine the two distinct environments, rural and metropolitan, where community banks operate. Previous studies have treated community banks as a homogenous group despite the fact that metropolitan community banks account for over 80% of US bank failures (Morrison, Jung, Jackson, Escobari, & Sturges, 2016). Using FDIC variables that contribute to bank profitability, this study demonstrates that there is a difference in the two competitive environments and highlights the need to segregate when conducting research on US community banks.

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 they 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 into 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), the 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 Congress deregulated the US financial services industry. It turns out that Stephen Friedman was wrong only about the number of banks blanketing the nation, as of 2020 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 this 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 (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, exogenous economic conditions affect community bank profits; 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 banks would offer higher interest rates to attract depositors; 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 correlated with higher profits. One possible explanation is that higher CAR leads to lower insurance premiums, and that contributes to higher profits. Under either argument, CAR is an important factor in explaining bank profitability (FDIC variable eqv).

MODELS

The data comes from the FDIC quarterly Performance and Conditions Ratios reports. Because this study focuses only on community banks, we restrict the data 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, we excluded institutions that joined the FDIC after January 2, 1998. 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 that used by Goddard, Molyneux, and Wilson (2004) to evaluate the determinants of profitability of banks across European countries. The content of the model is as follows:

$$\prod_{\mathrm{i,t}} = f\left(\prod_{\mathrm{i,t-1}},\ s_{\mathrm{i,t}},\ o_{i,t},\ \mathrm{c}_{i,t}\ d_{\mathrm{1,i}}\right) \tag{1}$$

Where $\prod i,t$ 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; $o_{i,t}$ is the off balance sheet or non-interest income; $c_{i,t}$ 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

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

Cross-sectional model, estimated using OLS

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

Dynamic panel model GMM

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

The pooled model, equation (2), assumes 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 correlate 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. This data indicates that on average, rural banks have higher return on assets, higher net interest margins, and higher non-interest income. These findings provide some support for the competition-fragility argument that more competition in banking, as seen in metropolitan areas, leads to lower net interest margins. Arguably, the higher net interest margins and contribution of non-interest income to profits in the concentrated rural bank markets supports the structure-conduct-performance paradigm that when few competitors exist in a market, they are more likely to collude, implicitly or explicitly, to extract higher profits.

Table 1

Descriptive Statistics

All Community 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 Community Banks							
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 Community Banks							
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			
					Nuber of obs =	296098
					F(5,296092) =	.
Model	2586444.01	5	517288.8		Prob > F =	0.0000
Residual	1007365.93		3.402205		R-squared =	0.7197
					Adj R-Squared =	0.7197
Total	3593809.94		12.1373		Root MSE =	1.8445

roaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]	
lnasset5	-0.0525325	0.0031807	-16.52	0.0000	-0.5876650	-0.4629850
noniiay	0.998067	0.0012559	794.68	0.0000	0.9956054	1.0005290
eqv	0.0013112	0.0009108	1.44	0.1500	-0.0004738	0.0030963
nimy	0.8185951	0.0036912	221.77	0.0000	0.8113605	0.8258297
nonixay	-1.002629	0.0018636	-538	0.0000	-1.0062810	-0.9989760
_cons	0.9590993	0.0447775	21.42	0.0000	0.8713366	1.0468620

Table 3

POOLED OLS ALL BANKS USING ECONOMY-NORMALIZED

Source	SS	df	MS			
					Nuber of obs =	296098
					F(5,296092) =	.
Model	2583750.98	5	516750.19		Prob > F =	0.0000
Residual	878563.16		2.967196		R-squared =	0.7462
					Adj R-Squared =	0.7462
Total	3462314.13		11.6932		Root MSE =	1.7226

droaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]	
dlnasset5	-0.0428519	0.0030309	-14.14	0.0000	-0.0487924	-0.0369113
dnoniiay	0.9984751	0.0011749	849.87	0.0000	0.9961724	1.0007780
deqv	0.0042829	0.000853	5.02	0.0000	0.0026110	0.0059549
dnimy	0.8220789	0.0035092	234.26	0.0000	0.8152010	0.8289569
dnonixay	-1.003457	0.0017441	-575.34	0.0000	-1.0068760	-1.0000390
_cons	-5.41E-06	0.0031656	0.00	0.9990	-0.0062099	0.0061991

Table 4						
POOLED OLS RURAL BANKS USING NON-ECONOMY-NORMALIZED						
Source	SS	df	MS		Nuber of obs =	160402
					F(5,160396) =	7987.28
Model	113453.59	5	22690.72		Prob > F =	0.0000
Residual	455662.02	6	2.8409		R-squared =	0.1994
					Adj R-Squared =	0.1993
Total	569115.61		3.5481		Root MSE =	1.6855
roaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]	
lnasset5	-0.0450983	0.0045527	-9.91	0.0000	-0.0540215	-0.0361751
noniiay	1.077926	0.0073078	147.50	0.0000	1.0636030	1.0922490
eqv	-0.0027492	0.0012271	-2.24	0.0250	-0.0051543	-0.0003441
nimy	0.9005445	0.0056208	160.22	0.0000	0.8895278	0.9115613
nonixay	-1.132732	0.0064456	-175.74	0.0000	-1.1453650	-1.1200990
_cons	0.9422624	0.0623413	15.11	0.0000	0.8200747	1.0644500

Table 5						
POOLED OLS RURAL BANKS USING ECONOMY-NORMALIZED						
Source	SS	df	MS		Nuber of obs =	160402
					F(5,160396) =	9984.79
Model	113154.89	5	22630.78		Prob > F =	0.0000
Residual	363544.70	6	2.2665		R-squared =	0.2374
					Adj R-Squared =	0.2373
Total	476699.59		2.9719		Root MSE =	1.5055
droaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]	
dlnasset5	-0.0447315	0.0041818	-10.7	0.0000	-0.0529277	-0.0365354
dnoniiay	1.085784	0.0065819	164.97	0.0000	1.0728840	1.0986850
deqv	-0.0001967	0.0010996	-0.18	0.8580	-0.0023518	0.0019584
dnimy	0.9196494	0.0051538	178.44	0.0000	0.9095480	0.9297508
dnonixay	-1.149914	0.0058443	-196.76	0.0000	-1.1613690	-1.1384590
_cons	0.0220373	0.003977	5.54	0.0000	0.0142424	0.0298321

Table 6						
POOLED OLS METRO BANKS USING NON-ECONOMY-NORMALIZED						
Source	SS	df	MS		Nuber of obs =	135696
					F(5,135690) =	.
Model	2472735.17	5	494547.035		Prob > F =	0.0000
Residual	549951.71		4.053		R-squared =	0.8181
					Adj R-Squared =	0.8181
Total	3022686.89		22.2756		Root MSE =	2.0132
roaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]	
lnasset5	-0.0604381	0.0049594	-12.19	0.0000	-0.0701585	-0.0507178
noniiay	0.9916712	0.0014136	701.54	0.0000	0.9889007	0.9944418
eqv	0.0017462	0.0013703	1.27	0.2030	-0.0009395	0.0044320
nimy	0.7977294	0.005632	141.64	0.0000	0.7866908	0.8084681
nonixay	-0.9910865	0.0021221	-467.03	0.0000	-0.9952458	-0.9869273
_cons	1.071039	0.0709305	15.1	0.0000	0.9320160	1.2100610

Table 7						
POOLED OLS METRO BANKS USING ECONOMY-NORMALIZED						
Source	SS	df	MS		Nuber of obs =	135696
					F(5,135690) =	.
Model	2470699.04	5	494139.81		Prob > F =	0.0000
Residual	512765.94		3.7790		R-squared =	0.8281
					Adj R-Squared =	0.8281
Total	2982464.98				Root MSE =	1.944
droaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]	
dlnasset5	-0.0412878	0.0048799	-8.4600	0.0000	-0.5085240	-0.0317232
dnoniiay	0.9913288	0.0013664	725.5100	0.0000	0.9886507	0.9940069
deqv	0.0044963	0.001328	3.3900	0.0010	0.0070992	0.0070992
dnimy	0.7958965	0.0055364	143.7600	0.0000	0.8067478	0.8067478
dnonixay	-0.9904214	0.0020519	-482.7000	0.0000	-0.9862998	-0.9863998
_cons	-0.0414837	0.0055142	-7.5200	0.0000	-0.0306759	-0.0306759

In the pooled OLS analysis from both the economy-normalize and non-economy-normalized data, the coefficient for net interest margin (nimy) is significantly higher for rural banks and the coefficient for bank size (asset5) is negative for both rural and metropolitan banks. The higher net interest rate margin in rural areas where banking competition is more concentrated supports the SCP paradigm. The negative coefficient for bank size (asset5) 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 calls for further investigation. It is noteworthy that there were changes in capital requirements after the 2008 financial crisis and this warrants comparison before and after the changes to gain a better understanding of these results.

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 that variable, and the data without any adjustment. Because this is quarterly data, we lag the dependent variable, pre-tax ROA, 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
				Prob > F =		0.0000
roaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]	
roaptx						
L4.	-0.0151202	0.001825	-8.28	0.0000	-0.1869720	-0.0115432
lnasset5	-0.2956692	0.0128646	-22.98	0.0000	-0.3208835	-0.2704548
noniiay	1.016689	0.0051139	198.81	0.0000	1.0066660	1.0267130
eqv	0.0239564	0.0021096	11.36	0.0000	0.0198216	0.0280912
nimy	0.8786408	0.0068121	128.98	0.0000	0.8652892	0.8919924
nonixay	-1.079463	0.0053617	-201.33	0.0000	-1.0899720	-1.0689540
_cons	3.559793	0.161227	22.08	0.0000	30243793	3.875794
sigma_u	0.5451846					
Sigma_e	1.8953757					
rho	0.07641415	(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	
				Prob > F =		0.0000	
droaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]		
droaptx							
L4.	-0.0014562	0.0018147	-0.80	0.4220	-0.0080131	0.0021006	
dlnasset5	-0.2532024	0.0167308	-15.13	0.0000	-0.2859942	-0.2204105	
dnoniiay	1.00999	0.0047955	210.61	0.0000	1.0005910	1.0193900	
deqv	0.0263796	0.0019936	13.23	0.0000	0.0224722	0.0302870	
dnimy	0.9175164	0.0065621	139.82	0.0000	0.9046549	0.9303780	
dnonixay	-1.076489	0.0050965	-211.22	0.0000	-1.0864780	-1.0665000	
_cons	-0.0057685	0.0034263	-1.68	0.0920	-0.0124839	0.0009469	
sigma_u	0.50932716						
Sigma_e	1.7628287						
rho	0.07704665	(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
	overall =	0.177			max =	52
				F(6,139831) =		2989.01
				Prob > F =		0.0000
roaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]	
roaptx						
L4.	-0.286746	0.0025348	-11.31	0.0000	-0.0336429	-0.2370630
lnasset5	-0.2600908	0.0179843	-14.46	0.0000	-0.2953396	-0.2248420
noniiay	1.177087	0.0108638	108.35	0.0000	1.1557940	1.1983800
eqv	0.010226	0.0029607	3.45	0.0001	0.0044231	0.0160290
nimy	0.9447741	0.009168	103.05	0.0000	0.9268051	0.9627431
nonixay	-1.21727	0.0105515	-115.36	0.0000	-1.2379500	-1.1965890
_cons	3.302526	0.2191399	15.07	0.0000	2.873016	3.732036
sigma_u	0.45151986					
Sigma_e	1.7541192					
rho	0.0621403	(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
	overall =	0.1937			max =		52
				F(6, 139831) =			3633.01
				Prob > F =			0.0000
droaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]		
droaptx							
L4.	-0.0086261	0.0025089	-3.44	0.0010	-0.0135536	-0.0037187	
dlnasset5	-0.0466864	0.023388	-17.39	0.0000	-0.4525265	-0.3608462	
dnoniiay	1.194264	0.0098972	120.67	0.0000	1.1748660	1.2136620	
deqv	0.0136587	0.0026671	5.12	0.0000	0.0084312	0.0188861	
dnimy	0.9976664	0.008516	117.15	0.0000	0.9809752	1.0143580	
dnonixay	-1.256684	0.0097787	128.51	0.0000	-1.2758500	-1.2375180	
_cons	-0.0843095	0.0077981	-10.81	0.0000	-0.0995937	-0.0690254	
sigma_u	0.51602911						
Sigma_e	1.5597466						
rho	0.09865752	(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
	overall =	0.7889			max =	52
				F(6, 119207) =		6508.77
				Prob > F =		0.0000
roaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]	
roaptx						
L4.	-0.0059829	0.0026497	-2.26	0.0240	-0.0111762	-0.0007896
lnasset5	-0.3870837	0.0204479	-18.93	0.0000	-0.4271612	-0.3470063
noniiay	0.9792774	0.0063348	154.59	0.0000	0.9668613	0.9916934
eqv	0.0349243	0.0031389	11.13	0.0000	0.0287720	0.0410765
nimy	0.8714233	0.011354	76.75	0.0000	0.8491697	0.8936768
nonixay	-1.054804	0.0069426	-151.93	0.0000	-1.0684110	-1.0411960
_cons	4.574221	0.263749	17.34	0.0000	4.057276	5.091167
sigma_u	0.77265					
Sigma_e	2.0447255					
rho	0.12494804	(fraction of variance due to u_i)				
F test that all u_i = 0 :		F(2651, 119207) =			Prob > F = 0.0000	

The time-series OLS results also show that the net interest rate margin of rural banks is higher than that of their metropolitan counterparts. The time-series OLS data also 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, although size of the coefficient is relatively small. This warrants further investigation. 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.

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
	overall =	0.8054			max =	52
				F(6, 119207) =		6710.78
				Prob > F =		0.0000
droaptx	Coef.	Std. Err.	t	P>(t)	[95% Conf. Interval]	
droaptx						
L4.	0.0017847	0.0026506	0.07	0.5010	-0.0034105	0.0069799
dlnasset5	-0.219934	0.0270817	-8.12	0.0000	-0.2730137	-0.1668543
dnoniiay	0.972894	0.0061332	158.63	0.0000	0.9608731	0.9849149
deqv	0.0339648	0.0030848	11.01	0.0000	0.0279186	0.0400111
dnimy	0.9223176	0.0113704	81.12	0.0000	0.9000318	0.9446034
dnonixay	-1.039375	0.0067974	-152.91	0.0000	-1.0526980	-1.0260530
_cons	0.025413	0.0107307	2.37	0.0180	0.004381	0.0464449
sigma_u	0.67401676					
Sigma_e	1.9709322					
rho	0.10472332	(fraction of variance due to u_i)				
F test that all u_i = 0 :		F(2651, 119207) = 2.95				Prob > F = 0.0000

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, we follow Goddard, Molyneux, and Wilson (2004), who encountered similar issues, and provide the results of the economy-normalized regressions with the above caveat.

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 chi 2(9) =		2444.07
				Prob > chi 2 =		0.0000
One-step results		(Std. Err. adjusted for clustering on crossid)				
		Robust				
dr0roaptx	Coef.	Std. Err.	z	P>(z)	[95% Conf. Interval]	
dr0roaptx						
L1.	0.3973775	0.0441071	9.01	0.000	0.3109292	-0.4838258
L2.	-0.0175836	0.0152226	-1.16	0.248	-0.0474193	0.0122521
L3.	-0.01011649	0.0191132	-5.29	0.000	-0.1386261	-0.0637036
L4.	0.0369237	0.118291	3.12	0.002	0.0137390	0.0601083
dlnasset5	-2.720921	0.222671	-12.22	0.000	-3.1573480	-2.2844940
dnoniiay	0.8255317	0.051451	16.05	0.000	0.7246896	0.9263738
deqv	0.0777918	0.0186109	4.18	0.000	0.0413152	0.1142685
dnimy	0.7787569	0.465123	16.74	0.000	0.6875944	0.8699194
dnonixay	-0.8508638	0.068657	-12.39	0.000	-0.9854290	-0.7162986
_cons	0.0321022	0.0397568	0.81	0.419	-0.0458197	0.1100241
Instruments for differenced equation						
	GMM-type: L(2/.).dr0aptx					
	Standard: D.dlnassat5 D.dnoniiay D.deqv D.dnimy D.dnoixay					
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 chi 2(9) =			52572.28
			Prob > chi 2 =			0.0000
One-step results	(Std. Err. adjusted for clustering on crossid)					
		Robust				
dr0roaptx	Coef.	Std. Err.	z	P>(z)	[95% Conf. Interval]	
dr0roaptx						
L1.	0.4498633	0.002912	154.49	0.000	0.4441559	0.4555707
L2.	-0.0310608	0.0029281	-10.61	0.000	-0.0036800	-0.0253219
L3.	-0.1364222	0.0027547	-49.52	0.000	-0.1418214	-0.1310231
L4.	0.0647087	0.002365	27.36	0.000	0.0600733	0.0693440
dlnasset5	-3.173356	0.075241	-42.18	0.000	-3.3208230	-3.0258840
dnoniiay	1.065877	0.0126253	84.42	0.000	1.0411320	1.0906220
deqv	0.0288549	0.0055402	5.21	0.000	0.0179963	0.0397135
dnimy	0.78339973	0.0138901	56.4	0.000	0.7561731	0.8106214
dnonixay	-1.117461	0.0127226	-87.81	0.000	-1.1424050	-1.0925170
_cons	-8499601	0.029723	-40.53	0.000	-891065	-0.8088553
Instruments for differenced equation						
	GMM-type: L(2/.).dr0aptx					
	Standard: D.dlnassat5 D.dnoniiay D.deqv D.dnimy D.dnoixay					
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 chi 2(9) =		1468.22
				Prob > chi 2 =		0.0000
One-step results				(Std. Err. adjusted for clustering on crossid)		
		Robust				
dr0roaptx	Coef.	Std. Err.	z	P>(z)	[95% Conf. Interval]	
dr0roaptx						
L1.	0.3685604	0.062088	5.94	0.000	0.0246870	0.4902506
L2.	-0.0129432	0.0175742	-0.74	0.461	-0.0473881	0.0215017
L3.	-0.0845967	0.0237472	-3.56	0.000	-0.0121140	-0.0380530
L4.	0.0199218	0.0136042	1.46	0.143	-0.0067419	0.0465855
dlnasset5	-1.644753	0.3033744	-5.42	0.000	-2.2387560	-1.0495500
dnoniiay	0.8151457	0.0397175	20.52	0.000	0.7373007	0.8929906
deqv	0.102721	0.0309129	3.32	0.001	0.0421327	0.1633092
dnimy	0.9003749	0.0895391	10.06	0.000	0.7248815	1.0758680
dnonixay	-0.8179056	0.0532217	-15.37	0.000	-0.9222183	-0.7135929
_cons	0.5602436	0.1056296	5.3	0.000	0.3532133	0.7672738
Instruments for differenced equation						
	GMM-type: L(2/.).dr0aptx					
	Standard: D.dlnassat5 D.dnoniiay D.deqv D.dnimy D.dnoixay					
Instruments for level equation				Standard: _cons		

CONCLUSIONS

This study demonstrates that US community banks are not a homogenous group. Rural and metropolitan community banks have differences on the variables contributing to profitability. Therefore, it is important to segregate the two when conducting studies on community banking in the US. This study compares 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 rural 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 substantially 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. Perhaps, in a rural community with only a few banks 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 achieved 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, we ran all studies using economy-normalized data where we subtracted the individual bank numbers for each variable from 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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