2007

Causality Between Bank Lending and Employment Growth: Evidence From Small Business Lending

Eungmin Kang
St Cloud State University, ekang@stcloudstate.edu

Mary Edwards
St Cloud State University, MEEDWARDS@STCLOUDSTATE.EDU

Artatrana Ratha
St. Cloud State University, aratha@stcloudstate.edu

CAUSALITY BETWEEN BANK LENDING AND EMPLOYMENT GROWTH:

EVIDENCE FROM SMALL BUSINESS LENDING

Eungmin Kang, Mary E. Edwards and Artatrana Ratha

ABSTRACT

This paper investigates the linkage between small business bank lending and small business employment growth by testing two hypotheses: first, whether there exists any causal relationship between bank's small business lending and the small business employment at the disaggregate level and, second, whether the evidence on the causality from the disaggregate data is consistent with the evidence from the aggregate data and the pooling data. The general hypothesis would be that the greater the level of regional aggregation, the more probable that we can find clear causality between bank credit and economic activity, but the empirical results from the aggregate data do not always represent the true causality existing from the disaggregate data when the aggregation bias exists. The findings of this study support both hypotheses: aggregating data does help in identifying the causality, and also the data aggregation sometimes misrepresent the true causal relationship of less aggregated sample. We found that the pooling regression is an effective way to identify the problem in aggregation bias.

JEL Classification: E51, G21, R11.

Key Words: Small Business, Regional Growth, Bank Lending, Causality.

First Draft – Please do not quote without authors' permission.

- - - - - - - - - - - - - -

Authors are Associate Professor, Professor, and Assistant Professor of Economics, respectively, at St. Cloud State University, St. Cloud, Minnesota. The paper is for the presentation at the Midwest Economics Association 71st Annual Conference, Minneapolis, Minnesota, March 23-25, 2007. Please send correspondence to: Eungmin Kang, Department of Economics, St. Cloud State University, St. Cloud, Minnesota 56301. E-mail: kang@stcloudstate.edu.

I. INTRODUCTION

The role of bank lending in economic growth has been gaining new interest in recent years and the empirical evidence on the causality between bank lending and the national economic growth in foreign countries has grown substantially. For instance, a few recent articles support the hypothesis that causality runs from bank credit to economic growth: Vaithilingam, Guru and Shanmugam (2003) found this result when they studied the banking industry in Malaysia using a Vector Auto Correction Model. Hassan Al-Tamimi, Al-Awad and Charif (2001) studied 8 Arab countries and identified a short-term link between financial development and economic growth, but the linkage was weak for the long-run. Berger, Hassan and Klapper, (2004), in a comprehensive study of 49 countries including the U.S., determined that the efficiency and market share of small community banks were important determinants of improved economic performance of most countries. On the other hand, Luintel and Khan (1999) used a Multivariate Vector Autoregression model and found bidirectional causality for most of 10 developing countries in their study.

In the U.S., however, few empirical studies investigate the causality of bank lending and growth. This is probably because the banking industry in the U.S. does not yet operate in a fully integrated geographic market. Despite the facts that (1) geographic restrictions against bank branch expansion no longer exist and (2) the banking markets are much more integrated than two decades ago, most banks in the U.S., with the exception of several money center banks, still maintain their local and regional market characteristics. Without a fully integrated national banking market, it would be difficult to empirically identify true causality between bank lending and economic growth by using aggregate data.

Despite the inherent problem in aggregate data, some earlier studies attempted to identify the causality at the national level for the U.S. For example, Lown (1988) found strong evidence to support the hypothesis that bank credit caused aggregate economic activity. Friedman and Kuttner (1993) also found that financial deregulation and the expansion of bank credit played a significant role in economic growth during the 1980s. Romer and Romer (1990), however, found no evidence on the causality between bank lending and aggregate economic activity, and concluded that bank lending and economic growth are pretty much contemporaneous.

A few earlier studies explored causality at less aggregated levels, but also reported conflicting evidence. Barkley and Helander (1985), for example, found a uni-directional causality running from the growth of regional economy to the growth of bank lending. Their results suggest that strong local growth in retail sales provides an incentive for banks to expand their local lending. Samolyk (1992), however, found opposite evidence from the pooled state-level real personal income data for the U.S. between 1983 and 1990. Supporting the traditional view on the credit-income relationship, her evidence shows that bank loans generate the local economic growth. A similar study by Amos, Kermani and Wingender (1990), on the other hand, found bi-directional causality between bank lending and GDP by state from 1965 to 1985 and concluded that regional growth stimulates bank credit expansion and in turn, the bank credit affects regional growth.

The conflicting results of these studies may be due to different measures of economic activity (retail sales, real personal income and GDP) or dissimilar sample periods, but the level of regional aggregation may also be a factor that causes this conflicting evidence at a disaggregated level. In fact, the effect of bank loans on a regional economy may vary significantly depending on how broadly the bank markets and regional economy are defined. Unlike the regional economic activity that may be measured by specific geographic delineation (i.e., cities, metropolitan areas, states or even larger Census regions), the market for bank lending has become more difficult to measure, especially after the initial movement of interstate banking in the early 1980s and the following interstate banking legislation that effectively eliminate the geographic delineation of banking market in 1997. For instance, if a local business is not able to borrow from its local bank, it may now be able to borrow from banks in other cities or other states. Empirical evidence on the causal linkage between bank lending and regional economy in the U.S. may not be well represented without a reasonable delineation of local banking markets and local economies whose economic activities are not significantly influenced by outside credit sources.

Another problem we will address in this study is whether the evidence from the aggregate data is a fair representation of the existing relationship shown in small disaggregated samples. When a region is dominated by a large city (or state), the empirical results may be different from the results of less densely populated areas. The unique characteristics of smaller samples tend to disappear in the aggregation process. One way to identify and adjust for the potential problems is analyzing the pooled data which maintain some level of small sample characteristics and, therefore, may identify the inconsistency in the empirical evidence between disaggregate and aggregate data.

In this context, this paper examines the causality between small business lending and small business employment. The small business sector is an important backbone of the U.S. economy. According to the Local Area Unemployment Statistics (LAUS), in 2006, the small businesses employ 57% of all workers in the private supersectors of the economy and generate 48% of total wages in the U.S.[1] The underlying assumption of this study is that most small businesses are local in nature: they tend to hire workers from their geographic regions, and they seek funds for operation from local or regional banks. The local characteristics of bank lending and employment enable us to identify their linkages at reasonably disaggregated levels (individual state or census region). The study addresses two important empirical questions: first, is there any causal relationship between a bank's small business lending and the small business employment at the disaggregate level and, second, is the evidence on the causality from the disaggregated data consistent with that from aggregated data or pooled data, using identical measures of economic activity and sample periods along with the same empirical methods . The next section of the paper will describe the empirical methodology and data used in this study. Section III will discuss the empirical findings and the conclusions will follow.

[1] The private supersectors are defined by BLS NAICS classification, which employ about 85% of all workers in the U.S. in the following 11 industries - Construction, Education and Health Services, Financial Activities, Information, Leisure and Hospitality, Manufacturing, Natural Resources and Mining, Other Services, Professional and Business Services, Transportation and Utilities, and Wholesale and Retail Trade. The government sector and farm employment are excluded in this study.

II. MODELS AND METHODOLOGY

Our principal hypothesis is that empirical results from the aggregate data do not always represent the true causality existing from the disaggregate data due to aggregation bias. To investigate the problem, we compare the test results from the disaggregated data with those using the aggregate data and pooled data. Specifically, we compare the results of our test using three levels of aggregation: (1) aggregate national data with data disaggregated into (2) the eight Census regions, and then by (3) individual states to investigate the linkage between the growth of small business lending and the growth of local small business employment from both disaggregate, aggregate and pooled data samples.

To identify the causality between small business employment (EMP) and small business bank lending (LOAN), we perform the bivariate Granger Causality Test (Granger, 1969) on the state-level disaggregate data, the aggregate regional and national data, and pooled sample data for the period of 1993 and 2006. The standard bivariate Granger Causality specification is:

$$EMP_t = \alpha_o + \Sigma\beta_i\, EMP_{t-i} + \Sigma\gamma_i\, LOAN_{t-i} + \varepsilon_t \qquad (1)$$

$$EMP_t = \alpha_o + \Sigma\beta_i\, EMP_{t-i} + \varepsilon_t \qquad (2)$$

$$LOAN_t = \alpha_o + \Sigma\beta_i\, LOAN_{t-i} + \Sigma\gamma_i\, EMP_{t-i} + \varepsilon_t \qquad (3)$$

$$LOAN_t = \alpha_o + \Sigma\beta_i\, LOAN_{t-i} + \varepsilon_t \qquad (4)$$

The restricted and unrestricted equations are estimated by Ordinary Least Squares (OLS). The Sum of Squared Residuals (SSR) from the restricted equations are compared with those estimates from the restricted equations by using F-tests. In our study, only the first-order lagged variables (EMP_{t-1} and $LOAN_{t-1}$), are used in the estimation mainly due to the lack of sufficient time-series observation in the data.

Next, in order to identify the existence of cointegration between EMP and LOAN, we employ the error correction version of Autoregressive Distributed Lag (ARDL) model suggested by Pesaran (2005). The model is also known as the bound testing approach to cointegration and has been utilized extensively in the international finance literature.[2] The existence of cointegration among the variables in the equations above is determined by the negative and significant coefficient for the error correction term as well as the significant coefficient for the lagged variables. The specification of the bivariate Autoregressive Distributed Lag (ARDL) is:

$$\Delta EMP_t = \alpha_o + \Sigma\beta_i \, \Delta EMP_{t-i} + \Sigma\gamma_i \, \Delta LOAN_{t-i} + \delta 1 EMP_{t-1} + \delta 1 LOAN_{\,t-1} + \varepsilon_t \qquad (5)$$

$$\Delta LOAN_t = \alpha_o + \Sigma\beta_i \, \Delta LOAN_{t-i} + \Sigma\gamma_i \, \Delta EMP_{t-i} + \delta 1 LOAN_{t-1} + \delta 1 EMP_{\,t-1} + \varepsilon_t \qquad (6)$$

We also estimate the pooled regression by using and the Cross-sectional and Time-series Error Component method (TSCSREG Procedure in SAS) by pooling the disaggregate state data for the causality testing at the regional and the national level. The random effect model is employed in order to adjust for the unobserved cross-sectional heteroscedasticity among the different states and regions. The model was originally proposed by Fuller and Battese (1974) and Da Silva (1975) and popularised by Baltagi (1995) more recently. The model is specified by redefining the error terms in the Granger Causality model (equations 1 – 4) as below:

$$\varepsilon_t = \alpha_i + \gamma_t + e_{it}, \quad i = 1, \ldots N, \text{ and } t = 1, \ldots t, \qquad (7)$$

where,

α_i *is cross-sectional random effect,*

γ_t *is time-series random effect*

e_i *is a residual effect unaccounted for any time-series or cross-sectional effect*

The random effect model is the model with random constant terms, but with fixed slope parameters. The model also assumes that unobserved individual heterogeneity is not correlated with the variables in the regression. Under these assumptions, the OLS estimation produces inefficient but unbiased estimation. This study, based on the Hausman test, adopts the random effect model instead of fixed effect model in order to capture the unique characteristics of individual states in the random constant terms. We assume that the parameters which represent the linkage between small business employment and small business lending are be stable and consistent.

[2] See Bahmnai-Oskooee and Ratha (2004) for detailed discussions on the ARDL model.

The pooled causality model above is unique from other pooled regression studies in a sense that it includes lagged autoregressive terms in the pooled regression. It is noteworthy, however, that a complication may rise from adding such a dynamic in the regression: the lagged dependent variable may be correlated with the error terms in the regression (Green, 2003). An alternative estimation method that utilizes some instrumental variables may be considered in such case. Our study, however, was not able to perform the alternative estimation mainly due to the lack of sufficient time-series observations in the sample.

Small businesses in this study are defined as firms with fewer than 100 paid employees. Annual employment data for small businesses (small business employment) are obtained from the first quarter LAUS files from the Bureau of Labor Statistics between 1993 and 2006. The total amount of small business loans made by individual banks (small business lending) is reported annually in the Federal Reserve's *Call and Income Reports* for years 1993 to 2006. Small business lending of an individual bank in this study consists of bank loans smaller than $250,000. The study includes only domestic banks headquartered in the 50 states and D.C. The 12 largest money center banks with domestic assets over $100 billion are excluded from the sample since their business covers multiple regions throughout the nation. Table 1 list the large money-center banks excluded from the sample.

The descriptive statistics of the data and variables used in the study are shown in Table 2. In 2006, 62 million workers are employed in small businesses (EMP) with paid employees less than 100, which consist of 57% of total employment in the supersectors in the U.S. It becomes 91 million workers and 83% of total employment when the small- and medium-sized firms considered together (EMPMT). The amount of small business bank lending with less than $250,000 per loan (LOAN) totaled $156 billion in 2006. [3]

[3] It becomes $286 billion if the lending include the small business loans with less than $1 million per loan (LOANST). Only EMP and LOAN are used in this study for the purpose of excluding the medium sized company (employment between 100 and 500) from the estimation.

III. ESTIMATION RESULTS AND FINDINGS

Table 3 shows the results of the Granger Causality tests using OLS estimation and data aggregated at the national, regional and state levels. The hypothesis of causality is substantiated for total 24 states and D.C. at a 10% or lower significance level. Among them, 11 states and D.C. support the hypothesis of a unidirectional causality running from the small bank lending to the small business employment, but 10 other states support the alternative hypothesis of a unidirectional causality from employment to bank lending. Finally, bi-directional causality appears for three states – Virginia, Alaska and Hawaii.

We then aggregate the data to conform to census regions. At this level of aggregation, 6 out of 9 regions showed a unidirectional causality at 10% or less significance level. Two regions, East South Central and Mountain, appear to have the causality running from bank lending to employment, but other four regions, (New England, Middle Atlantic, East North Central and South Atlantic) show the causality from employment to bank lending.

When we analyze aggregated data for the entire nation, we identify causality running from the small business employment to small business bank lending at 1% significance level, which supports the findings of Barkley and Helander (1985) and contradicts Vaithilingan, et al. (2003). The result implies that strong growth of local small businesses provides an incentive for banks to expand their local business lending.

Table 4 reports the results of the Autoregressive Distributed Lag (ARDL) model estimation. The negative sign and the significance of the error correction (EC) terms confirmed that the two variables, small business lending and small business employment are cointegrated with each other in most states (44 states and D.C.), regions (7 out of 9), and in the U.S. The significant long-run coefficient for the lagged explanatory variable, however, are identified only in 7 states. The same results are produced when the dependent and independent variables switch places. The analysis of regionally aggregate data provides evidence that 4 out of 9 regions show a significant long-run relationship among these variables. Using national data, we also find evidence of cointegration among these two variables, but the coefficient is not significant enough to confirm a long-run relationship. We speculate that the mixed evidence is the result of either (1) insufficient lagged variable used in the model (due to insufficient time-series observation), or (2) existence of aggregation bias – a causal relationship prevailing in individual disaggregated samples becomes less evident when the data are excessively aggregated. In the latter case, a typical example is found in New England region where two states exhibit a clear causal relationship between bank lending and small business employment, but the relationship disappears when we combine all 6 states together into a regional aggregate data. Following the same reasoning, causality is not evident when we use national aggregate data, even though the causality is be found in the samples of four different regions in the U.S.

Table 5 present the estimation results of pooled regression. The pooled regression methods enable us to extract more information from the available data and overcome our dual problems of insufficient time-series observations and cross-sectional heteroscedasticity across different states and regions in the study. The causal link between small business lending and small business employment is shown in all 9 regions in the random effect estimation results. In the East South Central and Mountain regions, the unidirectional causality runs from lending to employment, while other 4 regions - Middle Atlantic, East North Central, South Atlantic and Pacific – show the causality running the opposite direction at a 10% or lower significance level. The final two regions, New England and West South Central, provide evidence of bi-directional causality between the lending and employment. The pooled regression results are also quite consistent at the national level. Both pooled estimates – one for pooling all the states and D.C. and the other for pooling 9 regional aggregate data – show a clear unidirectional causality running from the bank lending to employment; i.e., a growth of loans to small business helps the small businesses and their employment to grow. Compared with the estimation results with the aggregate data, the pooled regression methods are found to be much more effective in identifying the causal link between the growth of small business lending and the growth of small business employment in the regional and national samples. We find that the pooled regression method is especially useful when the data suffer from the problems related to the cross-sectional heteroscedasticity and/or insufficient time-series observations.

IV. CONCLUSIONS

The study examines two empirical questions: first, whether there exists any causal relationship between bank's small business lending and the small business employment at the disaggregate level and, second, whether the evidence on the causality from the disaggregate data is consistent with the evidence from the aggregate data and the pooling data. The general hypothesis would be that the greater the level of regional aggregation, the more probable that we can find clear causality between bank credit and economic activity, but the empirical results from the aggregate data do not always represent the true causality existing from the disaggregate data when the aggregation bias exists. The findings of this study support both hypotheses: aggregating data does help in identifying the causality, and also the data aggregation sometimes misrepresent the true causal relationship of less aggregated sample. We found that the pooling regression is an effective way to identify the problem in aggregation bias.

There are a few issues related to the pooled estimation method that warrant further investigation. First, the random effect model in this study assumes that the linkage between the employment and bank lending is fixed, but the existence of random parameter is a possibility. With sufficient observations, the study might be able to look into the randomness of the causal parameter. Secondly, as mentioned earlier, the addition of a lagged dependent variable in the pooled regression could cause some complexity in interpreting the estimation results because the possible correlation between the lagged dependent variable and the error terms. If this is the case, an alternative estimation method must be used, for example, instrumental variable method or GMM estimation procedure. Additionally, the cointegration testing process might need to be modified if the lagged variables are correlated with the error terms in the pooled regression, which may call for a new technique such as panel cointegration test.

This study can be extended in several ways. While the study used the Census region as the base of comparison, it is not necessarily the best delineation of regional boundaries. It may be either further aggregated or disaggregated to capture the dynamics of bank loan markets and the source of credit supply into local small businesses. Also, a Monte-Carlo examination of the effects of different pooling procedures on causality analysis might also be helpful in identifying the potential bias stemmed from aggregation or pooling bias. Furthermore, models with various control variables representing different economic aspects of different regions, and disaggregated loan types to different types of small business might offer improved results.

REFERENCES

Al-Tamimi, Hussein A. Hassan, Mouawiya Al-Awad, and Husni A. Charif. 2001. Finance and growth: Evidence from some Arab countries. *Journal of Transnational Management Development* 7/2, 2001: 3-18.

Amos, Orley M. Jr., Kermani, Majid, and Wingender, John R., "An Empirical Test of the Interaction Between Regional Financial Markets and Regional Growth," *Review of Regional Studies, Vol.24 (1),* 1994, 55-69.

Bahmnai-Oskooee, Mohsen and Arta Ratha (2004), "Bilateral J-Curve between US and her Trading Partners – The ARDL Approach", *Journal of Economics and Finance*, Volume 28, Number 1, Spring, pp. 32-38

Baltagi, Badi. Econometic Anaysis of Panel Data, New York: John Wiley and Sons, 1995.

Barkley, David L. and Helander, Peter E., "Commercial Bank Loans and Non-metropolitan Economic Activity: A Question of Causality," *Review of Regional Studies* 15(1), Winter 1985, 26-32.

Berger, Allen N., Iftekhar Hasan and Leora Klapper, "Further Evidence on the Link between Finance and Growth: An International Analysis of Community Banking and Economic Performance." *Journal of Financial Services Research*, 25:2/3, 2004, 169-202.

Da Silva, J.G., "The Analysis of Cross-Sectional Time-Series Data," Ph.D. dissertation, Department of Statistics, North Carolina State University, 1975.

Friedman, Benjamin M., and Kenneth N. Kuttner. 1993. Another look at the evidence on money-income causality. *Journal of Econometrics* 57, (1-3) (May-June 1993): 189-203.

Fuller, W.A. and Battese, G.E., "Estimation of Linear Models with Crossed Error Structure," *Journal of Econometrics*, Vol.2, 1974, 67-78.

Granger, C.W.J., "Investigating Causal Relationships by Econometric Models and Cross Spectral method." *Econometrica,* 1969, 37:424-38.

Green, William H., Econometric Analysis, 5th Edition, New Jersey: Prentice Hall Inc., 2003

Lown, Cara S. 1988. The credit-output link vs. the money-output link: New evidence. *Federal Reserve Bank of Dallas Economic Review* 0, (0) (November 1988): 1-10.

Luintel, Kul B. and Mosahid Khan, "A Quantitative Reassessment of the Finance-Growth Nexus: Evidence from a Multivariate VAR." *Journal of Development Economics, Vol.60,* 1999, 381-405.

Pesaran, M. H. and Y. Shin (1995), "An Autoregressive Distributed Lag Modeling Approach To Cointegration Analysis," In Centennial Volume of Ragner Frisch, Edited By S. Strom, A. Holly, and P. Diamond (Eds), Cambridge University Press, Cambridge.

Romer, Christina D., and David H. Romer. 1990. New evidence on the monetary transmission mechanism. *Brookings Papers on Economic Activity* 0, (1) (1990): 149-198.

Samolyk, Katherine A., "Bank Performance and Regional Economic Growth: Evidence of a Regional Credit Channel." *Federal Reserve Bank of Cleveland, Working Paper: 9204*, 1992.

Vaithilingam, Santha, Balachandher K. Guru and Bala Shanmugam, "Bank Lending and Economic Growth in Malaysia." *Journal of Asia-Pacific Business, Vol. 5(1),* 2003, 51-69.

TABLE 1:

U.S.-CHARTERED MONEY-CENTER BANKS WITH CONSOLIDATED ASSETS of $100 BILLION or MORE. As of December 31, 2006

Bank Name	Rank	Bank Location	Domestic Assets (Mil $)	Domestic Branches
BANK OF AMER NA	1	CHARLOTTE, NC	1,084,130	5,826
JPMORGAN CHASE BK	2	COLUMBUS, OH	652,824	2,852
CITIBANK/CITIGROUP	3	LAS VEGAS, NV	537,861	1,005
WACHOVIA BK NA	4	CHARLOTTE, NC	487,894	3,159
WELLS FARGO BK	5	SIOUX FALLS, SD	398,546	4,052
U S BK NA/U S BC	6	CINCINNATI, OH	216,581	2,822
SUNTRUST BK	7	ATLANTA, GA	182,628	1,942
HSBC BK USA NA	8	WILMINGTON, DE	153,266	414
FIA CARD SVC NA	9	WILMINGTON, DE	131,437	0
REGIONS BK	10	BIRMINGHAM, AL	131,924	2,251
NATIONAL CITY BK	11	CLEVELAND, OH	133,894	1,468
BRANCH BKG&TC	12	WINSTON-SALEM, NC	117,134	912

Source: Federal Reserve Board Statistical Release.

TABLE 2.
DESCRIPTIVE STATISCS OF DATA AND VARIABLES

SMALL BUSINESS EMPLOYMENT (2006, Unit=Thousand)

	EMP EMP<100	EMPMT EMP<500	EMPT ALL
Mean	54,960,559	80,472,478	99,293,448
Median	55,824,522	82,381,508	101,934,584
Maximum	62,843,148	91,403,571	110,265,889
Minimum	45,705,827	68,427,507	86,915,599
Std. Dev.	5,381,072	7,859,530	8,341,735

SMALL BUSINESS BANK LENDING (2006, Unit=Thousand)

	LOAN LOAN<$250,000	LOANST LOAN<$1 MIL
Mean	124,373,070	228,181,980
Median	125,903,326	233,318,561
Maximum	156,999,177	286,361,476
Minimum	81,085,194	150,100,063
Std. Dev.	26,487,420	47,613,158

SMALL BUSINESS EMPLOYMETN AND LENDING: RATIOS

	EMPR	EMPMR	LOANR	LOANMR
Mean	0.56	0.81	0.08	0.14
Median	0.56	0.81	0.08	0.13
Maximum	0.57	0.83	0.10	0.16
Minimum	0.54	0.80	0.07	0.12
Std. Dev.	0.01	0.01	0.01	0.01

TABLE 3:
GRANGER CAUSALITY TEST WITH AGGREGATE DATA

MODEL 1: $EMP_t = \alpha_o + \Sigma\beta_i EMP_{t-i} + \Sigma\gamma_i LOAN_{t-i} + \varepsilon_t$
MODEL 2: $LOAN_t = \alpha_o + \Sigma\beta_i LOAN_{t-i} + \Sigma\gamma_i EMP_{t-i} + \varepsilon_t$

	STATES AND REGIONS	MODEL 1: EMP <= LOAN Chi-Square		MODEL 2: LOAN <= EMP Chi-Square	
Nation		2.48		14.14	***
New England		1.70		2.84	*
	Connecticut	0.94		1.80	
	Maine	2.78	*	2.58	
	Massachusetts	0.15		0.97	
	New Hampshire	1.41		2.05	
	Rhode Island	2.80	*	0.01	
	Vermont	1.22		8.60	***
Middle Atlantic		0.42		3.64	*
	New Jersey	0.28		8.52	***
	New York	0.10		4.86	**
	Pennsylvania	2.34		0.85	
East North Central		0.00		3.44	*
	Illinois	6.03	**	0.03	
	Indiana	2.27		0.00	
	Michigan	0.18		0.27	
	Ohio	0.33		2.70	
	Wisconsin	5.09	**	0.15	
West North Central		0.32		2.50	
	Iowa	0.70		0.72	
	Kansas	0.31		1.07	
	Minnesota	0.11		0.75	
	Missouri	1.15		1.62	
	Nebraska	1.12		2.64	
	North Dakota	0.02		0.65	
	South Dakota	2.45		1.26	

*** 1% significance level ** 5% significance level * 10% significance level

TABLE 3 (Continued):
GRANGER CAUSALITY TEST WITH AGGREGATE DATA

South Atlantic		1.17		6.93	***
	Delaware	0.21		1.90	
	District of Columbia	13.85	***	0.56	
	Florida	1.95		6.53	**
	Georgia	0.00		2.71	
	Maryland	0.54		0.12	
	North Carolina	1.77		0.18	
	South Carolina	0.03		6.04	**
	Virginia	4.56	**	15.77	***
	West Virginia	1.02		0.22	
East South Central		7.38	***	0.56	
	Alabama	2.59		2.70	
	Kentucky	0.01		4.14	**
	Mississippi	0.55		11.47	***
	Tennessee	4.63	**	0.04	
West South Central		2.57		0.73	
	Arkansas	0.19		0.64	
	Louisiana	0.10		0.96	
	Oklahoma	1.23		2.05	
	Texas	1.26		0.48	
Mountain		7.17	***	0.01	
	Arizona	1.46		2.76	*
	Colorado	0.09		3.45	*
	Idaho	1.56		0.00	
	Montana	3.44	*	1.26	
	Nevada	3.16	*	0.65	
	New Mexico	4.81	**	1.18	
	Utah	2.11		8.82	***
	Wyoming	2.65		1.62	
Pacific		0.07		1.74	
	Alaska	4.47	**	17.19	***
	California	0.22		1.67	
	Hawaii	14.46	***	23.00	***
	Oregon	0.98		2.02	
	Washington	1.52		0.38	

TABLE 4:
ESTIMATION OF ARDL MODEL WITH AGGREGATE DATA

STATE CODE	MODEL 1: EMP <= LOAN d(LOAN) Coeff.	T-Stat		EC(-1) Coeff.	T-Stat		MODEL 2: LOAN <= EMP d(EMP) Coeff.	T-Stat		EC(-1) Coeff.	T-Stat	
Nation	-0.112	-0.813		0.171	0.465		-0.239	-0.843		-0.516	-7.546	**
New England	-0.043	-1.554		-0.078	-0.949		-4.496	-1.554		-1.000		
Connecticut	0.008	0.716		-0.160	-1.928	*	1.729	1.116		-0.091	-0.414	
Maine	-0.014	-1.170		-0.108	-2.199	*	1.263	1.433		-0.143	-0.651	
Massachusetts	0.013	0.236		-0.221	-2.910	**	-0.555	-1.159		-1.000		
New Hampshire	0.046	2.605	**	-0.115	-2.948	**	6.241	2.053	*	-0.539	-2.589	**
Rhode Island	0.003	0.918		-0.129	-2.308	**	2.460	0.370		-0.430	-1.298	
Vermont	-0.324	-2.757	**	-0.469	-3.458	**	-0.926	-3.159	**	-1.000		
Middle Atlantic	-0.081	-4.222	**	0.094	1.532		-7.117	-4.200	**	-0.718	-5.015	**
New Jersey	-0.032	-0.905		-0.203	-1.415		-3.832	-6.733	**	-1.000		
New York	-0.084	-4.367	**	0.119	1.415		-8.097	-4.367	**	-0.614	-5.281	**
Pennsylvania	0.042	1.460		-0.068	-1.271		0.105	0.196		-0.401	-1.345	
East North Central	-0.025	-0.764		-0.146	-0.986		-0.343	-0.281		-0.301	-3.100	**
Illinois	-0.023	-0.648		0.009	0.070		1.030	1.049		-0.387	-2.009	*
Indiana	-0.095	-5.862	**	-0.133	-2.751	**	-8.133	-5.862	**	-1.000		
Michigan	0.013	0.236		-0.221	-2.910	**	-0.555	-1.159		-1.000		
Ohio	-0.015	-1.114		-0.161	-1.444		1.969	1.398		-0.212	-1.761	
Wisconsin	0.138	1.748		-0.416	-2.535	**	2.289	11.758	**	-1.000		
West North Central	0.053	3.157	**	-0.398	-4.932	**	9.449	3.157	**	-1.000		
Iowa	0.101	2.248	**	-0.515	-3.368	**	0.744	0.716		-0.154	-0.814	
Kansas	0.007	0.191		-0.227	-1.907	*	0.765	0.788		-0.350	-1.758	
Minnesota	0.028	2.641	**	-0.121	-2.250	**	15.712	2.641	**	-0.297	-1.375	
Missouri	0.063	1.391		-0.313	-3.279	**	2.129	4.840	**	-1.000		
Nebraska	0.028	0.585		-0.168	-1.329		1.752	2.217	*	-0.700	-3.137	**
North Dakota	-0.012	-0.682		-0.032	-0.182		-3.502	-1.023		-0.344	-2.007	*
South Dakota	0.001	0.159		-0.265	-3.921	**	2.743	0.831		-0.161	-0.645	

** 5% significance level   * 10% significance level

TABLE 4 (CONTINUED):
ESTIMATION OF ARDL MODEL WITH AGGREGATE DATA

South Atlantic	0.112	2.324	**	-0.401	-2.932	**	3.042	16.074	**	-1.000		
Delaware	0.014	1.719		-0.150	-1.873	*	2.126	1.071		-0.087	-0.368	
District of Columbia	-0.010	-0.778		-0.492	-3.054	**	-7.637	-4.924	**	-1.000		
Florida	0.019	0.358		-0.005	-0.066		-0.535	-1.686		-0.599	-2.473	**
Georgia	-0.005	-0.254		-0.165	-2.588	**	1.123	1.290		-0.366	-1.657	
Maryland	-0.032	-0.885		-0.042	-1.055		0.316	0.958		-1.000		
North Carolina	0.040	1.820	*	-0.454	-2.916	**	8.260	14.053	**	-1.000		
South Carolina	-0.016	-0.692		-0.111	-1.212		-2.481	-1.073		-0.254	-1.594	
Virginia	0.053	0.812		-0.012	-0.112		1.177	0.812		-1.000		
West Virginia	0.011	0.499		-0.159	-1.806		-0.814	-0.555		-1.000		
East South Central	-0.032	-0.688		-0.043	-0.195		1.365	1.369		-0.358	-2.374	**
Alabama	-0.017	-0.728		-0.064	-0.319		-0.846	-0.271		-0.477	-2.830	**
Kentucky	-0.024	-0.435		-0.180	-2.497	**	-0.293	-0.749		-0.328	-1.661	
Mississippi	0.014	0.426		-0.359	-1.902	*	1.995	1.521		-0.281	-1.679	
Tennessee	-0.032	-1.015		-0.107	-1.339		-2.954	-1.015		-1.000		
West South Central	0.096	1.275		-0.464	-3.451	**	1.964	13.059	**	-1.000		
Arkansas	0.035	0.910		-0.315	-2.577	**	0.604	0.511		-0.448	-2.058	*
Louisiana	-0.004	-0.065		-0.268	-1.308		0.249	0.235		-0.234	-1.214	
Oklahoma	0.063	1.178		-0.350	-1.940	*	1.274	1.325		-0.452	-2.132	*
Texas	0.144	1.955	*	-0.291	-2.953	**	1.398	9.153	**	-1.000		
Mountain	0.062	2.582	**	-0.285	-3.793	**	0.273	0.366		-0.083	-0.377	
Arizona	0.035	3.129	**	-0.228	-4.628	**	14.322	3.877	**	-1.000		
Colorado	0.060	1.164		-0.212	-3.881	**	0.689	2.134	*	-1.000		
Idaho	0.010	0.923		-0.080	-1.555		0.351	0.280		-0.329	-1.440	
Montana	0.027	0.412		-0.172	-0.764		0.435	0.530		-0.359	-2.070	*
Nevada	0.026	0.759		-0.136	-3.527	**	0.611	1.725		-0.447	-1.462	
New Mexico	-0.104	-2.394	**	-0.033	-0.386		-2.868	-1.989	*	-0.724	-3.895	**
Utah	-0.045	-1.006		-0.140	-1.142		-2.223	-1.006		-0.199	-2.013	*
Wyoming	-0.028	-1.354		-0.008	-0.157		-0.545	-1.192		-0.224	-1.520	
Pacific	0.001	0.028		-0.072	-1.348		-0.342	-0.800		-0.294	-1.300	
Alaska	-0.006	-0.194		-0.136	-1.660		-2.263	-4.402	**	-0.642	-3.814	**
California	0.012	0.586		-0.071	-1.333		-0.486	-0.830		-0.202	-0.937	
Hawaii	0.064	1.278		0.125	1.222		0.906	2.031	*	-0.634	-2.789	**
Oregon	0.019	1.443		-0.067	-0.809		9.520	1.615		-1.000		
Washington	-0.021	-0.969		-0.105	-1.582		-0.171	-0.162		-0.532	-1.693	

TABLE 5:
ESTIMATION RESULTS OF POOLED REGRESSION (RANDOM EFFECT MODEL)

REGIONS	OBS. CS	OBS. TS	MODEL 1: EMP<=LOAN T-Stat		F-Stat		MODEL 2: LOAN<=EMP T-Stat		F-Stat	
Nation										
Pooled States	51	13	3.28	***	3.37	*	0.10		1.06	
Pooled Regions	9	13	-37.62	***	5.26	**	0.93		0.89	
New England	6	13	50.77	***	5.66	**	2.24	**	1.17	
Middle Atlantic	3	13	0.03		0.22		1.73	*	2.32	
East North Central	5	13	-0.31		-1.87		1.71	*	5.23	**
West North Central	7	13	29.84	***	3.12	*	-1.73	*	0.62	
South Atlantic	9	13	0.03		0.56		-2.46	**	5.01	**
East South Central	4	13	-11.26	***	8.82	***	0.54		-0.44	
West South Central	4	13	-2.98	***	3.24	*	6.34	***	4.66	**
Mountain	8	13	33.79	***	8.26	***	1.43		-0.51	
Pacific	5	13	0.34		0.00		1.88	*	5.11	**

*** 1% significance level   ** 5% significance level   * 10% significance level