Natural Disasters and Bank Performance: Preliminary Report

Bradley T. Ewing
Jerry S. Rawls Professor in Operations Management, Jerry S. Rawls College of Business & Wind Science and Engineering Research Center, Texas Tech University

Scott E. Hein
Professor and Briscoe Chair of Bank Management and Finance, Jerry S. Rawls College of Business, Texas Tech University

Jamie Brown Kruse
Professor of Economics and Director, Natural Hazards Mitigation Research Center, East Carolina University

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Natural Disasters and Bank Performance

I. Introduction

Wind disasters such as hurricanes and tornadoes occur frequently in the United States. The estimated average annual damage caused by wind hazards is around $6 billion dollars, which is more than 50% of total weather damage and more than 40% of total natural hazard damage (Meade and Abbott, 2003). A single large hurricane can cause massive losses. For example, 1992's Hurricane Andrew is credited with losses of $26.5 billion.[1] Tornadoes can also cause large losses. In fact, the May 3rd 1999 tornado in Oklahoma was responsible for $1.2 billion in damages.[2]

When a hurricane or tornado outbreak occurs, evidence indicates that regional labor markets, insurance markets, as well as housing markets exhibit strong responses to the event(e.g., Ewing and Kruse, 2002; Ewing, Kruse and Thompson, 2003; Ewing, Hein, and Kruse, 2003; Ewing and Covarrubias, 2003; and Ewing, Kruse and Wang, 2004). It is logical then to ask whether a natural disaster can therefore have a direct effect on the performance of banks, especially community banks, which reside in the affected region. There are several reasons why we might expect a community bank to be vulnerable to economic shocks caused by a natural disaster. For one, the geographic concentration of customer base in terms of loan customers as well as demand deposit customers means that a significant proportion of the bank's clientele may be directly harmed by the natural disaster, especially when insurance coverage is either non-existent or deficient. Community banks tend to be less diversified geographically than their larger competitors. According to conventional wisdom, community banks have greater credit risk due to their geographic concentration of their loan portfolio and therefore are more vulnerable to local economic shocks. A second source of vulnerability is the disproportionate number of small business loan customers typical to many community banks. A hallmark of a community bank is "relationship lending" that relies less on credit scoring and more on soft information such as a borrower's character. Due to their ability to collect soft information, community banks are considered a significant source of credit for small businesses. Several studies indicate that there is a negative relationship between the size

[1] National Hurricane Center.
[2] National Weather Service Office in Norman, Oklahoma.

of the banking institution and the proportion of assets devoted to small-business lending (Berger et al., 1995, 1998, 2001; Keeton, 1995; Strahan and Weston, 1998). Small business enterprises are considered to be particularly vulnerable to natural disasters. Alesch, et al. (2001) report on a longitudinal study of a sample of small business after a variety of natural disasters (earthquake, flood, hurricane). They were able to classify only 60% of the small businesses as "recovered" four years following the disaster. Some small businesses failed because of direct damage to premises, equipment and merchandise. However, small businesses can fail two or three years later because the customer base has disappeared and/or business equity has been slowly eroded away. Community banks have a strong relationship to the people and businesses in a geographic region. Severe wind events produce an economic shock to a regional economy that is multifaceted. In most cases, health, lives, homes and businesses are all affected making it hard for a geographically constrained business to diversify the risk. Idiosyncratic risk and market risk are two components of credit risk. A bank can diversify away idiosyncratic risk by balancing its loan portfolio with customers whose default probabilities are not perfectly correlated. A severe windstorm can potentially increase the default probability across an otherwise diverse group of loan customers. In this study we propose to examine the time series behavior of regional bank performance in response to severe wind storm events.

Our analysis utilizes event study methodology that allows for the possibility that changes in measures of bank performance may be significantly affected by a severe wind storm. We propose to examine three bank ratios: nonperforming loans to total loans, net charge offs to total loans, and return on assets (ROA) in an attempt to capture the impact on community banks both in the short term and in the longer term after a wind disaster. [3] Hurricane damage is concentrated in the coastal states whereas tornadoes have been documented in every one of the lower forty-eight states. The highest occurrence of tornadoes is in Texas, Oklahoma and Kansas. Results of this study might be important

[3] In future work, if we can obtain CAMELS ratings for banks in the affected areas we would also like to examine bank's CAMELS ratings in response to disasters. CAMELS stand for Capital adequacy, Asset quality, Management, Earnings, Liquidity and Sensitivity to market risk. Bank examiners assign and overall rating from 1 to 5. The safest banks are rated a "1" with a "5" indicating the riskiest banks. An important breakpoint is if the CAMELS rating are worse than a 2. A CAMELS rating of 3 is likely to prompt supervisory action.

and helpful to local policy makers, especially those that work on regional economic development. Moreover, the results should benefit the operational strategies of the banks themselves by providing information that can lead to better risk management.

We examine bank performance in several tornado-prone areas and hurricane-prone areas. This study will focuses on the Metropolitan Statistical Area (MSA) level of aggregation. The U.S. Census Bureau defines an MSA generally as an area that has a central city with a population of 50,000 or more and adjacent communities having a high degree of social and economic integration with that central city. The MSA markets that we study include Nashville, Oklahoma City, and Fort Worth-Arlington, each of which has been hit by one or more major tornadoes; and Corpus Christi, Miami, and Wilmington, NC each of which has been hit by one or more major hurricanes.

II. Regional Economic Profiles and Wind Disaster Occurrences in Sample Areas

The Fort Worth-Arlington MSA (FW) consists of two major cities, Fort Worth and Arlington. These cities are located in north-central Texas (TX). This MSA is an important commercial and vacation center and has a population of 1.8 million. Major industries include retail trade, manufacturing, transportation and warehousing, and professional and business services. Single-family housing units account for 66 percent of the local residential housing market. Out of 637,000 occupied housing units, 64 percent are owner occupied units.[4] The evening of March 28, 2000, one tornado ripped through high rise buildings in downtown Fort Worth just after the evening rush hour, while another hit Arlington. In all, 50 buildings were hit in Fort Worth and there was damage to more than 1000 homes in Arlington.[5] Total damage was estimated at $450 million.[6]

Nashville is the capital of Tennessee (TN) and is the central city of the Nashville MSA (NV). This MSA has a population of 1.2 million.[7] As an entertainment and transportation center, Nashville has competitive advantages in industries such as publishing and printing, finance and insurance, health care management, music and

[4] 2002 American Community Survey Profile, www.census.gov.
[5] CNN Weather Channel, www.cnn.com/WEATHER/.
[6] National Weather Service Office in Fort Worth, Texas.
[7] 2002 American Community Survey Profile, www.census.gov.

entertainment, automobile, higher education and tourism.[8] Single-family housing units account for 68 percent of the local residential housing market. Out of 484,000 occupied housing units, 68 percent are owner occupied units.[9] On the afternoon of April 16, 1998, two tornadoes went through the downtown area of Nashville. They damaged more than 300 buildings, including the Capitol building.[10] Many homes and buildings in the eastern section of Nashville were damaged as well. The total estimated damage was $100 million according to the National Climate Data Center (NCDC).

The Oklahoma City MSA (OKC) is located in central Oklahoma (OK). OKC includes five counties. The central city is Oklahoma City, the state's capital. This region has a population of 1.1 million. The local economy depends on construction and real estate, health care, education, wholesale and retail, and mining.[11] Tinker Air Force Base is located southeast of Oklahoma City and contributes more than $1.9 billion annually to the local economy.[12] Single-family housing units account for 73 percent of the local residential housing market. Out of 420,000 occupied housing units, 65 percent are owner occupied.[13] On May 3, 1999, perhaps the most destructive group of tornadoes in U.S. history hit Oklahoma and Kansas in the late afternoon and evening. It started in southwest Oklahoma, went northeast to Oklahoma City, then to Kansas. Most areas hit by the tornadoes in OKC were residential communities. Almost 10,000 homes were damaged or destroyed in Oklahoma, including more than 8,000 in OKC. This tornado outbreak is estimated to have caused around $1.2 billion of damage.[14]

Before describing the regional economic profiles of the three hurricane-prone areas, we must address the criteria used to identify hurricane disasters for this study. The nature of hurricanes is quite different from that of tornadoes. Tornadoes are formed under the same unstable weather conditions that produce severe thunderstorms. The conditions that support and sustain a tornado on the ground last a relatively short time—usually a span of minutes. Hurricanes are formed by warm wet oceanic air. The synoptic life of a hurricane lasts for a number of days and typically will directly affect a much

[8] Regional Profile from the Nashville Area Chamber of Commerce, www.nashvilleareainfo.com.
[9] 2002 American Community Survey Profile, www.census.gov.
[10] CNN Weather Channel, www.cnn.com/WEATHER/.
[11] 2002 American Community Survey Profile, www.census.gov.
[12] Greater Oklahoma City Chamber of Commerce, www.okcchamber.com.
[13] 2002 American Community Survey Profile, www.census.gov.
[14] National Weather Service Office in Norman, Oklahoma.

larger geographic area than a tornado. The circulation of hurricanes can be hundreds of miles across, but even a large tornado spans less than a mile.[15] According to our criteria, we included a hurricane in our study only if it was rated Category 1 or higher on the Saffir-Simpson Hurricane Scale (SS), and the center of this hurricane passes within 60 miles of the MSA.[16] Using this standard, we eliminate tropical storms and depressions, and ensure all the hurricanes included in this study passed close to, if not directly over, the study areas.

Corpus Christi, TX, is a coastal city on the Gulf of Mexico. As the center of the Corpus Christi MSA (CC), it is an important naval military base and popular destination for vacationers. This MSA has a population of 371,000. The local economy depends on petrochemical, military, tourism, agriculture and health care industries. Single-family housing units account for 71 percent of the local residential housing market. Out of 132,000 occupied housing units, 65 percent are owner occupied units.[17] As a coastal city, hurricanes and tropical storms are a known hazard. While there were six tropical storms and four hurricanes that caused concern for local residents over the past twenty years, only one hurricane came within close proximity to this area. Hurricane Bret hit nearby on August 23, 1999 and led to a large scale evacuation. The eye of this hurricane passed within 60 miles of this area, and wind speed in the eye wall was 103 miles per hour (mph).[18] Bret brought widespread flash flooding. The total damage to homes and businesses was around $1.5 million.[19]

The Miami MSA (MI) has a tropical climate and is located near the tip of the Florida (FL) peninsula along the Atlantic Ocean. This MSA's central city is Miami, a popular destination for more than 10 million visitors every year. With one of the largest airports in U.S., tourism is the most important industry to the local economy. The other major industries are trade, banking and international finance, light manufacturing, and clothing.[20] This MSA has a population of 2.3 million. Single-family housing units account for 53 percent of the local residential housing market. Out of 784,000 occupied

[15] Virginia Academy of Science, www.vacadsci.org.
[16] The wind speed of Category One is equal to or greater than 74 miles per hour.
[17] 2002 American Community Survey Profile, www.census.gov.
[18] The National Hurricane Center "Best Track" files, Storm Trakker 5.5, by Michael Bryson. Data are retrieved from www.hurricanealley.net.
[19] Southern Regional Climate Center, www.srcc.lsu.edu.
[20] "Miami (Florida)," Microsoft® Encarta® Online Encyclopedia 2004, Http://encarta.msn.com.

housing units, 60 percent are owner occupied units.[21] There have been eight tropical storms and three hurricanes that affected this area in the past 20 years. Two of these wind storms had severe impacts on the area. One of the most destructive land-falling hurricanes of this century, Hurricane Andrew, hit the Miami-Dade county area on August 24, 1992. The hurricane's eye passed within 26 miles of this MSA with maximum wind speed of 138 mph.[22] 25,524 homes were destroyed and 101,241 damaged.[23] It proved to be the most expensive natural disaster in U.S. history. The estimated total damage reached $26.5 billion.[24] Dade County was a major disaster area, where the storm caused around $25 billion damage.[25] On October 16, 1999, Hurricane Irene struck the Miami area. The center of the hurricane was 40 miles away and produced maximum sustained winds of 80 mph.[26] I t brought heavy rainfall and significant flooding which produced an estimated $600 million in damage.[27]

The Wilmington MSA (WN) is located on the Atlantic coast. It has a population of 233,450. The central city is Wilmington, North Carolina (NC). Like other coastal areas, tourism is an important industry. The local economy also depends on retail trade, construction, manufacturing, education and health care, and arts and entertainment. Single-family housing units account for 63 percent of the local residential housing market. Out of 98,621 occupied housing units, 54 percent are owner occupied units.[28] In the past twenty years, four hurricanes hit this area.[29] The storm season of 1996 brought two hurricanes to Wilmington. On July 12, 1996, Hurricane Bertha passed by this area. It was a Category 2 hurricane at landfall with wind speed of more than 96 mph.[30] The estimated damage in this area was more than $38 million.[31] Less than two months later, on September 6, Wilmington was hit by Hurricane Fran. It was a Category 3 land-falling hurricane with wind speed in excess of 111 mph. Fran was one of the most destructive

[21] 2002 American Community Survey Profile, www.census.gov.
[22] 2002 American Community Survey Profile, www.census.gov.
[23] National Climate Data Center.
[24] National Hurricane Center.
[25] National Weather Service Office in Norman, Oklahoma.
[26] 2002 American Community Survey Profile, www.census.gov.
[27] National Hurricane Center.
[28] U.S. Census Bureau, Census 2000.
[29] 2002 American Community Survey Profile, www.census.gov.
[30] State Climate Office of North Carolina.
[31] National Weather Service in Wilmington, North Carolina.

hurricanes to date in North Carolina and caused $1.275 billion damage. Two years later, on August 26, 1998, Hurricane Bonnie was a direct hit to this area with wind speed of more than 111 mph. The damage was near $1 billion in North Carolina alone.[32] Before the end of 2002, the last land-falling hurricane in this area was Hurricane Floyd on September 16, 1999; with a wind speed of more than 96 mph. Floyd destroyed 7,000 homes and damaged 56,000 homes in North Carolina. The state's total damage was about $3 billion.[33]

III. A Brief Literature Review

A limited number of studies discuss facets of the regional economic impact of hurricanes and tornadoes. In addition, research exists on housing prices, housing supply and the regional economy, in general, that is related to other natural hazards, such as floods, earthquakes, and abnormal levels of temperature and precipitation. Ewing, Kruse and Wang (2004) examine the effect of severe wind events on the mean and variance of housing price indices of six metropolitan statistical areas that are vulnerable to hurricanes and/or tornadoes. The six metropolitan statistical areas studied are the same areas to be utilized in the research we propose. Three areas experienced significant tornado activity (Fort Worth-Arlington, Nashville, and Oklahoma City) and three areas are vulnerable to hurricane (Corpus Christi, Miami, and Wilmington, NC). They found that wind storms correspond to an immediate fall in total MSA housing value of around one-half to two percent. There are some differences in how long market values continue to decline in the periods following the wind storm; however, most of the decline is completed within four quarters after the wind storm. The percentage change in the housing price index and the corresponding change in total housing market value by MSA for the period of the wind storm and over the four quarters following the wind storm are based on the median housing price and the stock of single housing units for the year 2000. The market value fell from between one-half percent (Nashville) to 1.2 percent (Oklahoma City) in the case of a tornado. Given the size of these markets, these changes result in substantial changes in market values. For instance, in the period that the tornado hit the area, market value

[32] Southeast Regional Climate Center.
[33] National Weather Service in Raleigh, North Carolina.

fell an estimated $300 million in Oklahoma City, $235 million in Fort Worth, and $188 million in Nashville. One quarter after the tornado, the value of single housing units in Oklahoma City had declined by nearly an additional $40 million. That compares to further declines of nearly $70 million for Nashville and over $175 million in Fort Worth. The rather strong autoregressive nature of housing price changes in Fort Worth translates into these housing market losses continuing to be rather large (relatively) and more persistent than found in the other markets. In fact, even four quarters after the tornado, the Fort Worth market declined by $75 million.

The percentage change in the housing price index following hurricanes is similar to the change caused by tornadoes. In the period the hurricane occurred, market value fell from between 1.80 percent (Corpus Christi and Miami) to less than one-half of one percent (Wilmington-Bertha and Fran). Again, we find that in the markets with stronger autoregressive components (i.e., Corpus Christi and Miami) the declines in housing prices and, thus, values, last longer. The declines range from a high of almost one-half of a percent to nearly zero. Panel B shows the corresponding estimated change in total housing market values for the hurricanes considered. In the period of the hurricane, value fell from $34 million (Wilmington-Bertha and Fran) to $582 million (Miami). Not surprisingly, Miami experienced huge subsequent declines in housing market value following both Hurricane Andrew ($217 million one quarter after the event) and Hurricane Irene ($160 million one quarter after the event). Housing market value in Corpus Christi fell over $37 million one quarter after Hurricane Bret. Wilmington, being both smaller and experiencing four hurricanes, showed much smaller changes in total housing market value (about $1-5 million one quarter after a hurricane).

Harrison (2001) focused on the housing market in flood plains located in Alachua County, Florida. He found that the houses in a flood zone sell at a discount relative to houses located in other areas, but the price differential is less than the present value of future flood insurance premiums. Eves (2002) studied the flood-prone areas in Sydney, Australia using annual data and found that the long-term risk of ownership for properties in flood-liable and flood-free areas is very similar, although the value of properties in the flood-liable areas is lower than that of properties in the flood-free areas. Examining data on the four major Census regions, Coulson and Richard (1996) found that unseasonable temperature and precipitation had a small but not insubstantial effect on housing starts and completions. Fergus (1999) focused on how abnormal precipitation and temperature affect housing construction. He concluded that builders often adjust production rapidly to offset favorable or unfavorable weather effects.

Ellson et al. (1984) presented econometric models of earthquake simulations for the Charleston, South Carolina metropolitan area using annual data. They found that the regional economy is quite resilient in the long run and that it can recover to the baseline level as long as the national forces driving the regional economy remain the same. Murdoch et al. (1993) examined the effect of the Loma Prieta earthquake on housing prices in the San Francisco Bay area and found approximately a two-percent reduction in prices after the earthquake.

Hurricane- and tornado- related economic research has focused on mitigation measures, property damage, reconstruction, and business disruption. Stewart, et al. (2003) developed a hurricane-induced risk-cost-benefit analysis procedure related to retrofit cost and growth of new housing and discovered that some retrofit scenarios may become economically viable to insurers within only a few years. Fronstin and Haltmann (1994) estimated a damage model for Hurricane Andrew and found that newer houses sustained more damage from the hurricane than did older houses. In addition, they concluded that housing price is positively related to housing quality.

The evidence on employment growth indicates that economic growth may experience a boost after a severe wind event. Guimaraes and Woodward (1993) analyzed Hurricane Hugo. Their study showed that the rebuilding effort following the hurricane created a short-term economic boom before the economy returned to its normal growth path. They concluded that the construction sector was one of the sectors which benefited most from this boom. Ewing, Kruse and Thompson (2004) estimated time series models that allow for time-varying variance in employment growth and include intervention variables designed to capture both the initial impact and long run effects of the tornado. In terms of total employment growth, the Oklahoma City Metropolitan Statistical Area (MSA) experienced a long run increase in employment growth and a reduction in labor market risk following the tornado. The analysis also examined the effect of the weather event on eight industrial sectors. Five of eight sectors experienced significant decreases in labor market risk after the tornado. Thus, this evidence suggests that Oklahoma City and surrounding communities that make up the Metropolitan Statistical Area survived the disaster without suffering any long run adverse labor market effects.

The regional labor market impacts of tornadoes have generally varied by industry and by the respective tornado being examined [Ewing, Kruse, and Thompson (2002, 2003a, 2003b, 2004)]. However, several key generalizations can be made. First, of those industrial sectors that were significantly affected by a tornado, half of them experienced an increase in employment growth following the tornado. Moreover, most industries, including financial, insurance and real estate, FIRE, tended to exhibit a more stable labor market in the post-tornado period. Further examination of the Oklahoma City tornado revealed evidence that tornado effects were transmitted to nearby regional economies as would be suggested by supply chain linkages [Ewing, Kruse, and Thompson (2005)].

Yeager (2003) reports the results of a study designed to assess the effect of economic shocks on the performance of community banks. He uses a jump in unemployment of 4% to signify a regional economic shock. By comparing regions that suffered economic shocks to those that did not, he concludes that community banks appear to withstand the shocks quite well. He examines the same measures of bank performance that we propose to use. Some explanations that he advances for bank performance that is robust even in the presence of economic shocks are the speed with which workers find new jobs after plant closing, the reclamation of defunct plant facilities by new businesses and the participation of larger banks in a community bank's largest loans. Also, participation by government agencies such as FMHA and SBA with loan guarantees for higher risk customers help to reduce credit risk.

Taken together, the above cited literature suggests that wind disasters may have a significant impact on local bank performance. However, it is not clear if bank performance will respond the same for areas struck by tornadoes as it is for areas struck by hurricanes. Thus, the results of this study will provide information as to the impact and the response of the banking sector to tornadoes and hurricanes. The findings should prove useful to policymakers as well as the banking industry.

IV. Data

We initially collected bank performance data for all banks in each of the six MSAs impacted by wind disasters, as outlined in Table 1. The data were taken from the Federal Reserve Bank Conditions Report (Call and Income Report) available at the Federal Reserve Bank of Chicago website. In particular, for each bank we collect quarterly data on the bank's return on assets (ROA), loan loss provision, and loan charge offs. Since we have no better means of identifying community banks than others, we use the $1 billion total assets threshold to separate small (community) banks and large banks. Tables 2 through 7 report the summary statistics of the means and standard deviations for each separate MSA. We report both loan loss provisions and charge offs in dollar magnitudes as well as the natural log, which we use in the time series estimation results reported. One problem we ran into with our separating large and small banks was the relatively few numbers of banks in certain MSAs that had more than $1 billion in total assets. The results in Tables 6 and 7, for example, show that there were an insufficient number of large banks in the Corpus Christi and Wilmington MSAs for statistical analysis. In fact, while there are enough large banks in the Fort Worth area to calculate means and standard deviations, there were insufficient numbers of such large banks for regression analysis reported below.

The results we report now do not include any regional economic data, but rather are basis time series models to capture the dynamics in bank performance through the lag structure. Subsequent analysis plans to incorporate HPI data for the six sample areas examined in this paper. The state's economic business cycle is expected to be an important determinant of the regional real estate market. In fact, this exposes local economic growth to shocks from outside the immediate area (DiPasquale and Wheaton, 1996). Personal income includes the income that is received by persons from participation in production, from both government and business transfer payments, and from government interest. Income determines the purchasing power of households, which is closely related to the demand for houses. Similarly, TIPI is a measure for the Texas economy.[34]

[34] TIPI data are from the Federal Reserve Bank of Dallas.

V. Empirical Methodology

The analysis begins with a panel, time series/cross sectional investigation of the bank performance in each of the six MSAs impacted by our wind disasters. We investigate three bank performance measures, seeking to determine how each bank in the MSA was impacted by the wind disasters hitting their respective communities. We look at each community separately in the first pass investigation. The basis bank performance (BP) model we estimate for each MSA is given by:

$$BP_{i,t} = C + \sum_{j=1}^{4} \beta_j \, BP_{i,t-j} + \sum_{k=1}^{12} \Delta_k \ \text{Catdum}_{i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{i,t-l} + \varepsilon_{i,t}$$

We allow for four lags in the bank performance measure to capture the dynamics of the evolution of bank performance. We also include three separate quarterly dummy variables (Q), as we found much seasonal variation in our bank performance measures from one quarter to the next. Our primary focus of attention is on the coefficient estimates, Δ_1 and subsequent lags on the Catdum variable. The Catdum variable takes on a value of one in the quarter that the wind disaster occurs and the subsequent coefficients capture any lags in adjusting to the disaster. If more than one disaster hits a particular MSA, Catdum takes on a value of one for each disaster. If a disaster has an adverse impact on bank performance in the quarter of the disaster, one would expect to find a negative and significant coefficient estimate for Δ_1. If it takes a quarter to impact bank performance, then the second coefficient on the Catdum will be significant and so on. As such, we utilize a model capable of capturing both short-run and longer-run variations of changes in bank performance by applying a type of event study methodology. We report F-tests for both the sum of the Catdum coefficients and the joint hypothesis that all Catdum coefficients are equal to zero. The former tests the hypothesis that the disaster had a permanent effect on bank performance, while the latter tests the hypothesis that the disaster had any effect on bank performance, even in the short-run. Enders et al. (1990) proposed an intervention method to study how the application of metal detector technology would affect the number of skyjacking incidents. They measured this technology application in the model by using a jump dummy variable.[35] The occurrence of a severe wind event only lasts for a short time as opposed to a permanent change such

[35] A jump dummy variable is equal to 1 at the event date and thereafter, and 0 before the event.

as the application of a new technology. Thus, we use the pulse dummy variable to capture the occurrence of wind disasters.[36]

For each MSA, bank performance is investigated for all small banks, all large banks and a combined sample to allow an investigation as to whether or not the performance for large and small banks differs, especially in response to the disaster. Below we also report "Chow tests", testing the hypothesis that the coefficients for small and large banks are statistically different from one another.

VI Preliminary Findings

Oklahoma MSA

Table 8 reports the bank performance regression results for the Oklahoma MSA tornado of May 1999. The regressions start with small banks, large banks and then all banks combined. For each grouping of banks we estimate the impact of the tornado on three different bank performance measures: ROA, loan loss provision, and charge offs, allowing in all cases for quarterly seasonal variation and a lagged adjustment mechanism to capture the dynamics. Our focus of attention is on the coefficients on the Catdum variable, as this provides an estimate of the impact of the tornado, with any needed lag, on bank performance. Throughout we report F-tests on: (1) the sum of the Catdum coefficients, to examine whether or not there was a permanent effect on bank performance, and (2) the joint hypothesis that all Catdum coefficients equal zero, to examine whether or not there was a temporary impact of the tornado on bank performance.

Beginning with the small banks in the Oklahoma MSA, we find no evidence that small bank's ROA or loan loss provision we significantly altered by the tornado. None of the individual Catdum coefficients are estimated to be different from zero and none of the F-tests reject the hypotheses that the various combinations of the coefficients are different from zero. On the other hand, the estimation results for charge offs is indicative of a permanent increase in charge offs as the hypothesis that the sum of the Catdum coefficients is rejected at the 5.4% critical value. This evidence would indicate that the tornado caused a permanent increase in charge offs, but interestingly the increase did not

[36] The pulse dummy variable is equal to 1 at the time of the event, and 0 otherwise.

appear to translate to lowered earnings as ROA was not adversely impacted. The might occur, for example, as a result of increased loan demand in response to the wind disaster.

Turning our attention to the large banks in Oklahoma City we find no evidence to indicate that large bank performance was impacted by the tornado, as none of the individual Catdum coefficients are different from zero, nor do any of the F-tests suggest either a short-run or permanent effect. The results for all banks combined are reported next. For each bank performance measure, a Chow test is performed to test whether or not the estimated relationships are different for the small bank group versus the large bank group. In this disaster, as well as all subsequently examined we find no evidence to indicate that the estimated relationships differ for banks of different asset size, regardless of the bank performance variable examined. Considering then the all bank sample for Oklahoma, we find no evidence to indicate that the tornado caused a statistically meaningful change in either the bank's ROA or loan loss provisions from historical norms. On the other hand, the evidence that the tornado permanently and adversely impacted charge offs is even stronger as the hypothesis that all Catdum coefficients are equal to zero is rejected at the 5% significance level. Thus, we conclude that the Oklahoma tornado did not generally impact bank performance, with the exception of permanently higher charge offs.

Miami MSA

The results for Miami's two hurricanes, reported in table 9, are the most interesting and maybe the most unusual that we present. Starting with the small bank sample, we see that there is strong evidence that the hurricanes of August 1992 (Andrew) and October 1999 (much smaller in loss damages) resulted in improved small bank's ROA. At least three of the Catdum coefficients are found to be positive and statistically different from zero. Thus, there is strong evidence that the hurricanes at least temporarily improved bank profitability by this measure and some weaker evidence that this favorable impact was permanent. The statistical evidence is even stronger when we turn to loan loss provisions being impacted by the hurricanes. Indeed the findings indicate that the hurricanes led to reduced provisions for loan loss, but temporarily and permanently. The evidence pertaining to charge offs of small banks is also favorable, as it suggests that small banks' charge offs were actually reduced in response to the hurricanes, again both temporarily and permanently. Ironically then, the hurricanes appear to have favorably impacted small banks in Miami, resulting in improved bank performance, and lower loan loss provisions and charge offs for these banks.

The large banks in Miami do not provide the same statistical evidence seen for the small bank sample. Indeed there is no evidence to suggest that large banks' ROA, loan loss provisions, or charge offs changed as a result of the hurricanes. When the samples of banks, large and small, are combined an interesting paradox occurs. First, none of the Chow tests allow rejection of the hypothesis that the small bank performance is different from the large bank performance. On the other hand, however, the bank performance reactions are estimated to be statistically significant, unlike what is found for the large bank sample. In particular, there is statistical evidence suggesting that all banks found their ROAs to be higher, their loan loss provisions to be lower and their charge offs to be lower, both permanently and temporarily. We conclude that the small banks in Miami were the banks that had the favorable results, not the large banks, although we can not say the estimated responses are statistically different for the two samples. And the surprising result is that bank performance was favorably impacted by the hurricanes in Miami.

Nashville MSA

The next disaster examined was the tornado hitting Nashville in April 1998. Table 10 reports the bank performance regression results for this event. Here, due to the small number of large banks in the sample, we restricted the lack structure for the tornado to six quarters, one half the lengths in the previous two disaster estimation cases. The loss damage from this tornado is one of the smallest we consider, with an estimated loss of $100 million. The results reported in table 10 provide no evidence whatsoever that the tornado impacted bank performance either favorably or adversely, regardless of the performance benchmark or the sample of banks; small, large or all. Not one Catdum coefficient is significantly different from zero, nor do any of the F-tests allow rejection of the hypotheses.

Corpus Christi MSA

Next we report results for the hurricane that hit Corpus Christi in August 1999, causing again somewhat limited damages. In this MSA, as well as the next two MSAs examined, there are an insufficient number of large banks to allow estimation of a regression model. As such, we report only results for the small bank sample. Table 11 provides the basic estimation results. Again, as with Nashville, there is no evidence provided to suggest that the wind disaster impacted the banking community at all. None of the individual Catdum coefficients are different from zero and none of the F-tests allow rejection of our basic hypotheses of interest. It would appear that this disaster was a non-event for the small banks in the Corpus Christi MSA.

Fort Worth MSA

The regression estimation results for the small banks in the Fort Worth MSA response to the March 2000 tornado hitting that community are reported in table 12. The ROA regression results show no statistical impact stemming from this tornado. None of the Catdum coefficient estimates are individually or jointly different from zero. However, the next two regressions indicate the tornado adversely impacted small banks in this community. Loan loss provisions increased after the tornado and the impact appears to be permanent. In addition, charge offs also increased after the tornado, with some weak evidence suggesting the impact was permanent. Thus, we see that small banks in Forth Worth appeared to suffer more loan losses and were providing more for these as a result of the hurricane. Yet, we find no statistical evidence that the bottom line was adversely impacted, as ROA remained unchanged in the face of the tornado. Whether this conflict is due to statistical impression in the estimates or whether the loan losses adverse effects were offset by stronger loan demand remains an unanswered question.

Wilmington MSA

The final MSA considered is that of Wilmington, which was impacted by four different hurricanes during our period of investigation, ranging from July 1996 through September 1999. Again our analysis is confined to small banks in this community, due to the few numbers of large banks in our sample. ROA does not appear to have been impacted by these separate hurricanes, either individually or jointly. On the other hand, at least one of the Catdum coefficients estimates is significantly different from zero, in this case indicating an unexpected increase in loan loss provision after about a year and one half following the hurricanes. Charge offs for the small banks in the Wilmington MSA show no response to the hurricanes, however.

VII Summary and Agenda for Future Research

Interestingly, to date, we have found no evidence indicating that banks' ROAs have been impaired by the natural disasters we investigate. In fact, the only evidence we uncovered showing that ROAs were affected by wind disasters occurred in the Miami MSA and in this case the evidence indicates that the return on assets improved subsequently to the two hurricanes that hit this area. One of these hurricanes was Andrew and it was by far and away the most significant in terms of overall loss estimates from the disaster. The evidence for Miami is further unique in that loan loss provisions appear to have been reduced and charge offs lowered as a result of these hurricanes. None of the other communities we investigated showed favorable impacts on these two bank performance benchmarks. In fact, in Oklahoma, Fort Worth and Wilmington MSAs we found either evidence that loan loss provisions or charge offs (or both) increased following the wind disasters in these communities. We emphasize again however, that in none of this cases did these changes coincide with reduced ROA performance.

The results to this point are suggestive that if a disaster hits a community that it would be better for the banks in the community at least for the disaster to be on a truly large scale. The smaller disasters we investigated either had no impact on the banks or resulted in larger loan loss provisions or charge offs, while the biggest disaster resulted in all around improved bank performance. Of course, at this point our research has not explicitly considered the magnitude of the overall economic losses of the disasters, as we have treated all disasters equivalently in our investigation. Future research will aim to change this and distinguish these disasters based on estimates of economic loss. Future research will also take into explicit account the regional economic performance when the disasters occur. To date, our models have only incorporated time series elements to bank performance without allowing for cyclical variations driven by regional economic factors. We plan to add regional economic measures to our basic models to assure that our conclusions are not driven coincidentally by these ignored cyclical factors.

Table 1 Disaster Events Examined, Dates, and Damage Estimates

MSA	Disaster	Damage
Fort Worth (TX)	Tornado: March 28,2000	$450 million
Nashville (TN)	Tornado: April 16, 1998	$100 million
Oklahoma City (OK)	Tornado: May 3 ,1999	$1.2 billion
Corpus Christi (TX)	Hurricane: August 23 1999	$2 million
Miami (FL)	Hurricane: August 24, 1992 Hurricane: October 16, 1999	$26.5 billion $600 million
Wilmington (NC)	Hurricane: July 12 ,1996 Hurricane: September 6, 1996 Hurricane: August 26, 1998 Hurricane: September 16,1999	$38 million $1.3 billion $1.0 billion $3.0 billion

Note: MSA denotes Metropolitan Statistical Area.
Sources for Damage data:
National Hurricane Center
National Weather Service (Norman, Oklahoma).
National Weather Service Office (Fort Worth, Texas)
Southern Regional Climate Center.
State Climate Office (North Carolina.)
National Weather Service (Wilmington, North Carolina.)
Southeast Regional Climate Center.
National Weather Service (Raleigh, North Carolina.)

Table 2 Descriptive Statistics of Oklahoma MSA Banks (ROA)

	Mean	Std.dev
Large Banks:	. 004962710	.004183345
Small Banks:	.005949325	.008259996
All Banks:	. 005913911	.008150702

Descriptive statistics of Oklahoma MSA Banks (Loan Loss Provision)

	Mean	Std.dev
Large Banks:	2976.04	5867.08
Small Banks:	161.799	520.776
All Banks:	262.813	1326.68

Descriptive statistics of Oklahoma MSA Banks (ln (loan loss provision))

	Mean	Std.dev
Large Banks:	7.54622	1.21296
Small Banks:	4.26815	1.48129
All Banks:	4.39021	1.59750

Descriptive statistics of Oklahoma MSA Banks (Chargeoffs)

	Mean	Std.dev
Large Banks:	4686.25	7308.15
Small Banks:	186.970	509.464
All Banks:	348.467	1688.43

Descriptive statistics of Oklahoma MSA Banks (ln (Chargeoffs))

	Mean	Std.dev
Large Banks:	4.28052	1.72098
Small Banks:	3.99239	1.74372
All Banks:	4.13810	1.87055

Table 3 Descriptive Statistics of Miami MSA Banks (ROA)

	Mean	Std.dev
Large Banks:	.007574007	.006667721
Small Banks:	.003115596	0.011269
All Banks:	0.003651	0.010916

Descriptive statistics of Miami MSA Banks (Loan Loss Provision)

	Mean	Std.dev
Large Banks:	10819.64	34310.44
Small Banks:	422.316	1102.41
All Banks:	1646.54	12267.35

Descriptive statistics of Miami MSA Banks (ln (loan loss provision))

	Mean	Std.dev
Large Banks:	8.18368	1.44083
Small Banks:	5.18678	1.61086
All Banks:	5.5284	1.9397

Descriptive statistics of Miami MSA Banks (Chargeoffs)

	Mean	Std.dev
Large Banks:	9196.44	26286.37
Small Banks:	422.873	1118.64
All Banks:	1476.29	9588.79

Descriptive statistics of Miami MSA Banks (ln (Chargeoffs))

	Mean	Std.dev
Large Banks:	7.71788	1.71880
Small Banks:	4.7146	1.9254
All Banks:	5.1319	2.1635

Table 4 Descriptive Statistics of Fort Worth MSA Banks (ROA)

	Mean	Std.dev
Large Banks:	.0033102	.004283417
Small Banks:	.005684221	.009995752
All Banks:	.005663611	.009962292

Descriptive statistics of Fort Worth MSA Banks (Loan Loss Provision)

	Mean	Std.dev
Large Banks:	5773.1	5222.69
Small Banks:	166.285	362.977
All Banks:	214.955	791.376

Descriptive statistics of Fort Worth MSA Banks (ln (loan loss provision))

	Mean	Std.dev
Large Banks:	8.21003	1.06916
Small Banks:	4.54030	1.39908
All Banks:	4.58290	1.44979

Descriptive statistics of Fort Worth MSA Banks (Chargeoffs)

	Mean	Std.dev
Large Banks:	4927.15	5743.33
Small Banks:	227.535	572.409
All Banks:	268.330	887.177

Descriptive statistics of Fort Worth MSA Banks (ln (Chargeoffs))

	Mean	Std.dev
Large Banks:	7.86713	1.18237
Small Banks:	4.24718	1.69003
All Banks:	4.28052	1.72098

Table 5 Descriptive Statistics of Nashville MSA (ROA)

	Mean	Std.dev
Large Banks:	.005776133	.004895334
Small Banks:	.004729898	0.016976
All Banks:	.004868788	0.015912

Descriptive statistics of Nashville MSA Banks (Loan Loss Provision)

	Mean	Std.dev
Large Banks:	11705.05	26063.47
Small Banks:	275.8	575.973
All Banks:	1792.96	10246.49

Descriptive statistics of Nashville MSA Banks (ln (loan loss provision))

	Mean	Std.dev
Large Banks:	8.90162	1.28206
Small Banks:	5.00744	1.28216
All Banks:	5.47084	1.79824

Descriptive statistics of Nashville MSA Banks (Chargeoffs)

	Mean	Std.dev
Large Banks:	16048.65	20054.64
Small Banks:	238.110	582.002
All Banks:	2336.85	9065.08

Descriptive statistics of Nashville MSA Banks (ln (Chargeoffs))

	Mean	Std.dev
Large Banks:	9.08478	1.13460
Small Banks:	4.49996	1.68236
All Banks:	4.49996	1.68236

Table 6 Descriptive Statistics of Corpus Christi MSA (ROA)

	Mean	Std.dev
Small Banks:	.00660942	.007137771

Descriptive statistics of Corpus Christi MSA Banks (Loan Loss Provision)

	Mean	Std.dev
Small Banks:	122.362	492.195

Descriptive statistics of Corpus Christi MSA Banks (ln (loan loss provision))

	Mean	Std.dev
Small Banks:	4.46940	1.44391

Descriptive statistics of Corpus Christi MSA Banks (Chargeoffs)

	Mean	Std.dev
Small Banks:	302.635	784.936

Descriptive statistics of Corpus Christi MSA Banks (ln (Chargeoffs))

	Mean	Std.dev
Small Banks:	4.33644	1.85450

Table 7 Descriptive Statistics of Wilmington MSA (ROA)

	Mean	Std.dev
Small Banks:	.000757083	0.012485

Descriptive statistics of Wilmington MSA Banks (Loan Loss Provision)

	Mean	Std.dev
Small Banks:	188.917	312.470

Descriptive statistics of Wilmington MSA Banks (ln (loan loss provision))

	Mean	Std.dev
Small Banks:	4.62275	1.33351

Descriptive statistics of Wilmington MSA Banks (Chargeoffs)

	Mean	Std.dev
Small Banks:	74.9352	212.595

Descriptive statistics of Wilmington MSA Banks (ln (Chargeoffs))

	Mean	Std.dev
Small Banks:	3.28706	1.59204

Table 8 Bank Performance in the Oklahoma MSA, Catdum starting second quarter 1999

Small Banks: ROA

$$ROA_{i,t} = C + \sum_{j=1}^{4} \beta_j \, ROA_{i,t-j} + \sum_{k=1}^{12} \Delta_k \ Catdum_{i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.00468	<.0001
β_1	0.54256	<.0001
β_2	0.08894	<.0001
β_3	0.04921	0.0044
β_4	0.06491	<.0001
Δ_1	-0.00035619	0.6299
Δ_2	0.00013801	0.8524
Δ_3	-0.00014666	0.8447
Δ_4	-0.00083921	0.2693
Δ_5	0.0000214	0.978
Δ_6	0.0005732	0.4526
Δ_7	-0.00015976	0.8359
Δ_8	-0.00081876	0.286
Δ_9	-0.00016849	0.8266
Δ_{10}	-0.00025111	0 .7472
Δ_{11}	-0.00006743	0.9318
Δ_{12}	-0.00011677	0.8815
Ψ_1	-0.00822	<.0001
Ψ_2	-0.00226	<.0001
Ψ_3	-0.00043322	0.2178

Number of Observations Read: **2874**
Number of Observations Used: **2496**
Number of Observations with Missing Values: **378**

F Value Pr >F
152.09 <.0001
R-Square 0.5385 Ad] R-Sq 0.5350

Test for sum of Catdum variables equal to ‘0’:
F Value Pr > F
0.58 0.4452
Test for Catdum variables is jointly equal to ‘0’:
F Value Pr > F
0.27 0.9933

Small Banks:

$$LN\,(LLP)_{i,t} = C + \sum_{j=1}^{4} \beta_j \; LN\,(LLP)_{i,t-j} \;+ \sum_{k=1}^{12} \Delta_k \;\; Catdum_{i,t+k} \;+ \sum_{l=1}^{3} \Psi_l \; Q_{i,t-1}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.60569	<.0001
β_1	0.83387	<.0001
β_2	0.13518	<.0001
β_3	-0.01747	0.4445
β_4	-0.00011	0.9951
Δ_1	-0.00665	0.9465
Δ_2	-0.06484	0.5049
Δ_3	0.02289	0.8157
Δ_4	-0.05185	0.6051
Δ_5	0.04512	0.6487
Δ_6	-0.01889	0.8459
Δ_7	-0.01056	0.9143
Δ_8	-0.05015	0.6215
Δ_9	0.13193	0.1885
Δ_{10}	0.11804	0.2362
Δ_{11}	0.18188	0.0678
Δ_{12}	-0.07104	0.4915
Ψ_1	-1.73735	<.0001
Ψ_2	0.03252	0.6369
Ψ_3	0.09314	0.1337

Number of observations read: 2874
Number of observations used: 1391
Number of observations with missing values: 1483

F Value	Pr > F
444.40	<.0001
R-Square 0.8603	Ad] R-Sq 0.8584

Test for sum of Catdum variables equal to ‘0’:

F Value	Pr > F
0.34	0.5583

Test for Catdum variables is jointly equal to ‘0’:

F Value	Pr > F
0.69	0.7587

Small Banks: $LN(CHARGEOFF)_{i,t} = C + \sum_{j=1}^{4} \beta_j \; LN(CHARGEOFF)_{i,t-j} \; + \; \sum_{k=1}^{12} \Delta_k$ Catdum $_{i,t+k} + \sum_{l=1}^{3} \Psi_l \; Q_{i,t-l}$

Parameter	Parameter Estimate	P- value
Intercept(C)	1 .05331	<.0001
β_1	0.67461	<.0001
β_2	0.14206	<.0001
β_3	0.01534	0.4666
β_4	0.04993	0.0039
Δ_1	0.18272	0.2093
Δ_2	0.15343	0.2938
Δ_3	0.03227	0.8234
Δ_4	0.07523	0.6272
Δ_5	0.22191	0.146
Δ_6	-0.06068	0.6919
Δ_7	0.02518	0.8694
Δ_8	-0.01614	0.9203
Δ_9	0.13804	0.3848
Δ_{10}	0.05574	0.7265
Δ_{11}	0.17504	0.272
Δ_{12}	0.13654	0.4116
Ψ_1	-2.16015	<.0001
Ψ_2	-0.20369	0.0135
Ψ_3	0.03534	0.6537

Number of Observations Read: 2874
Number of Observations Used: 1934
Observations with Missing Values: 940

F Value Pr > F
272.13 <.0001
R-Square 0.7298 Adj R-Sq 0.7272

Test for sum of Catdum variables equal to '0':
F Value Pr > F
3.73 0.0535
Test for f Catdum variables is jointly equal to '0':
F Value Pr > F

0.62 0.8292

Large Banks:

$$ROA_{i,t} = C + \sum_{j=1}^{4} \beta_j \, ROA_{i,t-j} + \sum_{k=1}^{12} \Delta_k \ Catdum_{i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.00248	0.0184
β_1	0.54822	<.0001
β_2	0.0726	0.5744
β_3	-0.01072	0.9357
β_4	0.26115	0.0109
Δ_1	-0.00044	0.8178
Δ_2	-0.00126	0.5181
Δ_3	-0.0016	0.4097
Δ_4	0.00223	0.2534
Δ_5	-0.00089	0.6448
Δ_6	-0.00173	0.3792
Δ_7	-0.00211	0.2856
Δ_8	0.00295	0.1338
Δ_9	0.000539	0.7371
Δ_{10}	-0.00036	0. 8275
Δ_{11}	-0.00119	0.4645
Δ_{12}	0.00126	0.4381
Ψ_1	-0.00599	<.0001
Ψ_2	-0.00119	0.3776
Ψ_3	0.000127	0.9279

Number of Observations Read: 107
Number of Observations Used: 87
Number of Observations with Missing Values: **20**

F Value Pr > F
9.21 <.0001
R –square 0.7232 Adj R-square 0.6447
Test for sum of Catdum variables equal to '0'
F Value Pr > F
0.13 0.7247
Test for Catdum variables is jointly equal to '0':
F Value Pr > F
0.58 0.8471

Large Banks:

$$LN\ (LLP)_{i,\,t} = C + \sum_{j=1}^{4} \beta_j\ LN\ (LLP)_{i,\,t-j} + \sum_{k=1}^{12} \Delta_k\ \ Catdum_{i,\,t+k} + \sum_{l=1}^{3} \Psi_l\ Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	2.3739	0.0004
β_1	0.68187	<.0001
β_2	0.2813	0.0743
β_3	0.16023	0.3494
β_4	-0.3294	0.0027
Δ_1	-0.25785	0.5377
Δ_2	-0.53542	0.223
Δ_3	0.08757	0.8397
Δ_4	-0.39978	0.3468
Δ_5	0.43549	0.3009
Δ_6	-0.11484	0.7937
Δ_7	-0.18966	0.6659
Δ_8	-0.20684	0 . 6346
Δ_9	0.09159	0.7937
Δ_{10}	-0.13646	0.7135
Δ_{11}	0.18635	0.6113
Δ_{12}	-0.21881	0.5472
Ψ_1	-1 .96254	<.0001
Ψ_2	-0.57553	0.1499
Ψ_3	0.06498	0.8654

Number of observations read: 107
Number of observations used: 63
Number of observations with missing values: 44

F Value Pr > F
13.55 <.0001
R-Square 0.8569 Ad] R-Sq 0.7937

Test for sum of Catdum variables equal to ‘0’
F Value Pr > F
0.54 0.4653
Test for Catdum variables is jointly equal to ‘0’:
F Value Pr > F
0.42 0.9457

Large Banks:

$$LN(CHARGEOFF)_{i,t} = C + \sum_{j=1}^{4} \beta_j \, LN(CHARGEOFF)_{i,t-j} + \sum_{k=1}^{12} \Delta_k \, Catdum_{\,i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{\,i,t-1}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	1 .00534	0.0189
β_1	0.87497	<.0001
β_2	0.11191	0.4359
β_3	-0.08747	0.4438
β_4	0.01896	0.8096
Δ_1	0.22891	0.5095
Δ_2	0.05779	0.8655
Δ_3	0.13774	0.687
Δ_4	-0.45247	0.1772
Δ_5	0.1098	0.7459
Δ_6	0.17217	0.6101
Δ_7	0.15776	0.6409
Δ_8	0.04155	0.9005
Δ_9	0.16205	0.5566
Δ_{10}	-0.02657	0.9253
Δ_{11}	0.15114	0.593
Δ_{12}	0.23535	0.4032
Ψ_1	-1.73408	<.0001
Ψ_2	0.11277	0.7226
Ψ_3	0.25795	0.3083

Number of Observations Read: 107
Number of Observations Used: 87
Observations with Missing Values: 20
F Value Pr > F
31.39 <.0001
R-Square 0.8990 Adj R-Sq 0.8704
Test for sum of Catdum variables equal to ‘0’
F Value Pr > F
0.57 0.4538
Test for Catdum variables is jointly equal to ‘0’:
F Value Pr > F

0.38 0.9663

Oklahoma:
All Banks

$$ROA_{i,t} = C + \sum_{j=1}^{4} \beta_j \; ROA_{i,t-j} \;+\; \sum_{k=1}^{12} \Delta_k \;\; Catdum_{\,i,t+k} \;+\; \sum_{l=1}^{3} \Psi_l \; Q_{\,i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.004635	<.0001
β_1	0.5429	<.0001
β_2	0.0889	<.0001
β_3	0.0484	0 . 0044
β_4	0 . 0666	<.0001
Δ_1	-0.00037	0.6006
Δ_2	7.46E-05	0.9172
Δ_3	-0.00023	0.754
Δ_4	-0.00073	0.3218
Δ_5	-4.6E-05	0.9507
Δ_6	0.000431	0.5549
Δ_7	-0.00024	0.7466
Δ_8	-0.00069	0 . 3446
Δ_9	-0.000151	0.837
Δ_{10}	-0.000294	0.6934
Δ_{11}	-0.000191	0.8
Δ_{12}	-0.000033	0.9653
Ψ_1	-0.008165	<.0001
Ψ_2	-0.002249	<.0001
Ψ_3	-0.00043	0.2076

Number of Observations Read: **2981**
Number of Observations Used: **2595**
Number of Observations with Missing Values: **386**

Chow test:
F Value 1.13 Pr > F 0.3127
Total R-Square 0.5402

Test for sum of Catdum variables equal to ‘0’
F Value Pr > F
0.80 0.3709
Test for Catdum variables jointly equal to ‘0’

F Value Pr > F
0.24 0.9966
All Banks:

$$LN\,(LLP)_{i,\,t} = C + \sum_{j=1}^{4} \beta_j \; LN\,(LLP)_{i,\,t\text{-}j} \; + \sum_{k=1}^{12} \Delta_k \; Catdum_{\,i,t+k} \; + \sum_{l=1}^{3} \Psi_l \; Q_{\,i,t\text{-}l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.5475	<.0001
β_1	0 . 8407	<.0001
β_2	0.1403	<.0001
β_3	-0.0102	0.6478
β_4	-0.003101	0.8558
Δ_1	-0.0354	0.7139
Δ_2	-0.0835	0.3799
Δ_3	0.0221	0.8176
Δ_4	-0.0744	0.4469
Δ_5	0.0617	0.5184
Δ_6	-0.0159	0.866
Δ_7	-0.019	0.8411
Δ_8	-0.033	0.7361
Δ_9	0.1276	0.1867
Δ_{10}	0.1157	0.2289
Δ_{11}	0.1834	0.0564
Δ_{12}	-0.0685	0.4901
Ψ_1	-1.7436	<.0001
Ψ_2	0.0319	0.6363
Ψ_3	0.0909	0.1363

Number of observations read 2981
Number of observations used 1466
Number of observations with missing values 1515

Chow Test:
F Value Pr > F
0.50 0.9670
Total R-Square 0.8854

Test for sum of Catdum variables equal to '0'
F Value Pr > F
0.23 0.6298
Test for Catdum variables jointly equal to '0'

F Value Pr > F
0.81 0.6353
All Banks:

$$LN(CHARGEOFF)_{i,t} = C + \sum_{j=1}^{4} \beta_j \, LN(CHARGEOFF)_{i,t-j} + \sum_{k=1}^{12} \Delta_k \; Catdum_{\,i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{\,i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.9342	<.0001
β_1	0.6943	<.0001
β_2	0.1544	<.0001
β_3	0.0159	0.4348
β_4	0.0486	0.0031
Δ_1	0.1866	0.1837
Δ_2	0.1541	0.2744
Δ_3	0.043	0.7579
Δ_4	0.0584	0.6951
Δ_5	0.2239	0.123
Δ_6	-0.0474	0.7451
Δ_7	0 . 0408	0.7791
Δ_8	0.0319	0.8346
Δ_9	0.1486	0.3237
Δ_{10}	0.0599	0.6917
Δ_{11}	0.1776	0.2399
Δ_{12}	0.1755	0.2637
Ψ_1	-2.1652	<.0001
Ψ_2	-0.1926	0.0158
Ψ_3	0.0523	0.492

Number of Observations Read: 2981
Number of Observations Used: 2033
Number of Observations with Missing Values: 948
F Value Pr > F

Total R-Square 0.7785

Test for sum of Catdum variables equal to ‘0’
F Value Pr > F
5.11 0.0239

Test for Catdum variables jointly equal to '0'

F Value	Pr > F
0.72	0.7283

Table 9 Bank Performance in the Miami MSA, Catdum starting third quarter 1992 and fourth quarter 1999

Small Banks

$$ROA_{i,\,t} = C + \sum_{j=1}^{4} \beta_j\, ROA_{i,\,t-j} + \sum_{k=1}^{12} \Delta_k\; Catdum_{\,i,\,t+k} + \sum_{l=1}^{3} \Psi_l\, Q_{\,i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.00159	<.0001
β_1	0.57607	<.0001
β_2	0.0908	0.0011
β_3	0.06187	0.0031
β_4	0.1211	<.0001
Δ_1	0.000902	0 . 2433
Δ_2	0.0002	0.7996
Δ_3	0.000625	0.422
Δ_4	0.000923	0.234
Δ_5	0.0015	0.0541
Δ_6	0.00182	0.0472
Δ_7	-0.00253	0.0068
Δ_8	-0.00054	0.5607
Δ_9	0.00039	0.6795
Δ_{10}	0.00342	0.0003
Δ_{11}	-0.00243	0.0123
Δ_{12}	-0.00032	0.738
Ψ_1	-0.00341	<.0001
Ψ_2	-0.0004	0.4697
Ψ_3	0.000329	0.5292

Number of Observations Read: **4919**

Number of Observations Used: **1734**

Number of Observations with Missing Values: **3185**

F Value	Pr > F
110.17	<.0001

R-Square 0.5498 Ad] R-Sq 0.5448

Test for sum of Catdum variables equal to '0'

F Value	Pr > F
2.73	0.0988

Test for Catdum variables jointly equal to '0'

F Value	Pr > F
2.53	0.0027

Small Banks

$$LN\,(LLP)_{i,\,t} = C + \sum_{j=1}^{4} \beta_j \; LN\,(LLP)_{i,\,t-j} \quad + \sum_{k=1}^{12} \Delta_k \;\; Catdum_{\,i,t+k} \;\; + \sum_{l=1}^{3} \Psi_l \; Q_{\,i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.89973	<.0001
β_1	0.69669	<.0001
β_2	0.09031	0.0054
β_3	0.05435	0.0629
β_4	0.09978	<.0001
Δ_1	-0.1225	0.2354
Δ_2	-0.19944	0.0558
Δ_3	-0.26464	0.0125
Δ_4	-0.27023	0.0078
Δ_5	-0.12275	0.2253
Δ_6	0.1293	0.3076
Δ_7	-0.19271	0.1664
Δ_8	-0.05884	0.6674
Δ_9	-0.15157	0.2748
Δ_{10}	-0.04302	0.7578
Δ_{11}	0.3391	0.0232
Δ_{12}	0.17121	0.2186
Ψ_1	-1 .95184	<.0001
Ψ_2	-0.11789	0.2202
Ψ_3	-0.08345	0.357

Number of observations read: 4919
Number of observations used: 1119
Number of observations with missing values: 3800

F Value	Pr > F		
219.53	<.0001		
R-Square 0.7915	Ad] R-Sq 0.7879		

Test for sum of Catdum variables equal to '0'

F Value	Pr > F
6.21	0.0129

Test for Catdum variables jointly equal to '0'
F Value Pr > F
2.55 0.0025

Small Banks: $LN(CHARGEOFF)_{i,t} = C + \sum_{j=1}^{4} \beta_j \, LN(CHARGEOFF)_{i,t-j} + \sum_{k=1}^{12} \Delta_k \, Catdum_{i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{i,t-l}$

Parameter	Parameter Estimate	P- value
Intercept(C)	1.44582	<.0001
β_1	0.63183	< . 0001
β_2	0.14444	<.0001
β_3	-0.00056	0.9847
β_4	0.07766	0.0013
Δ_1	-0.06956	0.6278
Δ_2	-0.07913	0.5894
Δ_3	-0.49734	0.0009
Δ_4	-0.13779	0.3537
Δ_5	-0.07636	0.6121
Δ_6	-0.21353	0.2317
Δ_7	0.21154	0.2619
Δ_8	0.01588	0.9295
Δ_9	-0.11227	0.5394
Δ_{10}	-0.23629	-0.1855
Δ_{11}	0.42681	0.0292
Δ_{12}	-0.10093	0.5927
Ψ_1	-2.57992	<.0001
Ψ_2	-0.18877	0.1598
Ψ_3	-0.02562	0 . 8442

Number of Observations Read: 4919
Number of Observations Used: 1206
Observations with Missing Values: 3713
F Value Pr > F
134.37 <.0001
R-Square 0.6828 Adj R-Sq 0.6777

Test for sum of Catdum variables equal to '0'
F Value Pr > F
3.39 0.0660

Test for Catdum variables jointly equal to ‘0’

F Value	Pr > F
1.82	0.0413

Large Banks

$$ROA_{i,\,t} = C + \sum_{j=1}^{4} \beta_j \, ROA_{i,\,t-j} \;+ \sum_{k=1}^{12} \Delta_k \;\; Catdum_{\,i,\,t+k} \;+ \sum_{l=1}^{3} \Psi_l \, Q_{\,i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.00499	<.0001
β_1	0.62704	<.0001
β_2	0.06146	0.445
β_3	0.15958	0.0159
β_4	0.05844	0.2554
Δ_1	-0.0017	0.1898
Δ_2	0.00106	0.416
Δ_3	0.00217	0.0901
Δ_4	0.000568	0.6404
Δ_5	-0.0005	0.6833
Δ_6	0.000555	0.7101
Δ_7	-0.0002	0.8926
Δ_8	0.000241	0.8709
Δ_9	0.000562	0.7096
Δ_{10}	-0.00024	0.'8627
Δ_{11}	-0.00115	0.422
Δ_{12}	0.000268	0.8462
Ψ_1	-0.01184	<.0001
Ψ_2	-0.00346	0.0038
Ψ_3	-0.00179	0.0828

Number of Observations Read: 340
Number of Observations Used: 223
Number of Observations with Missing Values: **117**

F Value	Pr > F
27.11	<.0001

R –square 0.7173   Adj R-square 0.6909

Test for sum of Catdum variables equal to ‘0’

F Value	Pr > F
0.20	0.6520

Test for Catdum variables jointly equal to '0'
F Value Pr > F
0.58 0.8573

Large Banks

$$LN\,(LLP)_{i,\,t} = C + \sum_{j=1}^{4} \beta_j \; LN\,(LLP)_{i,\,t-j} \;+ \sum_{k=1}^{12} \Delta_k \;\; Catdum_{\,i,\,t+k} \;+ \sum_{l=1}^{3} \Psi_l \; Q_{\,i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	1. 0392	0.001
β_1	0.89701	<.0001
β_2	-0.11051	0.2586
β_3	0.11049	0.1243
β_4	0.03198	0.4282
Δ_1	0.1373	0.4598
Δ_2	-0.29573	0.1121
Δ_3	-0.06239	0.7367
Δ_4	0.20439	0.2676
Δ_5	0.01773	0.9243
Δ_6	-0.19599	0.4018
Δ_7	0.15931	0.5376
Δ_8	0.08464	0.7397
Δ_9	0.03876	0.8801
Δ_{10}	-0.10793	0.6353
Δ_{11}	-0.03121	0.8926
Δ_{12}	0.03894	0.864
Ψ_1	-1 .99934	<.0001
Ψ_2	0.16063	0.4433
Ψ_3	-0.21086	0.2543

Number of observations read: 340
Number of observations used: 172
Number of observations with missing values: 168
F Value Pr > F
55.19 <.0001
R-Square 0.8734 Ad] R-Sq 0.8576

Test for sum of Catdum variables equal to '0'
F Value Pr > F
0.0 0.9824

Test for Catdum variables jointly equal to ‘0’

F Value	Pr > F
0.48	0.9243

Large Banks

$$LN(CHARGEOFF)_{i,t} = C + \sum_{j=1}^{4} \beta_j \ LN(CHARGEOFF)_{i,t-j} + \sum_{k=1}^{12} \Delta_k \ Catdum_{\ i,t+k} + \sum_{l=1}^{3} \Psi_l \ Q_{\ i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.99533	0.0007
β_1	0.65141	<.0001
β_2	0.26068	0.0018
β_3	0.0173	0.781
β_4	0.02089	0.6149
Δ_1	0.02286	0.9237
Δ_2	0.02386	0.9202
Δ_3	0.03972	0.8671
Δ_4	0.16399	0.4662
Δ_5	-0.05996	0.7908
Δ_6	-0.1523	0.5886
Δ_7	0.63276	0.0275
Δ_8	-0.07333	0.7937
Δ_9	-0.25422	0.372
Δ_{10}	-0.23767	0.3665
Δ_{11}	0.36713	0.1699
Δ_{12}	-0.08319	0.7519
Ψ_1	-2.29946	<.0001
Ψ_2	-0.2507	0.2634
Ψ_3	0.12096	0.5391

Number of Observations Read: 340
Number of Observations Used: 223
Observations with Missing Values: 117

F Value	Pr > F
60.58	<.0001

R-Square 0.8501 Adj R-Sq 0.8360

Test for sum of Catdum variables equal to ‘0’

F Value Pr > F
0.34 0.5591
Test for Catdum variables jointly equal to ‘0’
F Value Pr > F
0.66 0.7860
All Banks

$$ROA_{i,t} = C + \sum_{j=1}^{4} \beta_j \, ROA_{i,t-j} + \sum_{k=1}^{12} \Delta_k \; Catdum_{i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.002025	<.0001
β_1	0.5691	<.0001
β_2	0.0953	0.0002
β_3	0.0572	0 . 0035
β_4	0.1314	<.0001
Δ_1	0, 000529	0.4457
Δ_2	0.000176	0.8038
Δ_3	0.000858	0.2209
Δ_4	0.000909	0.193
Δ_5	0.001292	0.0657
Δ_6	0.001537	0.0638
Δ_7	-0.002207	0.0087
Δ_8	-0.000425	0.6065
Δ_9	0.000333	0.6934
Δ_{10}	0.002902	0.0005
Δ_{11}	-0.002221	0.0102
Δ_{12}	-0.000179	0.8338
Ψ_1	-0.004332	<.0001
Ψ_2	-0.000812	0.1094
Ψ_3	0.00019	0.6854

Number of Observations Read: **5259**
Number of Observations Used: **2002**
Number of Observations with Missing Values: **3257**

Chow test:
F Value 1.50 Pr > F 0.0718
Total R-Square 0.5602

Test for sum of Catdum variables equal to ‘0’
F Value Pr > F

2.66 0.1030

Test for Catdum variables jointly equal to ‘0’

F Value Pr > F

2.47 0.0034

All Banks

$$LN\,(LLP)_{i,\,t} = C + \sum_{j=1}^{4} \beta_j\ LN\,(LLP)_{i,\,t\text{-}j} + \sum_{k=1}^{12} \Delta_k\ \text{Catdum}_{i,\,t+k} + \sum_{l=1}^{3} \Psi_l\ Q_{i,t\text{-}l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.7604	<.0001
β_1	0.727	<.0001
β_2	0.1086	0 . 0002
β_3	0.0598	0.0141
β_4	0.0736	0.0001
Δ_1	-0.0896	0.3262
Δ_2	-0.1811	0.0492
Δ_3	-0.2484	0.0083
Δ_4	-0.1986	0.0286
Δ_5	-0.0885	0.3277
Δ_6	0.1215	0.2851
Δ_7	-0.1741	0.1597
Δ_8	-0.0365	0.761
Δ_9	-0.1099	0 . 3664
Δ_{10}	-0.0155	0.8991
Δ_{11}	0 . 2445	0.0587
Δ_{12}	0.1554	0.2013
Ψ_1	-1 .9832	<.0001
Ψ_2	-0.1229	0.1544
Ψ_3	-0.0659	0.3991

Number of observations read: 5259

Number of observations used: 1325

Number of observations with missing values: 3934

Chow Test:

F Value Pr > F

0.91 0.5760

Total R-Square 0.8618

Test for sum of Catdum variables equal to ‘0’

F Value Pr > F

4.97 0.0259

Test for Catdum variables jointly equal to ‘0’

F Value	Pr > F
2.31	0.0064

All Banks

$$LN(CHARGEOFF)_{i,t} = C + \sum_{j=1}^{4} \beta_j \; LN(CHARGEOFF)_{i,t-j} + \sum_{k=1}^{12} \Delta_k \; Catdum_{\,i,t+k} + \sum_{l=1}^{3} \Psi_l \; Q_{\,i,t-1}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	1 .1220	<.0001
β_1	0.6577	<.0001
β_2	0.18	<.0001
β_3	-0.00045	0.9857
β_4	0.084	<.0001
Δ_1	-0.0654	0.6009
Δ_2	-0.1015	0.4282
Δ_3	-0.4685	0.0004
Δ_4	-0.117	0.3675
Δ_5	-0.0875	0.505
Δ_6	-0.2155	0.1672
Δ_7	0.2559	0.1186
Δ_8	-0.0059	0.9697
Δ_9	-0.1204	0.4468
Δ_{10}	-0.2174	0.1601
Δ_{11}	0.439	0.0087
Δ_{12}	-0.0804	0.6195
Ψ_1	-2.5246	<.0001
Ψ_2	-0.1682	0.1494
Ψ_3	0.0386	0.7261

Number of Observations Read; 5259
Number of Observations Used: 1469
Observations with Missing Values: 3790

Chow test

F Value	Pr > F
1.34	0.1459
Total R-Square	0.7767

Test for sum of Catdum variables equal to '0'

F Value	Pr > F
3.75	0.0530

Test for Catdum variables jointly equal to '0'

F Value	Pr > F
2.31	0.0063

Table 10 Bank Performance in the Nashville MSA, Catdum starting second quarter 1998

Small Banks

$$ROA_{i,t} = C + \sum_{j=1}^{4} \beta_j \, ROA_{i,t-j} + \sum_{k=1}^{6} \Delta_k \text{ Catdum}_{i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.00364	<.0001
β_1	0.51971	<.0001
β_2	-0.07398	0.0318
β_3	0.28904	<.0001
β_4	0.19487	<.0001
Δ_1	0.000663	0.7993
Δ_2	-0.00262	0.2899
Δ_3	-0.00083	0.7371
Δ_4	-0.00044	0.8649
Δ_5	-3E-05	0.9912
Δ_6	-0.00232	0.4071
Ψ_1	-0.00693	<.0001
Ψ_2	-0.00275	0.0099
Ψ_3	-0.00077	0.4763

Number of Observations Read: **980**
Number of Observations Used: **812**
Number of Observations with Missing Values: **168**

F Value Pr > F
106.00 <.0001
R-Square 0.6333 Ad] R-Sq 0.6273

Test for sum of Catdum variables equal to '0'
F Value Pr > F
0.72 0.3954
Test for Catdum variables jointly equal to '0'
F Value Pr > F
0.31 0.9302

Small Banks

$$\text{LN (LLP)}_{\text{i, t}} = \text{C} + \sum_{j=1}^{4} \beta_j \text{ LN (LLP)}_{\text{i, t-j}} + \sum_{k=1}^{6} \Delta_k \text{ Catdum}_{\text{i, t+k}} + \sum_{l=1}^{3} \Psi_l \text{ Q}_{\text{i, t-l}}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.62944	<.0001
β_1	0.91754	<.0001
β_2	-0.02255	0.64
β_3	0.03528	0.3652
β_4	0.02697	0.3507
Δ_1	-0.00338	0.9814
Δ_2	0.06041	0.6679
Δ_3	0.03056	0.8216
Δ_4	0.04179	0.7727
Δ_5	0.14836	0.2912
Δ_6	-0.08849	0.5445
Ψ_1	-1 .87984	<.0001
Ψ_2	0.28636	0.0094
Ψ_3	-0.02946	0.7773

Number of Observations Read: **980**
Number of Observations Used: **629**
Number of Observations with Missing Values: **351**

F Value Pr > F
297.89 <.0001
R-Square 0.8630 Ad] R-Sq 0.8601

Test for sum of Catdum variables equal to ‘0’
F Value Pr > F
0.28 0.5995
Test for Catdum variables jointly equal to ‘0’
F Value Pr > F
0.31 0.9302

Small Banks

$$\text{LN (CHARGEOFF)}_{i,\,t} = C + \sum_{j=1}^{4} \beta_j \text{ LN (CHARGEOFF)}_{i,\,t\text{-}j} + \sum_{k=1}^{6} \Delta_k \text{ Catdum}_{i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{i,t\text{-}l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	1 .15869	<.0001
β_1	0.70656	<.0001
β_2	0.07053	0.0892
β_3	0.05347	0.1112
β_4	0.04527	0.07
Δ_1	0.0024	0.9902
Δ_2	0.20311	0.2988
Δ_3	-0.13881	0.4926
Δ_4	0.29442	0.2032
Δ_5	0.32783	0.1798
Δ_6	-0.20615	0.4294
Ψ_1	-2.04566	<.0001
Ψ_2	-0.04652	0.7023
Ψ_3	-0.04531	0.693

Number of Observations Read: **980**
Number of Observations Used; **613**
Number of Observations with Missing Values: **367**

F Value	Pr > F
157.25	<.0001

R-Square 0.7734 Ad] R-Sq 0.7685

Test for sum of Catdum variables equal to '0'

F Value	Pr > F
0.75	0.3880

Test for Catdum variables jointly equal to '0'

F Value	Pr > F
0.95	0.4564

Large Banks

$$ROA_{i,t} = C + \sum_{j=1}^{4} \beta_j \ ROA_{i,t-j} + \sum_{k=1}^{6} \Delta_k \ Catdum_{i,t+k} + \sum_{l=1}^{3} \Psi_l \ Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.00581	<.0001
β_1	0.23139	0.0005
β_2	0.11296	0.0461
β_3	0.18241	0.0016
β_4	0.16991	0.0095
Δ_1	-0.00034	0.7746
Δ_2	-0.00044	0.7069
Δ_3	0.00172	0.2155
Δ_4	-0.00099	0.4754
Δ_5	-0.00041	0.7667
Δ_6	-0.00063	0.6529
Ψ_1	-0.0074	<.0001
Ψ_2	-0.00426	<.0001
Ψ_3	-0.00194	0.0046

Number of Observations Read: **150**
Number of Observations Used: **126**
Number of Observations with Missing Values; **24**

F Value Pr > F
30.98 <.0001
R-Square 0.7824 Ad] R-Sq 0.7571

Test for sum of Catdum variables equal to ‘0’
F Value Pr > F
0.10 0.7515

Test for Catdum variables jointly equal to ‘0’
F Value Pr > F
0.43 0.8607

Large Banks

$$\text{LN (LLP)}_{i,t} = C + \sum_{j=1}^{4} \beta_j \text{ LN (LLP)}_{i,t-j} + \sum_{k=1}^{6} \Delta_k \text{ Catdum}_{i,t+k} + \sum_{l=1}^{3} \Psi_l \text{ Q}_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	3.14208	<.0001
β_1	0.65206	<.0001
β_2	0.12312	0.3376
β_3	0.05112	0.6221
β_4	-0.11837	0.2229
Δ_1	-0.19593	0.5805
Δ_2	-0.19495	0.5788
Δ_3	0.54627	0.2787
Δ_4	0.71902	0.135
Δ_5	0.3305	0.4947
Δ_6	0.57568	0.2332
Ψ_1	-2.33489	<.0001
Ψ_2	-0.2726	0.4345
Ψ_3	-0.13218	0.6676

Number of Observations Read: **150**
Number of Observations Used: **77**
Number of Observations with Missing Values: **73**

F Value   Pr > F
22.89   <.0001
R-Square 0.8253   Ad] R-Sq 0.7892

Test for sum of Catdum variables equal to '0'
F Value   Pr > F
2.37   0.1287

Test for Catdum variables jointly equal to '0'
F Value   Pr > F
0.97   0.4506

Large Banks

$$\text{LN(CHARGEOFF)}_{i,t} = C + \sum_{j=1}^{4} \beta_j \ \text{LN(CHARGEOFF)}_{i,t-j} + \sum_{k=1}^{6} \Delta_k \ \text{Catdum}_{\ i,t+k} + \sum_{l=1}^{3} \Psi_l \ Q_{\ i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.93092	0.0035
β_1	1 .03670	<.0001
β_2	-0.10887	0.314
β_3	0.02322	0.6839
β_4	-0.00604	0.8713
Δ_1	-0.09885	0.5452
Δ_2	0.13354	0.4076
Δ_3	-0.01514	0.9376
Δ_4	0.28353	0.1413
Δ_5	-0.19618	0.3152
Δ_6	0.12777	0.5102
Ψ_1	-2.15831	<.0001
Ψ_2	0.45532	0.0429
Ψ_3	-0.15521	0.3331

Number of Observations Read: **150**
Number of Observations Used; **126**
Number of Observations with Missing Values: **24**

F Value Pr > F
127.69 <.0001
R-Square 0.9368 Ad] R-Sq 0.9295

Test for sum of Catdum variables equal to '0'
F Value Pr > F
0.26 0.6128

Test for Catdum variables jointly equal to '0'
F Value Pr > F
0.75 0.6139

All Banks

$$ROA_{i,t} = C + \sum_{j=1}^{4} \beta_j \, ROA_{i,t-j} + \sum_{k=1}^{6} \Delta_k \; Catdum_{i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.003662	<.0001
β_1	0.5118	<.0001
β_2	-0.069	0.0297
β_3	0.2836	<.0001
β_4	0.2027	<.0001
Δ_1	0.0006	0.786
Δ_2	-0.002434	0.2502
Δ_3	-0.000613	0.7761
Δ_4	-0.000606	0.7886
Δ_5	-2.02E-06	0.9993
Δ_6	-0.002173	0.3679
Ψ_1	-0.006947	<.0001
Ψ_2	-0.002748	0.0029
Ψ_3	-0.00077	0.4763

Number of observations read: 1130
Number of observations used: 946
Number of observations with missing values: 184

Chow Test:
F Value Pr > F
1.55 0.088
Total R-Square 0.6353

Test for sum of Catdum variables equal to ‘0’
F Value Pr > F
0.37 0.9001

Test for Catdum variables jointly equal to ‘0’
F Value Pr > F
1.10 0.356

All Banks

$$LN\ (LLP)_{i,t} = C + \sum_{j=1}^{4} \beta_j\ LN\ (LLP)_{i,t-j} + \sum_{k=1}^{6} \Delta_k\ Catdum_{i,t+k} + \sum_{l=1}^{3} \Psi_l\ Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.611	<.0001
β_1	0.897	<.0001
β_2	-0.00535	0.8964
β_3	0.0496	0.0850
β_4	0.026	0.2535
Δ_1	-0.00018	0.9989
Δ_2	0.0586	0.6528
Δ_3	0.0657	0.6127
Δ_4	0.092	0.5051
Δ_5	0.1438	0.2844
Δ_6	-0.0549	0.6933
Ψ_1	-1.9291	<.0001
Ψ_2	0.2331	0.0209
Ψ_3	-0.0505	0.5528

Number of observations read: 1130
Number of observations used: 710
Number of observations with missing values: 420

Chow Test:

F Value	Pr > F
1.10	0.3560
Total R-Square	0.9266

Test for sum of Catdum variables equal to '0'

F Value	Pr > F
0.81	0.3695

Test for Catdum variables jointly equal to '0'

F Value	Pr > F
0.37	0.8956

All Banks

$$LN(CHARGEOFF)_{i,t} = C + \sum_{j=1}^{4} \beta_j \ LN(CHARGEOFF)_{i,t-j} + \sum_{k=1}^{6} \Delta_k \ Catdum_{\ i,t+k} + \sum_{l=1}^{3} \Psi_l \ Q_{\ i,t-1}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.8337	<.0001
β_1	0.7488	<.0001
β_2	0.1003	0.0065
β_3	0.0587	0.0334
β_4	0.0422	0.0417
Δ_1	0.0336	0.8383
Δ_2	0.216	0.1909
Δ_3	-0.0987	0.5732
Δ_4	0.3061	0.1185
Δ_5	0.2539	0.2157
Δ_6	-0.148	0.493
Ψ_1	-2.0784	<.0001
Ψ_2	-0.0382	0.7197
Ψ_3	-0.0294	0.7595

Number of observations read: 1130
Number of observations used: 745
Number of observations with missing values: 385

Chow Test:

F Value	Pr > F
2.04	0.0.0130
Total R-Square	0.9087

Test for sum of Catdum variables jointly equal to '0'

F Value	Pr > F
1.43	0.2323

Test for Catdum variables jointly equal to '0'

F Value	Pr > F
1.10	0.3581

Table 11 Bank Performance in the Corpus Christi MSA, Catdum starting third quarter 1999

Small Banks: ROA

$$ROA_{i,t} = C + \sum_{j=1}^{4} \beta_j \, ROA_{i,t-j} + \sum_{k=1}^{12} \Delta_k \; Catdum_{\,i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{\,i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.00511	<.0001
β_1	0.58469	<.0001
β_2	0.08605	0.0671
β_3	0.06097	0.2131
β_4	0.00883	0.8245
Δ_1	0.00219	0.1871
Δ_2	0.00149	0.3726
Δ_3	-0.0023	0.1669
Δ_4	0.000343	0.847
Δ_5	0.00187	0.2616
Δ_6	0.00206	0.2168
Δ_7	-0.00396	0.0176
Δ_8	0.000311	0.8619
Δ_9	0.00047	0.7788
Δ_{10}	0.000153	0.9318
Δ_{11}	-0.0011	0.5315
Δ_{12}	0.00163	0.3928
Ψ_1	-0.00854	<.0001
Ψ_2	-0.00239	0.0029
Ψ_3	-0.00077	0.3073

Number of Observations Read: **600**
Number of Observations Used: **485**
Number of Observations with Missing Values: **115**

F Value	Pr > F
38.57	<.0001

R-Square 0.6118 Ad] R-Sq 0.5959

Test for sum of Catdum variables equal to ‘0’

F Value	Pr > F
0.24	0.6235

Test for Catdum variables jointly equal to ‘0’

F Value Pr > F
1.09 0.3690

Small Banks

$$LN\,(LLP)_{i,\,t} = C + \sum_{j=1}^{4} \beta_j\, LN\,(LLP)_{i,\,t-j} + \sum_{k=1}^{12} \Delta_k \;\; Catdum_{i,\,t+k} + \sum_{l=1}^{3} \Psi_l\, Q_{i,\,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.68302	0.0034
β_1	0.84769	<.0001
β_2	0.0654	0.3924
β_3	-0.14908	0.0185
β_4	0.13825	0.005
Δ_1	-0.15878	0.6334
Δ_2	-0.16984	0.6095
Δ_3	0.06631	0.8597
Δ_4	0.11784	0.7534
Δ_5	0.26483	0.4221
Δ_6	0.06253	0.8494
Δ_7	0.40041	0.2236
Δ_8	0.01336	0.9644
Δ_9	-0.19758	0.5063
Δ_{10}	0.01558	0.9622
Δ_{11}	0.20297	0.-5367
Δ_{12}	0.6529	0.0483
Ψ_1	-1 .89693	<.0001
Ψ_2	0.34944	0.1206
Ψ_3	0.39261	0.0414

Number of observations read: 600
Number of observations used: 213
Number of observations with missing values: 387

F Value Pr > F
42.74 <.0001
R-Square 0.8080 Adj R-Sq 0.7890

Test for sum of Catdum variables equal to ‘0’
F Value Pr > F
1.04 0.3096
Test for Catdum variables jointly equal to ‘0’
F Value Pr > F

0.63 0.8174

Small Banks: $LN(CHARGEOFF)_{i,t} = C + \sum_{j=1}^{4} \beta_j\, LN(CHARGEOFF)_{i,t-j} + \sum_{k=1}^{12} \Delta_k$ Catdum $_{i,t+k} + \sum_{l=1}^{3} \Psi_l\, Q_{i,t-l}$

Parameter	Parameter Estimate	P- value
Intercept(C)	1 .20471	<.0001
β_1	0.6597	<.0001
β_2	0.0947	0.0661
β_3	0.04048	0.3331
β_4	0.08131	0.0228
Δ_1	-0.24031	0.4975
Δ_2	-0.31752	0.3721
Δ_3	0.35795	0.3123
Δ_4	-0.16793	0.6361
Δ_5	-0.09242	0.7943
Δ_6	-0.1903	0.5663
Δ_7	0.29064	0.3792
Δ_8	-0.35192	0.3213
Δ_9	0.03096	0.9256
Δ_{10}	0.20767	0.5595
Δ_{11}	0.42122	0.2352
Δ_{12}	0.04015	0.9173
Ψ_1	-2.34552	<.0001
Ψ_2	-0.14737	0.4305
Ψ_3	-0.09374	0.5723

Number of Observations Read; 600
Number of Observations Used: 412
Observations with Missing Values: 188

F Value Pr > F
65.00 <.0001
R-Square 0.7591 Adj R-Sq 0.7474

Test for sum of Catdum variables equal to ‘0’
F Value Pr > F
0.00 0.9928

Test for Catdum variables jointly equal to '0'
F Value Pr > F
0.51 0.9098

Table 12 Bank Performance in the Fort Worth MSA, Catdum starting first quarter 2000

Small Banks

$$ROA_{i,t} = C + \sum_{j=1}^{4} \beta_j \ ROA_{i,t-j} + \sum_{k=1}^{8} \Delta_k \ Catdum_{i,t+k} + \sum_{l=1}^{3} \Psi_l \ Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.00539	<.0001
β_1	0.31223	<.0001
β_2	0.03815	0.0478
β_3	0.22008	<.0001
β_4	0.16195	<.0001
Δ_1	-0.0002165	0.8236
Δ_2	0.0007038	0.475
Δ_3	0.0009853	0.312
Δ_4	0.0003825	0.6946
Δ_5	-0.00154	0.1132
Δ_6	-0.0008541	0.3867
Δ_7	-0.00153	0.1218
Δ_8	-0.0015	0.1301
Ψ_1	-0.00741	<.0001
Ψ_2	-0.00343	<.0001
Ψ_3	-0.00179	<.0001

Number of Observations Read: **2284**
Number of Observations Used: **1949**
Number of Observations with Missing Values: **335**

F Value Pr > F
112.00 <.0001
R-Square 0.4650 Ad] R-Sq 0.4608

Test for sum of Catdum variables equal to '0'
F Value Pr > F
1.54 0.2146

Test for Catdum variables jointly equal to '0'
F Value Pr > F

1.25 0.2578

Small Banks

$$LN\ (LLP)_{i,\,t} = C + \sum_{j=1}^{4} \beta_j\ LN\ (LLP)_{i,\,t-j} + \sum_{k=1}^{8} \Delta_k\ \ Catdum_{i,\,t+k} + \sum_{l=1}^{3} \Psi_l\ Q_{i,\,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	1 .14648	<.0001
β_1	0.6329	<.0001
β_2	0.17347	<.0001
β_3	0.06368	0.0187
β_4	0.01083	0.6171
Δ_1	0.60525	<.0001
Δ_2	0.38966	0.0098
Δ_3	0.08911	0.5277
Δ_4	0.04772	0.7208
Δ_5	0.0887	0.5199
Δ_6	0.18491	0.1988
Δ_7	0.19509	0.1671
Δ_8	0.07339	0.5959
Ψ_1	-1 .95057	<.0001
Ψ_2	-0.33754	0.0001
Ψ_3	-0.08245	0.2897

Number of Observations Read: **2284**
Number of Observations Used: **1006**
Number of Observations with Missing Values; **1278**
F Value Pr > F
219.29 <.0001
R-Square 0.7687 Ad] R-Sq 0.7651

Test for sum of Catdum variables equal to '0'
F Value Pr > F
15.72 <0.0001

Test for Catdum variables jointly equal to '0'
F Value Pr > F
3.43 0.0007

Small Banks

$$LN(CHARGEOFF)_{i,t} = C + \sum_{j=1}^{4} \beta_j \ LN(CHARGEOFF)_{i,t-j} + \sum_{k=1}^{8} \Delta_k \ \text{Catdum}_{i,t+k} + \sum_{l=1}^{3} \Psi_l \ Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	1 .10376	<.0001
β_1	0.57709	<.0001
β_2	0.19191	<.0001
β_3	0.01468	0.4777
β_4	0.09601	<.0001
Δ_1	0.25582	0.1506
Δ_2	-0.05165	0.7671
Δ_3	-0.09806	0.5605
Δ_4	-0.01723	0.9171
Δ_5	0.56231	0.0007
Δ_6	-0.03513	0.8267
Δ_7	-0.06762	0.6737
Δ_8	-0.01239	0.9394
Ψ_1	-2.12075	<.0001
Ψ_2	-0.33501	0.0001
Ψ_3	0.03522	0.658

Number of Observations Read; **2284**
Number of Observations Used: **1612**
Number of Observations with Missing Values: **672**

F Value Pr > F
266.57 <.0001
R-Square 0.7147 Ad] R-Sq 0.7120

Test for sum of Catdum variables equal to ‘0’
F Value Pr > F
1.20 0.2740
Test for Catdum variables jointly equal to ‘0’
F Value Pr > F
1.70 0.0941

Table 13 Bank Performance in the Wilmington MSA, Catdum starting third quarter 1996, third quarter 1998, and third quarter 1999

Small Banks

$$ROA_{i,t} = C + \sum_{j=1}^{4} \beta_j \, ROA_{i,t-j} + \sum_{k=1}^{12} \Delta_k \; Catdum_{i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{i,t-l}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	0.000841	0.7598
β_1	0.83109	<.0001
β_2	0.02113	0. 8575
β_3	0.31683	0.0054
β_4	-0.19557	0.1156
Δ_1	-0.0001168	0.9757
Δ_2	-0.00178	0.6586
Δ_3	0.00293	0.4478
Δ_4	0.00431	0.2459
Δ_5	0.00144	0.7087
Δ_6	-0.0001101	0.9772
Δ_7	-0.00143	0. 6962
Δ_8	0.00388	0.2623
Δ_9	0.00164	0.6295
Δ_{10}	0.00361	0.2753
Δ_{11}	-0.00207	0.5267
Δ_{12}	0.00314	0.3156
Ψ_1	-0.00383	0.2725
Ψ_2	-0.0022	0.5086
Ψ_3	-0.00465	0.2137

Number of Observations Read: **108**

Number of Observations Used: **84**

Number of Observations with Missing Values: **24**

F Value	Pr > F
5.47	<.0001

R-Square 0.6189 Ad] R-Sq 0.5058

Test for sum of Catdum variables equal to ‘0’

F Value	Pr > F
1.64	0.2043

Test for Catdum variables jointly equal to ‘0’

F Value Pr > F

0.49 0.9157

Small Banks

$$\text{LN (LLP)}_{\text{i, t}} = \text{C} + \sum_{j=1}^{4} \beta_j \text{ LN (LLP)}_{\text{i, t-j}} + \sum_{k=1}^{12} \Delta_k \text{ Catdum}_{\text{i, t+k}} + \sum_{l=1}^{3} \Psi_l \text{ Q}_{\text{i, t-l}}$$

Parameter	Parameter Estimate	P- value
Intercept(C)	1 .50907	0.031
β_1	0.69721	0.0001
β_2	0.09737	0.6028
β_3	-0.08202	0.5434
β_4	0.01089	0.9167
Δ_1	-0.49479	0.3234
Δ_2	0.47133	0.2866
Δ_3	0.26767	0.5539
Δ_4	-0.27385	0.5453
Δ_5	-0.45403	0.398
Δ_6	1 .14929	0.0226
Δ_7	-0.03848	0.9342
Δ_8	-0.47536	0.2231
Δ_9	-0.5904	0.1603
Δ_{10}	-0.26926	0.5804
Δ_{11}	0.31287	0.4412
Δ_{12}	-0.10427	0.7601
Ψ_1	-1 .54204	0.0053
Ψ_2	0.64346	0.2885
Ψ_3	1 .23940	0.0515

Number of observations read: 108

Number of observations used: 57

Number of observations with missing values: 51

F Value Pr > F

4.99 <.0001

R-Square 0.7192 Ad] R-Sq 0.5750

Test for sum of Catdum variables equal to ‘0’

F Value Pr > F

0.07 0.7947

Test for Catdum variables jointly equal to ‘0’

F Value Pr > F
1.70 0.1081

Small Banks: $LN(CHARGEOFF)_{i,t} = C + \sum_{j=1}^{4} \beta_j \, LN(CHARGEOFF)_{i,t-j} + \sum_{k=1}^{12} \Delta_k$ Catdum $_{i,t+k} + \sum_{l=1}^{3} \Psi_l \, Q_{i,t-l}$

Parameter	Parameter Estimate	P- value
Intercept(C)	1 .41119	0.1276
β_1	0.66111	0.0006
β_2	0.02537	0.8982
β_3	-0.04921	0.7426
β_4	0.01681	0.9092
Δ_1	-0.39987	0.6605
Δ_2	0.06742	0.941
Δ_3	-0.79512	0.4151
Δ_4	0.60288	0.5118
Δ_5	0.36902	0.6777
Δ_6	0.02402	0.9795
Δ_7	0.14865	0.8892
Δ_8	-0.78168	0.3679
Δ_9	-0.01776	0.9834
Δ_{10}	0.1289	0.8813
Δ_{11}	0.6013	0.4505
Δ_{12}	0.13916	0.8386
Ψ_1	-1 .67387	0.0553
Ψ_2	0.26499	0.7615
Ψ_3	0.57518	0.5592

Number of Observations Read: 108
Number of Observations Used: 54
Observations with Missing Values: 54

F Value Pr > F
2.01 0.0367
R-Square 0.5295 Adj R-Sq 0.2666

Test for sum of Catdum variables equal to '0'
F Value Pr > F

0.00	0.9756

Test for Catdum variables jointly equal to ‘0’

F Value	Pr > F
0.28	0.9880

References

Alesch, D. J., J. N. Holly, E. Mittler, and R. Nagy. 2001. Organizations at Risk: What Happens When Small Businesses and Not-for-Profits Encounter Natural Disaster. Small Organizations Natural Hazards Project Technical Report. University of Wisconsin, Green Bay. Published by Public Entity Risk Institute.

Berger, A., R. DeYoung, 2001. The effects of geographic expansion on bank efficiency. *Journal of Financial Services Research* 19:163-184.

Berger, A., A. Kashyap, and J. Scalise, 1995. The transformation of the U.S. banking industry: What a long strange trip it’s been. *Brookings Papers on Economic Activity*, 55-218.

Berger, A. A. Saunders, J. Scalise, and G. Udall, 1998. The effects of bank mergers and acquisitions on small business lending. *Journal of Financial Economics*, 50:187-229.

Bollerslev, Tim. 1986. Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* 31: 307-327.

Bollerslev, Tim, Ray Y. Chou, and Kenneth F. Kroner. 1992. ARCH Modeling in Finance: A Selective Review of the Theory and Empirical Evidence. *Journal of Econometrics* 52: 5-59.

Calhoun, Charles A. 1996. OFHEO Housing Price Indexes: HPI Technical Description, www.ofheo.gov

Case, Karl E., and Robert J. Shiller. 1989. The Efficiency of the Market for Single-Family Homes. *American Economic Review* 79: 125-137.

Enders, Walter. 2004. Applied Econometric Time Series. *Second Edition, John Wiley & Sons, Inc.*

Enders, Walter, Todd Sandler, and Jon Cauley. 1990. Assessing the Impact of Terrorist-Thwarting Policies: An Intervention Time Series Approach. *Defense Economics* 2: 1-18.

Engle, Robert. 1982. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of the U. K. Inflation. *Econometrica* 50: 987-1008.

Coulson, N. Edward and Christian Richard. 1996. The Dynamic Impact of Unseasonable Weather on Construction Activity. *Real Estate Economics* 24: 179-194.

DeSilva, Dakshina G., Jamie B. Kruse, and Yongsheng Wang. (2004). Catastrophe-Induced Destruction and Reconstruction in *Economics and Wind*, (in press) B. Ewing and J. Kruse, Eds., Nova Science, NY.

Diebold, Francis X. 2004. Elements of Forecasting. *Third Edition*, *South-Western and Thompson Publication*.

DiPasquale, Denise, and William C. Wheaton. 1996. Urban Economics and Real Estate Markets. *Prentice Hall.*

Ellson, Richard W., Jerome W. Milliman, and R. Blaine Roberts. 1984. Measuring the Regional Economic Effects of Earthquakes and Earthquake Predictions. *Journal of Regional Science* 24 (4): 559-579.

Eves, Chris. 2002. The Long-term Impact of Flooding on Residential Property Values. *Property Management* 20 (4): 214-227.

Ewing, Bradley T., Scott E. Hein, and Jamie B. Kruse. 2003. Insurer Stock Price Responses to Hurricane Floyd: An Event Study Analysis Using Storm Characteristics, Report to National Institute of Standards and Technology, U.S. Department of Commerce.

Ewing, Bradley T. and Jamie B. Kruse. 2002. The Impact of Project Impact On The Wilmington, North Carolina, Labor Market. *Public Finance Review* 30(4): 296-309.

Ewing, Bradley T., Jamie B. Kruse, and Mark A. Thompson. 2003. Labor Market Responses to Tornadoes. *Proceedings of the 11th International Conference on Wind Engineering, Lubbock, Texas.*

Ewing, B. T., Kruse, J. B., and Thompson, M. A. (2005) *Transmission of Labor Market Shocks across Regions: Evidence from the May 3, 1999 Oklahoma City Tornado*. Prepared for U.S. Department of Commerce, National Institute of Standards and Technology, 2005.

Ewing, B. T., Kruse, J. B., and Thompson, M. A. (2004) *Labor Market Effects of the Oklahoma City Tornado: A Time Series Panel Data Analysis*. Prepared for U.S. Department of Commerce, National Institute of Standards and Technology.

Ewing, B. T., Kruse, J. B., and Thompson, M. A. (2003a) *The Economic Impact of the Fort Worth Tornado on Employment*. Prepared for U.S. Department of Commerce, National Institute of Standards and Technology.

Ewing, B. T., Kruse, J. B., and Thompson, M. A. (2003b) *The Economic Impact of the Nashville Tornado on Employment*. Prepared for U.S. Department of Commerce, National Institute of Standards and Technology.

Ewing, B. T., Kruse, J. B., and Thompson, M. A. (2002) *The Economic Impact of the Oklahoma City Tornado on Employment*. Prepared for U.S. Department of Commerce, National Institute of Standards and Technology.

Ewing, Bradley T., and Guillermo Covarrubias. 2003. Weather Shocks to Insurance Stock Prices, and Volatility Persistence. *Proceedings of the 11th International Conference on Wind Engineering, Lubbock, Texas.*

Fergus, James T., 1999, Where, When, and by How Much Does Abnormal Weather Affect Housing Construction? *Journal of Real Estate Finance and Economics* 18 (1): 63-87.

Fronstin, Paul, and Alphonse G. Holtmann. 1994. The Determinants of Residential Property Damage Caused by Hurricane Andrew. *Southern Economic Journal* 61: 387-397.

Graham, J. Edward and William W. Hall. 2002. Catastrophic Risk and Behavior of Residential Real Estate Market Participants. *Natural Hazards Review* 3 (3): 92-97.

Guimaraes, P., F.Hefner, and D.Woodward. 1993. Wealth and Income Effects of Natural Disasters: An Econometric Analysis of Hurricane Hugo. *The Review of Regional Studies* 23(2): 97-114.

Gujarati, Damodar N. 2003. Basic Econometrics. *Fourth edition, McGraw-Hill Publication.*

Harrison, David M., Greg T. Smersh and Arthur L. Schwartz, Jr. 2001. Environmental Determinants of Housing Prices: The Impact of Flood Zone Status. *Journal of Real Estate Research.* 21 (1/2): 3-20.

Harvey, Andrew C. 1994. Time Series Models. *Second edition, MIT Press.*

Hamilton, James D. 1994. Time Series Analysis. *Princeton University Press.*

Keeton, W. 1995. Multi-office bank lending to small businesses: Some new evidence. *Federal Reserve Bank of Kansas City Economic Review*, 45-57.

Meade, Charles, and Megan Abbott. 2003. Assessing Federal Research and Development for Hazard Loss Reduction. *RAND Report,* pp 39.

Murdoch, James C., Harinder Singh and Mark Thayer. 1993. The Impact of Natural Hazards on Housing Values: The Loma Prieta Earthquake. *Journal of the American Real Estate and Urban Economics Association* 21(2): 167-184.

Simmons, Kevin and Jamie B. Kruse. 2000. Market Value of Mitigation and Perceived Risk: Empirical Results. *Journal of Economics* 26(1): 41-51.

Simmons, Kevin, Jamie B. Kruse, and Doug Smith. 2002. Valuing Mitigation: Real Estate Market Response to Hurricane Loss reduction Measures. *Southern Economic Journal* 68(3): 660-671.

Stewart, Mark G., David V. Rosowsky, and Zhigang Huang. 2003. Hurricane Risks and Economic Viability of Strengthened Construction. *Natural Hazards Review,* February: 12-19.

Strahan, P. and J. Weston, 1998. Samll business lending and the changing structure of the banking industry. *Journal of Banking and Finance*. 22:821-845.

Yeager, Timothy J. 2004. The demise of community banks? Local economic shocks are not to blame. *Journal of Banking and Finance* 28:2135-2153.

Appendix Table 1: Descriptive Statistics

Growth Rates of State Economic Measure

	Mean	Median	Std. Dev.	Kurtosis
Texas	0.013	0.015	0.043	4.458
Tennessee	0.068	0.064	0.024	3.626
Oklahoma	0.063	0.050	0.050	3.697
Florida	0.088	0.077	0.042	2.526
North Carolina	0.065	0.067	0.021	3.289

Notes: Data are quarterly observations. Sample periods are as follows: Fort Worth-Arlington 1977:4 to 2002:4; Nashville 1979:4 to 2002:4; Oklahoma City 1977:3 to 2002:4; Corpus Christi 1981:2 to 2002:4; Miami 1976:2 to 2002:4; and Wilmington 1985:2 to 2002:4. Texas state level housing price series is used in the Corpus Christi and Fort Worth analyses; however, these two regions have different sample ranges due to data availability. For the state of Texas, the longer sample (1977:4 –2002:4) is reported in Panel A. National level data are used in each of the regional analyses; however, sample ranges vary due to data availability. Descriptive statistics corresponding to the longest sample range (1976:2-2002:4) is reported is reported above. In Panel B, we report descriptive statistics for the Texas Industrial Production Index and personal income for each of the other states.