El Niño and Agricultural Lending in the Southeastern U.S.A.

Valentina Hartarska

Associate Professor

Department of Agricultural Economics and Rural Sociology,

210 Comer Hall, Auburn Al 36830

e-mail: hartarska@auburn.ed

Denis Nadolnyak

Assistant Professor

Department of Agricultural Economics and Rural Sociology

209B Comer Hall, Auburn Al 36830

e-mail: nadolda@auburn.edu

El Niño and Agricultural Lending in the Southeastern U.S.A.

ABSTRACT

We study how agricultural loan portfolios in commercial banks serving agricultural producers are affected by inter-annual climate variability in the Southeast U.S. - a region strongly affected by the El Nino Southern Oscillation (ENSO). We use panel data for 473 agricultural banks from six southeastern states over the period of 1991-2010, together with several ENSO indexes. We find that non-neutral ENSO years that typically have higher incidence of weather extremes are associated with smaller levels of non-performing loans suggesting that farmers' losses in extreme years are helped by support mechanisms. Consistent with recent theoretical work, and findings about US community banks, our results suggest that the impact of the ENSO is mitigated by complementary financial markets and support mechanisms.

Key Words: Agricultural Commercial Banks, Climate Variability, ENSO

JEL Codes: G21, Q14

El Niño and Agricultural Lending in the Southeastern U.S.A.

Introduction

Extreme climate events affect agricultural producers' incomes and can lead to long lasting negative consequences for banks and their clients in the absence of competitive complementary insurance markets (Garmaise and Moskowitz, 2009). There is evidence from developing countries that extreme weather negatively impacts agricultural producers and the banks that lend to them (Berg and Schrader, 2009). The impact of climate variability on US commercial banks lending to agricultural producers has not been studied but research has explored the impact of extreme events on community banks' portfolios (Ewing, Hein, and Kruse, 2005). Since US agriculture relies on government support mechanisms, it is not clear if such support would suggest outcomes associated with competitive or with non-competitive insurance markets. Thus, we set out to find out how climate variability measured by El Niño Southern Oscillation affects the agricultural loan portfolios of US banks lending to agricultural producers.

Meteorological data indicate higher frequency of extreme weather in recent years, with 9 out of the 10 hottest years on record happening during the period from 2000 to 2010 according to the National Oceanic and Atmospheric Association (NOAA) and to the Met Office Hadley Center and Climate Research Units (U.K.), and with 10 out of 10 hottest years over the same period according to the NASA Goddard Institute for Space Studies (*The Economist*, 2010). Arguably, climate change is manifested in increased frequency of the El Niño Southern Oscillation (ENSO) extremes commonly known as El Niño (warm phase) and La Niña (cold phase). Since the strength of the ENSO events is measurable and predictable with high skill level, ENSO data can be used to study how agricultural producers are affected by intra-annual climate variations.

The increased incidences of extreme temperatures and rainfall have a high impact in geographical areas that are relatively more affected by the ENSO, one of which is the Southeastern U.S. (Higgins et al., 2002; Halpert and Ropelewski, 1992).[1] Moreover, crop production in this region is mostly rain-fed, making its agriculture more vulnerable to weather variability and appropriate for a study of the impact of weather on agricultural lenders' portfolios. This is important as Schlenker, Hanemann, and Fisher (2005) argue that irrigation may bias estimates of the impact of climate on agricultural production.

Agronomists have documented significant ENSO impact on crop yields in the Southeast (Royce, Fraisse, and Baiggorria, 2011). While ENSO phases' impact differs among crops, data suggest that neutral years result in higher yields, El Niño years result in lower yields due to freezes and excessive moisture, whereas La Niña years are beneficial for some crops, e.g. corn and peanuts, and harmful for others, e.g. cotton (Shin et al., 2010; Martinez, Baigorria, and Jones, 2009; Baigorria et al., 2008). The overall impact of ENSO on agriculture is hard to isolate because agricultural production in general and crop production in particular are diversified. Producers manage risks by choosing crops, planting dates, chemical application timing, etc., but yields still remain volatile and dependent on the weather, especially without irrigation. This remaining yield volatility is expected to impact producer income and, therefore, solvency, which would be reflected in variations in the performance of agricultural loan portfolios of the lenders.

Both banks and producers could benefit from the use of ENSO forecasts if the performance of agricultural portfolios of commercial banks is affected by ENSO phases. Given the existence of such an association, a bank could use climate forecasts to offer better contract terms and more adequately provision for expected losses while borrowers could use climate forecasts in production and financial risk management decisions. Moreover, results would be suggestive of the degree to which the financing needs of the producers are met by existing financial markets and government support mechanisms and if weather related risks are sufficiently diversified through the existing financial system.

The rest of the paper is organized as follows. Section 2 describes the relevant literature, including on financial intermediaries and insurance markets and climate variability as well as related agronomic and meteorological work; Section 3 describes the theoretical framework and empirical approach; Section 4 describes the data; section 5 discusses the results, and section 6 concludes.

2. Climate Impact on Agriculture and Agricultural Financial Markets.

The literature linking extreme weather events to bank lending is only emerging. So far, it highlights an important role for well-developed complementary insurance markets. Garmaise and Moskowitz (2009) show that insurance market imperfections can restrict provision of bank credit and prevent positive net present value projects from being undertaken. This can limit market participation of less wealthy investors and hamper development especially in disadvantaged areas. These authors provide supportive empirical evidence from extreme events such as hurricanes and earthquakes. Other theoretical work focuses on developing option-pricing methodologies to calculate probability distributions for improving credit risk evaluations for lenders who cannot find needed insurance or cannot rely on governments to cover catastrophic events (Kau and Keenan, 1999).

Empirical evidence mainly comes from studies about developing countries. Collier, Katchova, and Skees (2010) find that, in Peru, El Niño events that caused catastrophic flooding affected financial institutions serving the poor. In particular, the bank they study restructured four percent of its portfolio after an El Niño event struck, but there was no impact on the proportion of delinquent loans. Berg and Schrader (2009) present evidence from Banco ProCredit in Ecuador showing that the demand for credit increased after a volcanic eruption while the probability of receiving a microloan did not change for existing clients and decreased for new clients. They conclude that microcredit in rural Ecuador has an insurance function because it helps client-farmers to maintain access to credit after catastrophic events.

Evidence from developed financial markets is scarcer. In the U.S., Ewing, Hein, and Kruse (2005) examine community bank performance in several tornado- and hurricane-prone areas. Community banks are similar to agricultural banks in that both tend to be less diversified geographically and are more vulnerable to local economic shocks because they serve local small business customers and farmers, respectively. Ewing, Hein and Kruse (2005) use an event study methodology and find regional differences in banks' performance: in the aftermath of catastrophic events, banks' performance in the Miami MSA, Florida, was different from that of banks serving Fort Worth and Wilmington MSAs in Oklahoma. More importantly, the authors find that the affected banks do better than the non-affected banks and that these positive post-event differences depend on the severity of the event, which again suggests a role for complementary insurance markets.

In a study related to the present study, Nadolnyak and Hartarska (2010) use simple mean comparisons of agricultural banks' portfolio performance indicators during various years classified by the Nino 3.4 index and find that, in La Niña years, agricultural banks in the Southeast U.S. extend more and larger loans than in neutral years suggesting a link between the ENSO and agricultural bank lending.

ENSO data, according to the Centre for Ocean-Atmospheric Prediction Studies, are classified into three phases based on indexes derived from observed sea surface temperature

(SST) anomalies: El Niño - warm SST anomalies in the Pacific, La Niña –cool SST anomalies, and neutral. In North America, El Niño creates warmer-than-average winters in the upper Midwest and in the Northwest, reducing snowfall. Central and southern California, northwest Mexico, and the southwestern U.S. become significantly wetter. The northern Gulf of Mexico states and the southeastern states are wetter and cooler than average during the El Niño phase of the oscillation with the impact on the southeastern states significantly more pronounced in the winter than in the warm season (Climate Prediction Center). La Niña causes mostly the opposite effects of El Niño and below-average precipitation causing droughts but reducing floods is expected in the winter and summer months.

The economic impact of the ENSO in the Southeast is significant because of the prevalence of rainfed agriculture that is relatively more vulnerable to volatility in precipitation, solar radiation, and temperatures affecting crop growth both directly and indirectly through their impacts on soil moisture, creating (un)favorable conditions for disease, etc. Research suggests that ENSO phases are correlated with crop yields but the impact differs among crops. For example, in the southeast U.S., neutral years generally result in higher yields, El Niño years result in lower yields, whereas La Niña years are beneficial for some crops (corn, peanuts) and may be harmful for cotton (Royce, Fraisse, and Baiggorria, 2011; Baigorria et al., 2008, 2010; Shin et al., 2010; Martinez, Baigorria, and Jones, 2009). The negative impact of El Niño is due to freezes and/or floods early in the season (although recent results leave some ambiguity). La Niña may have negative impact due to lack of rainfall and higher temperatures in the summer, while the higher amount of solar radiation promotes plant growth.

Aggregate impacts of the ENSO on production *risk* have also been analyzed. For example, ENSO events were found to be positively associated with county level agricultural disaster payments (Nadolnyak and Hartarska, 2011). In particular, El Niño years which have higher precipitation and freeze frequency were associated with substantially higher crop disaster payments, whereas in La Niña years associated with droughts and heat the effect was smaller. ENSO events were also found to affect production risk at more moderate levels in crop insurance analysis: the downward volatility of corn, cotton, and peanut yields in the Southeast has been consistently higher in El Niño years giving rise to potential adverse selection and suggesting conditioning insurance premiums (Nadolnyak, Vedenov, and Novak, 2008).

Weather extremes usually cause significant negative shocks to farm income but there are emerging tools to deal with such shocks. For example, weather derivatives based on temperature indexes, e.g., cooling and heating degree days, consecutive days of sub-freezing temperatures, and cumulative precipitation are increasingly used in emerging studies on natural disasters in agriculture (Miranda and Vedenov, 2001; Vedenov and Barnett, 2004; Richards, Manfredo, and Sanders, 2004). These indexes are specifically designed for disaster and farm income loss measurement, like freeze or flood indexes, and are available on a disaggregated local level. Thus, if the ENSO is linked to farmers' ability to repay their loans, knowledge of such links would be helpful to farmers who could make better use of the available financial risk management tools in coping with climate related risks.

Framework of Analysis: Empirical Approach

We study how default and delinquency on agricultural loans in the southeastern U.S. are affected by inter-annual climate variations. The ENSO reflects variations in occurrence of severe weather which, in turn, causes yield losses and negative shocks to farm incomes, thus affecting loan repayment. The main hypothesis is that ENSO phases affect default and delinquency of agricultural loans. Of particular interest is the default on loans for crop production because rain-fed crop production in the Southeast is vulnerable to fluctuation in the weather. We assume that farmers who took loans are well informed, e.g., they know what crop to grow given their land productivity, skills, available insurance, and production risk management tools. We focus on loans secured by farm land because this allows isolating crop production loans, since the second category of agricultural loans for which data is collected - agricultural production loans - also includes loans for animal agriculture.

The basic framework for the analysis come from the literature on mortgage backed loans which models default as a function of strategic default variables, and the interaction of repayment capacity and shocks (Quigley and Van Order, 1991). Agricultural borrowers default strategically when the value of the collateral (land) is less than what is owed on the loan. Non-strategic default occurs due when shock events affect borrowers' cash flows to an extent that they are unable to repay. Idiosyncratic shock events such as divorce or illness affect individual farmers and their impact cannot be captured by aggregate bank level data. It can be assumed, however, that this idiosyncratic impact is stable due to diversification within the agricultural loan portfolio for the average bank. Systemic shock events such as those due to weather extremes affect all farmers simultaneously and can be studied with data from commercial banks.

To isolate the impact of inter-annual climate variation on defaults, we must control for strategic default as well as other events affecting individual borrower repayment (Quercia et al 1995). With individual loan data, default is thus a function of the value of strategic default option (based on the collateral value and the contemporaneous interest rates), as well as by measures of the shocks (Hartarska and Gonzalez Vega, 2005). With aggregate level data, we control for the impact of strategic default by including the land value (on county level) since Briggeman, Gunderson, and Gloy (2009) found these are leading indicators of bank losses. Thus, we test the hypothesis that default and delinquencies in the agricultural portfolios of the banks in the region are affected by the ENSO phases controlling for strategic default and controls. The empirical model is:

$$D_{ijt}= \beta_0+ \beta_1 ENSO_{t-1}+ \beta_2 LandValue_{ijt} +\beta_3 LandValue_{ijt-1}+\beta_3 DummyFinCrisis_{t-1}+\gamma' controls_{ijt-1}+e_{ijt}$$

where D_{ijt} measures default/delinquency on agricultural loans secured by farmland for bank *i* in state *j* in year *t*. The main variable is the value of loans in default (also nonperforming, or nonaccrual, loans) which borrowers cannot repay. Other dependent variables we explore are loans delinquent 90 days or more as well as loans delinquent for 30 days or more. We further test whether realized bank losses on these portfolios (loans charged off) are affected by the ENSO indexes. However, since we focus on loans secured by farmland, lenders can sell the collateral and usually recuperate their funds without incurring substantial losses. Therefore, we do not expect to see ENSO impact on that particular variable.[2]

Inter-annual climate variability is measured by ENSO indexes. The choice of specific ENSO index is important because the relationship between regional climate and different indexes can vary. Since the most important determinant of the ENSO is the sea surface temperature (SST), the geographical area of measurement makes a difference (i.e., Nino 3 has lower mean SSTs than Nino 3.4). Likewise, proximity to "main centers of convection" and "direct convective response" through which the SST deviations impact global climate is important (Trenberth, K.E., 1997). The base period for calculating the SST deviations is also variable and must be representative of the century record – usually 1950-1979 because since then the SSTs have been positively biased, i.e., more El Niño. Seasonality of the index is also important as SST deviations are the highest in northern winter. In this regard, annual ENSO phase assignments are less informative because most ENSO events begin between May and September (Climate Prediction Center).

Based on these characteristics, the main ENSO indexes used in explaining the regional weather in the southeast U.S. are the Oceanic Nino Index (ONI), Japan Meteorological Agency (JMA) index, and the Multivariate ENSO Index (MEI). The first two are 5 and 3 month running means of the SST anomalies (deviations from the mean) recorded in the Nino 3.4 and Nino 3 regions of the Pacific Ocean, respectively. ENSO phase classification is based on the magnitude of these anomalies. The MEI is a composite ENSO index computed on a sliding bi-monthly basis and based on six main observed variables over the tropical Pacific: sea surface temperature, sea-level pressure, zonal and meridional components of the surface wind, surface air temperature, and total cloudiness fraction of the sky. MEI is considered a better predictor because it includes multiple climactic parameters.

Choosing an interval over which the index is measured is important because it must correspond to the regional growing season (plus 1-2 months before for soil moisture) and account for the time it normally takes for the global atmosphere to respond to the tropical SST anomalies (NOAA). In this regard, most recent aggregate data analysis of scores shows that MEI averaged over the March-June period – the most critical period of crop growth as well as the regional ENSO impact – is best predictor for corn, cotton, and peanut yields (Royce, Fraisse, and Baigorria, 2011). As its significance for crop yields is tested against that of the ONI and JMA indexes, we use these three indexes as regressors in the banking data.

All ENSO indexes are for the year preceding defaults as they are associated with the growing season of the year in which production loans are taken. Agricultural loan repayment schedule is developed to match farmers' repayment capacity which is determined by the value of output and the timing of the cash flows from harvest sale. Since it takes time for a loan to show as non-performing in the bank financial records (first it is classified as delinquency 30 days or more and then delinquent 90 days or more), we can observe possible weather related impact only in the year following the growing season, hence the need to use growing season, or one year lagged, ENSO indexes.

In order to control for possible strategic defaults, land values are included in the current year and in the year of loan origination (when farmland serving as collateral was valued). Farmers may sell land not used as collateral to repay their loan depending on land prices, but overvalued land in the year of the loan may affect their choice on whether to default and have the bank possess the less valuable land. Recent studies of agricultural bank losses find that current and previous years' land values are a leading indicator for agricultural bank losses suggesting motives for strategic default (Briggeman, Gunderson, and Gloy, 2009).

Other control variables suggested by the literature include bank size to capture possible differences in scale efficiencies; the dollar value of loans extended by the two biggest groups of agricultural lenders – the Farm Credit System and commercial banks to capture supply side effect; annual crop values to capture possible impact of farm output production (impact of shocks other than weather variation); the ratio of debt to equity of the farm operators and the number of farms each year to capture demand for loans. We also control for the impact of the financial crisis by including a simple dummy that equals one if the year was 2009 and 2010 and zero otherwise.

Since theoretical work suggests that complementary insurance markets matter, agricultural loan default is likely to be affected by the farm support mechanisms such as disaster payments, and crop insurance. These variables are highly correlated with current weather extremes, and somewhat less so with lagged measured of ENSO, since farmers are usually compensated for losses in the year of extreme or catastrophic event. However, we only have data for disaster payments for much shorter period are available, and to avoid multicollinearity, we use a stepwise approach running a regression without ENSO to check how disaster payments may affect default.

Data

The banking data come from the Federal Reserve call reports and consist of observations for the period 1991-2010. All agricultural commercial banks operating in the Southeastern states highly affected by the ENSO events - Alabama, Florida, Georgia, Louisiana, Mississippi, and South Carolina - are included in the dataset. The focus is on variables that measure performance of loans secured by farmland, assuming that these are the loans primarily for crop production. This is important because the impact of weather on crop production is more direct than that on animal production and because the largely non-irrigated crop production is more sensitive (Schlenker, Hanemann, and Fisher, 2005).

There are many definitions of an agricultural bank. The standard definition by the Federal Deposit Insurance Corporation (FDIC) is that an agricultural bank has a ratio of agricultural to total loans of no less than 25 percent. Applying this definition would result in too few observations for a meaningful region-wide analysis.[3] The Federal Reserve System has an alternative definition according to which an agricultural bank has a ratio of agricultural to total loans greater than the mean for all banks. This definition is more appropriate given increased diversification in banking in recent years and has been used more recently (e.g., Settlege, Preckler, and Settlege, 2009). We also use this definition since our empirical strategy is to create a sample of banks with more focus of agricultural lending than the average bank in this region.

In the sample, 56 percent of the annual observations are from banks with some agricultural loans. The ratio of agricultural to total loans for all banks in the region is 5.8 percent. Applying the FED definition of agricultural bank, we obtain 473 agricultural banks with about 3,000 annual observations over the study period. For these banks, the average ratio of agricultural to total loans is 16.3 percent.

Agricultural banks in the region are smaller on average than the non-agricultural commercial banks. While total assets per bank in the region are $1.3 billion ranging from $2 million to $198 billion, agricultural banks' total assets are $198 million for the average bank, ranging from $8 million to $3 billion. Agricultural banks lend $116 million annually on average with about $10 million per bank in loans secured by farmland, with the largest bank lending $138 million. It is the performance of these crop production loans, hypothesized to be mostly affected by the ENSO that is the focus of this paper. Loans in default and delinquent loans are recorded in the year following lending since agricultural production loans become due after the crops have been sold.

Table 1 presents the summary statistics of the variables used in the analysis. All values are in 2010 dollars adjusted by the CPI. The main dependent variable – nonperforming loans secured by farmland – has a mean of $130,500, with a maximum of $9.4 million. Data for loans delinquent for 30 days or longer is available only for observations after 2000 and amounts to $108,000 on average with the highest of $9.6 million. Loans delinquent for 90 days or longer are only $28,000 with a maximum of $5.3 million.

The climate variables are of three types. The first group consists of three dummies for the categorical JMA index. According to this classification 60 percent of the observations are from neutral years, 11 percent from La Niña, and 29 percent from El Niño years. The next group of dummies measuring ENSO events is based on the ONI index which has 7 categories. Summary statistics shows that 40 percent of the observations are from neutral years, 11 each from Weak and Medium La Niña, 10 percent from Medium El Niño, 15 percent from Strong El Niño, and 19 percent from Weak El Niño. The third measure of the ENSO is the continuous MEI index averaged over the most critical stage of crop growth period February to August, as suggested by estimates by Royce, Fraisse, and Baigorria (2011). The average MEI value for the sample is 0.45 which corresponds to a Neutral to Weak El Niño and is consistent with the observation that the last decade has been unusually hot (*The Economist*, 2010).

The data on land values per acre of farmland is by state and comes from the USDA NASS dataset. This variable controls for strategic default motives as Briggeman, Gunderson, and Gloy (2009) found that current and lagged land values affect agricultural loan portfolio performance. The USDA data for US farm operators balance sheets for the year of loan origination are used to measure the average leverage in the industry (debt to equity ratio), the supply of credit by competitors (commercial banks and the Farm Credit System), the number of farms, and the value of real estate loans distributed in the year of loan origination. Disaster payments by states and type of the agricultural disaster are collected from the Environmental Working Group database and are available for the sub-period of 1995-2009.

Discussion of the Results

Table 2 presents the results from fixed effects regressions, clustered on individual banks, of nonaccrual loans secured by farm land on three groups of ENSO indexes and controls. The first column uses the JMA index, the second column uses the ONI index, and the third column uses the MEI index averaged over the growing season. Neutral year is the omitted dummy variable for the categorical JMA and ONI indexes. The last column presents results from a regression without the ENSO indexes but with disaster payments. The last column shows the results from a regression which includes disaster payments but excludes ENSO, in a stepwise fashion, typically used to avoid multicollinearity; this regression also uses shorter data set since payment data are available for shorter period.

We find support for the hypothesis that the ENSO and inter-annual climate variability affects loan default. The signs, however, point to a role for complementary insurance markets and likely sufficient (or over-) compensation of producer losses. Non-neutral years during which the weather is characterized by high temperature and low humidity that may cause more sever droughts, or low temperature causing freezes may be expected to be associated with higher levels of loan defaults. We find, however, that both El Niño and La Niña are associated with smaller values of loans in defaults relative to the neutral phase. For example, based on the JMA index and compared to a neutral year, in La Niña year, the average bank has $84,000 less in non-performing loans, while El Niño is associated with $94,440 less per bank in non-performing loans. We interpret these results to the presence of complementary insurance markets although we do not know what percentage of a bank's portfolio was to farmers with insurance. Farmers may be forced to rely on their own cash flows if milder weather related losses more typical in a neutral or mild year are not sufficiently large to trigger insurance compensation, disaster payment or other compensatory mechanisms.

Based on the ONI index which characterizes years as neutral phase, and warm (El Niño) and cold phases (La Niña) classified as Weak, Medium, and Strong, we also find negative, statistically significant and large difference between non-neutral and neutral phases. A medium strength La Niña results in the lowest level of non-performing loans or $347,000 less per bank compared to the neutral phase, followed by Strong El Niño with $326,000 less in loans per bank, then Weak La Niña with $258,000 and Medium El Niño with $181,000 less in loans.

The later result is consistent with the result from Model 3 which uses non-linear specification of the MEI index averaged over the plant growing period, with positive values corresponding to the warm (El Niño) and negative values corresponding to the cold (La Niña) ENSO phases. We find the inflection point of the index at 0.43 which is exactly in Weak El Niño spectrum, confirming that defaults peak in neutral to weak El Niño years.

We interpret these results to mean that significant yield losses during non-neutral years trigger insurance and farm support mechanisms that help farmers recuperate losses and maintain sufficient cash flows to remain current on their crop production loans. Since such mechanisms are not triggered by less severe events associated with neutral years, farmers may end up defaulting more often on their loans in neutral year.

For the sample from 1996-2009 for which state level agricultural disaster payments are available, we find that states and years with larger disaster payments have banks with fewer nonperforming loans, perhaps because the supporting financial markets helped farmers to avoid delinquency and default. We detect a small but statistically significant link between disaster payments and default per bank. For example, for the state of Alabama in 1997 -a neutral year – disaster payments were only $264,494, and for 1998 which was a (weak) El Niño year were $220,255 but in a (Medium) La Niña year these payments were $51.3 million. The change in non-performing loans corresponding to the change from about $0.25 million to $51.3 million in disaster payments is almost $30,000 less in default for the average bank in Alabama, all else equal. While these results are economically negligible in the portfolio of the average bank they do show that there is a link between climate fluctuations and crop production but that financial markets are doing what they are supposed to do – diversifying away extreme weather risks.

Table 3 presents more detailed results from regressions where ENSO is measured by the continuous MEI index. Since continuous ENSO indexes contain more information, they are more suitable for short time series, and the MEI is found to be the index that best explains major crop yields in the Southeast (Royce, Fraisse, Baigorria, 2011). Since the ENSO phenomenon and this index have a lot of memory (as an AR process) in between late Fall to late Spring, we test the predictive power of the lagged bi-monthly MA values of this index, which could be useful to banks in their provision for bad loans and by farmers to optimize production as well as financing decisions.

Consistent with the results in Table 2, results with the bimonthly MEI index also suggest that the largest volume of nonaccrual loans occurs in the values of the index associated with neutral years showing an inverted U relationship peaking over the values associated with neutral or mild El Niño. These values for each bimonthly regression are presented at the bottom of Table 3. The first five columns use bimonthly MEI lagged one year to account for the growing season that actually affected default of agricultural loans secured by land. The last four columns correspond to late fall and winter of the year preceding borrowing and planting and still have significant predictive power because the ENSO cycle starts building in the Fall and persists to the next spring. The results suggest that indeed preceding fall ENSO phases measured by the bimonthly MEI index may be useful in predicting climate over the crop growing period and thus in budgeting for expected default with the highest default expected in the neutral to mild El Niño.

Table 4 provides results from similar regressions but with different dependent variables: loans overdue more than 30 days (for years after 2000), loans overdue more than 90 days, and loans charged off after the bank sold the collateral. While loans overdue for more than 30 days are measured at 6 month, loans overdue 90 days or more are estimated at 9 months after loan origination since these are the quarterly results that most closely fit the actual banking practice and because these models achieve the best possible fit which, however, is disappointingly low. We present the results nevertheless because, although a very small variation of the data is explained as the low R^2 shows, they fit with the main results of the previous regressions.

Model 1 in Table 4 shows that, during the second quarter of a year following a La Niña event, loans delinquent for more than 30 days were $86,000 larger on average per banks compared to a neutral year using the JMA ENSO index, and larger by $66,000 and $68,000 in a Medium and Weak La Niña, respectively, according to the ONI index (Model 2). The same index predicts that Medium El Niño years result in $56,000 per bank more in loans delinquent for longer than 90 days (Model 3). These data suggest that the delinquency related cash flow problems experienced by agricultural producers may be related to the weather fluctuations reflected in the ENSO data. However, since non-performing loans exhibit the opposite relationship, it is logical to conclude that farmers either restructured their loans (unfortunately, the data do not allow us to test this hypothesis) of received compensatory cash flows that allowed them to become current on their loans. The final regression in Table 4 shows that, indeed, bank losses (charge offs associated with agricultural production loans backed by farmland) are lower by about $100,000 following a strong El Niño growing season for the average banks although the significance is only marginal.

The results so far suggest that farmers-clients of agricultural banks are affected by the regional inter-annual climate variability but that the financial system and government support mechanisms help mitigate these risks. Since the non-neutral ENSO years with higher incidence of extreme weather events produce fewer loan defaults than the years in the neutral range, there may be more than sufficient producer compensation mechanisms involved. This finding is consistent with Ewing, Hein and Kruse (2005) who found that community banks serving areas affected by natural disasters produce better results in the aftermath of a catastrophic event, likely due to well- functioning complementary insurance markets.

Our results also suggest that controlling for the strategic default opportunity is important because land values affect loan default. Higher land values at the time loans were extended are associated with larger defaults in the following year, while higher land values at the time of default are associated with smaller proportion of portfolio in default. We also see that the overall leverage of farmers is associated with higher level of default as expected: the debt-equity ratio is positive and significant in 9 out of the 15 regressions presented, consistent with Briggeman, Gunderson, and Gloy, 2009. Similarly, in 9 of 15 regressions the total value of crop production is associated with higher default levels possibly due to a price effect.

Regarding other supply side effects such as loans provided to agricultural producers by commercial banks and FCS institutions that control for the level of competition, there is no robust impact, although some statistically significant results in Table 3 suggest that larger supply of credit is associated with smaller proportion of loans in defaults, somewhat contrary to expectations. These results may be doe to the aggregate country level of the data. More farms are also associated with fewer defaults in the agricultural loan portfolios, while more farmland is associated with more loans in default perhaps due to use of more marginal land for crop production. Finally, while we use simple dummy variable to control for the possible impact of the financial crisis which led to significant increase in default, this variable is not always statistically significant, especially in the group of regressions with the continuous MEI indexes. Estimated coefficients for categorical variables are interpreted in comparison to the estimated coefficient on the constant, and results may be due to differences in classification of years 2009 and 2010 by the three different ENSO indexes. This dummy is significant in the regressions with dummy variables ENSO phases because, as it could be expected, it measures annual differences suggesting perhaps that a better measure for the impact of the financial crisis may be needed.

Conclusion

In this paper, we study the possibility that the portfolios of loans for agricultural crop production of commercial agricultural banks are affected by inter-annual climate variability represented by the value of several ENSO indexes in a geographical area where climate depends on the ENSO. We find that non-neutral years which typically have higher incidence of weather extremes are associated with smaller value of non-performing loans. These results indicate that, while inter-annual climate variability affects agricultural producers, weather extremes do not impact their banks negatively.

The results support the notion that the agricultural financial market in the US functions well and commercial banks adequately manage climate related risks associated with agricultural lending in the Southeastern USA. Viewed through the prism of the emerging literature on bank lending and catastrophic risk events, these findings seem to suggest that ENSO events impact is mitigated in extreme years because farmers utilize well existing insurance mechanisms or government disaster relief payments, while in years with less extreme weather, farmers cover their smaller losses on their own and thus are more vulnerable.

Future work may need to explore if the same results hold for the portfolios of the Farm Credit System institutions and if they are affected by climate since these institutions represent the other major agricultural lender almost equal in lending volume to commercial banks. That would be especially important because some data show that the FCS institutions lend mostly to commercial agriculture, while the commercial banks studied here may also to lend to farmers for whom farming may not be the main source of income and cash flows.

FOOTNOTES

[1] Other regions of the world most affected by ENSO are southeast Africa, southeast Asia, and the coastal areas of South and Central America

[2] Indeed, the average losses per bank are only $25,000 which is very small compared to the more than $10 million in extended loans per bank.

[3] It would result in very few annual observations and only 14 banks – one in Alabama, five in Georgia, and eight in Mississippi.

References

Baigorria G.A., J.W. Hansen, N. Ward, J.W. Jones, and J.J. O'Brien. 2008. “Assessing Predictability of Cotton Yields in the Southeastern United States Based on Regional Atmospheric Circulation and Surface Temperatures,” *Journal of Applied Meteorology and Climatology*, 47:76-91.

Berg, G. and J. Schraderx. 2009. “Can Microcredit Help to Cope with Aggregate Shocks? Evidence from Ecuador,” Working Paper Presented at the First European Microfinance Conference at the Free University of Brussels, Brussels, Belgium.

Briggeman, B. C., M.A. Gunderson, and B.A. Gloy. 2009. “The Financial Health of Agricultural Lenders,” *American Journal of Agricultural Economics*, 91(5):1406-13.

Climate Prediction Center. U.S. Temperature and precipitation Impacts. Ranking available online at http://www.cpc.ncep.noaa.gov/products/precip/CWlink/ENSO/enso.anal.shtml

Collier, B., A.L. Katchova, and J. Skees. 2011. "Loan Portfolio Performance and El Niño , an Intervention Analysis."*Agricultural Finance Review*, in print.

Economist, The. “The Hottest Years on Record,” Dec 3rd 2010, 15:35 by The Economist online at http://www.economist.com/blogs/dailychart/2010/12/climate_change?page=3

Environmental Working Group. Farm Subsidy Database. Available online at http://farm.ewg.org/

Ewing B., S.Hein, and J. Kruse. 2005. “*Natural Disasters and Bank Performance*” Report available online at http://www.ecu.edu/cs-cas/hazards/research.cfm.

Garmaise M.J. and T.J. Moskowitz. 2009. “Catastrophic Risk and Credit Markets” The *Journal of Finance*, Vol. LXIV, No. 2: 657 -707.

Halpert, M. S. and C. F. Ropelewski. 1992.“Surface temperature patterns associated with the Southern Oscillation,” *Journal of Climate*, 5:577-593.

Hartarska, V. and D. Nadolnyak. 2010. “Climate variability and bank lending in the Southeast USA,”*Agriculture and Agricultural Science Procedia*, 1:157–162.

Higgins, R. W., V. E. Kousky, H.-K. Kim, W. Shi, and D. Unger. “High frequency and trend adjusted composites of United States temperature and precipitation by ENSO phase,” NCEP/Climate Prediction Center ATLAS No. 10. 2002.

Kau, J., and D. Keenan. 1999. “Catastrophic Default and Credit Risk for Lending Institutions,” *Journal of Financial Services Research*, 15(2):87-102

Miranda, M., and D. Vedenov. 2001. “Innovations in Agricultural and Natural Disaster Insurance,” *American Journal of Agricultural Economics*, 93(3):650-655.

Nadolnyak, D., D. Vedenov, and J.L. Novak. 2008. “Information Value of Climate-Based Yield Forecasts in Selecting Optimal Crop Insurance Coverage,” *American Journal of Agricultural Economics*, 90(5):1248-1255.

Quercia, Roberto G., George W. McCarthy, and Michael A. Stegman (1995), “Mortgage Default among Rural, Low-income Borrowers,” *Journal of Housing Research*, Vol. 6, No. 2, pp. 349-369.

Quigley, John M. and Robert Van Order (1991). “Defaults on Mortgage Obligations and Capital Requirements for U.S. Savings Institutions: A Policy Perspective,” *Journal of Public Economics*, Vol. 44, No. 3, pp. 353-370.

Richards, T. J., M.R. Manfredo, and D. R. Sanders. 2004. “Pricing Weather Derivatives,” *American Journal of Agricultural Economics*, 86(4):1005-17.

Royce F.S., C.W. Fraisse, and G.A. Baigorria. 2011. “ENSO classification indices and summer crop yields in the Southeastern USA,” *Agricultural and Forest Meteorology*. 2011 (Forthcoming; doi:10.1016/j.agrformet.2011.01.017)

Schlenker, W., W. M. Hanemann, and A. C. Fisher. 2005. “Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach,” *American Economic Review*, 2005, 95(1):395-406.

Settlege, D.M., P.V. Preckler, and L.A. Settlege. 2009. “Risk Adjusted Efficiency and Risk Aversion in the Agricultural Banking Industry,” *Agricultural Finance Review*, 69(3): 314-329.

Trenberth, K.E. 1997. “the definition of el nino,” *Bulletin of the American Meteorological Society*, 78(12):12771-12777.

Vedenov, D., and B. Barnett. 2004. “Efficiency of weather derivatives for agricultural risk management,” *Journal of Agricultural and Resource Economics*, 29:387-403.

TABLES

Table 1. Summary Statistics (annual observations), agricultural banks in the Southeast USA

Variable	Obs	Mean	Std. Dev.	Min	Max
Non performing loans backed by real estate ('000 $)	2,996	130.5	534.3	0	9,408.0
RE Loans Delinquent >30 days	2,926	108.3	328.6	0	9,627.6
RE Loans Delinquent >90 days	2,996	28.1	169.7	0	5,319.0
Real Estate charge off ('000%)	2,996	25.3	149.5	0	3,150.6
MEI Feb-August	2,996	0.448	0.677	-0.713	1.609
Mei squared	2,996	0.659	0.852	0.000	2.587
JMA La Niña	2,996	0.105	0.350	0	1
JMA Neutral	2,996	0.600	0.487	0	1
JMA El Niño	2,996	0.294	0.430	0	1
ONI Medium El Niño	2,996	0.102	0.303	0	1
ONI Medium La Niña	2,996	0.105	0.350	0	1
ONI Neutral	2,996	0.400	0.492	0	1
ONI strong El Niño	2,996	0.156	0.363	0	1
ONI Weak El Niño	2,996	0.191	0.282	0	1
ONI Weak La Niña	2,996	0.105	0.300	0	1
Bank Size (mln assets)	2,996	198.9	255.4	6.5	2971.1
Land value ($ per farmland acre)	2,996	2,238.4	947.5	1,171.6	5,783.9
RE loans by FCS (billions)	2,996	40.1	7.8	32.2	59.4
RE Loans by banks (billions)	2,996	35.3	7.8	25.1	51.2
Number of farms (millions)	2,996	2.2	0.0	2.1	2.2
Value of real estate (millions)	2,996	1,275.6	288.1	995.7	1,841.8
Debt/equity ratio	2,996	15.8	2.2	12	19
Value of crops (billion $)	2,996	33.9	5.8	23.9	44.4
Dummy financial crisis	2,996	0.09	0.28	0	1

Table 2. Fixed Effects regressions of non-performing loans (loans in default) on ENSO and controls, annual data for southeastern agricultural banks

	1	2	3	4
JMA La Niña	-83.69***			
	(27.43)			
JMA El Niño	-94.44*			
	(53.06)			
ONI Weak El Niño		39.64		
		(34.26)		
ONI Weak La Niña		-258.5***		
		(68.47)		
ONI Medium La Niña		-347.4***		
		(88.36)		
ONI Medium El Niño		-181.1*		
		(96.05)		
ONI Strong El Niño		-326.1**		
		(143.9)		
MEI (growing season avg)			295.9***	
			(77.42)	
MEI^2 (growing season avg)			-303.7***	
			(82.65)	
Disaster Payments				-0.564**
				(0.240)
Bank Size	1.089***	1.099***	1.110***	1.101***
	(0.250)	(0.243)	(0.241)	(0.253)
Land Value	-0.186***	-0.231***	-0.176***	-0.148***
	(0.0464)	(0.0536)	(0.0451)	(0.0422)
Lagged Land Value	0.234***	0.286***	0.224***	0.211***
	(0.0535)	(0.0620)	(0.0526)	(0.0505)
Lag RE Loans by FCS	26.69	-51.49*	59.52***	-9.694
	(18.48)	(28.63)	(18.08)	(15.22)
Lag RE Loans by banks	-51.82	-6.509	-88.32***	2.871
	(35.38)	(34.07)	(27.97)	(18.75)
Lag Number of Farms	1456	-701.7	2172	-10200**
	(2442)	(2280)	(2449)	(3976)
Lag Value of Real Estate	0.640	0.514	1.686***	-0.634
	(0.521)	(0.341)	(0.579)	(0.406)
Lag Debt/Equity Ratio	33.05	86.85***	108.8***	29.93*
	(27.65)	(29.50)	(33.01)	(16.33)
Lag Value of Crops	21.68***	-5.989	43.25***	41.42***
	(7.857)	(11.87)	(10.76)	(10.36)
Dummy Financial Crisis	-14.87	995.1***	-554.9*	1,181***
	(271.0)	(323.3)	(324.3)	(452.9)
States Controls	yes	yes	yes	yes
Constant	-4415	2024	-9127	20986**
	(5499)	(4884)	(5896)	(8691)
Observations	2968	2968	2968	2944
R-squared	0.138	0.143	0.137	0.141
Number of banks	473	473	473	470

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. Fixed Effects regressions of non-performing loans (loans in default) on MEI index and controls, annual data for southeastern agricultural banks

	1	2	3	4	5	**6**	**7**	**8**	**9**
Months of MEI index	*JanFeb*	*FebMar*	*MarApr*	*AprMay*	*MayJun*	*SepOct*	*OctNov*	*NovDec*	*DecJjan*
MEI (t-1)	58.30***	42.43**	38.09**	261.7***	114.6**				
	(17.97)	(17.93)	(17.97)	(73.90)	(50.51)				
MEI (t-1) ^2	-89.29***	-71.76***	-53.27**	-157.4***	-53.92				
	(22.45)	(20.32)	(22.95)	(60.36)	(64.02)				
MEI(t-2)						70.34***	116.8***	32.14**	-1.276
						(20.08)	(28.09)	(15.74)	(26.66)
MEI (t-2) ^2						-101.0***	-150.3***	-109.8***	55.28**
	(22.45)	(20.32)	(22.95)	(60.36)	(64.02)	(23.66)	(32.45)	(24.76)	(22.19)
Bank Assets	1.052***	1.034***	1.040***	1.060***	1.082***	1.061***	1.089***	1.081***	1.051***
	(0.268)	(0.279)	(0.277)	(0.262)	(0.257)	(0.264)	(0.247)	(0.252)	(0.273)
Land Value	-0.176***	-0.159***	-0.136***	-0.162***	-0.168***	-0.171***	-0.212***	-0.194***	-0.168***
	(0.0462)	(0.0453)	(0.0437)	(0.0445)	(0.0451)	(0.0458)	(0.0500)	(0.0477)	(0.0497)
LagLand Values	0.233***	0.217***	0.191***	0.218***	0.213***	0.225***	0.267***	0.248***	0.221***
	(0.0535)	(0.0514)	(0.0494)	(0.0518)	(0.0515)	(0.0533)	(0.0585)	(0.0558)	(0.0564)
Lag RE Loans by FCS	-6.801	-3.845	18.13	2.759	17.81	15.09	-15.04	7.596	40.08***
	(12.42)	(14.01)	(13.06)	(10.63)	(15.12)	(12.21)	(11.71)	(12.34)	(14.87)
Lag RE Loans by banks	-8.196	-5.968	-24.50	-36.84*	-39.04*	-26.28	-19.79	-36.28*	-36.66
	(18.11)	(19.79)	(19.21)	(19.33)	(22.68)	(20.08)	(17.69)	(19.87)	(23.05)
Lag Number of Farms	1348	867.6	840.7	1823	415.6	2351	2224	1805	754.9
	(2572)	(2566)	(2561)	(2664)	(2413)	(2668)	(2581)	(2568)	(2366)
Lag Value of Real Estate	0.397	0.215	0.282	0.737*	0.605	0.530	1.065***	0.716*	0.0686
	(0.363)	(0.374)	(0.383)	(0.433)	(0.476)	(0.381)	(0.406)	(0.377)	(0.468)
Lag Debt/Equity Ratio	40.10**	22.69	19.19	53.73**	44.22	38.66*	109.1***	44.67**	-13.09
	(20.28)	(20.99)	(20.53)	(24.04)	(29.15)	(20.24)	(25.76)	(19.69)	(38.78)
Lag Value of Crops	13.26	10.53	19.89**	3.929	23.96***	19.53**	5.840	19.22**	27.70***
	(8.476)	(9.543)	(9.147)	(9.682)	(7.789)	(8.014)	(8.639)	(8.499)	(10.01)
Dummy Financial Crisis	232.4	258.9	17.27	234.2	43.83	-31.34	234.7	109.0	-193.0
	(260.9)	(264.7)	(274.4)	(257.5)	(308.4)	(277.6)	(255.2)	(261.5)	(279.7)
State Controls	216.3***	222.5***	217.6***	210.9***	237.8***	220.7***	217.3***	219.2***	218.0***
	(26.52)	(28.20)	(27.22)	(26.49)	(28.87)	(26.86)	(25.39)	(25.92)	(28.37)
Constant	-3980	-2608	-3107	-4770	-2543	-6687	-6684	-5122	-2887
	(5693)	(5683)	(5713)	(5832)	(5640)	(5968)	(5777)	(5671)	(5474)
Observations	2968	2968	2968	2968	2968	2938	2938	2938	2938
R-squared	0.139	0.138	0.135	0.138	0.135	0.136	0.141	0.139	0.134
Number of id	473	473	473	473	473	467	467	467	467
MEI value as defaults peak +	-0.33	-0.30	-0.36	-0.83	-1.06	-0.35	-0.39	-0.15	-0.01

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

+ Calculated value of the MEI index at which defaults pick. This falls in *Neutral* to *Weak El Nino* years.

Table 4 Fixed Effects regression results from loans in default on Mei index and controls, monthly data for southeastern agricultural banks

	at 6 months	at 9 months	at 12 months	12 mo
VARIABLES	Delinq >30days	Delinq >30days	Delinq >90days	Charge offs
JMA La Niña	85.86*			
	(45.68)			
JMA El Niño	-95.34			
	(76.09)			
ONI Medium La Niña		66.26*	12.08	-72.56
		(37.81)	(13.46)	(57.21)
ONI Medium El Niño		-136.0	55.76*	82.31
		(83.69)	(30.19)	(89.06)
ONI Strong El Niño			30.19	-101.8*
			(33.18)	(62.57)
ONI Weak El Niño		-17.52	-2.901	31.88
		(16.77)	(10.51)	(27.24)
ONI Weak La Niña		68.20**	7.164	-63.89
		(30.12)	(12.05)	(43.95)
Bank Size	-0.0252	0.247*	0.116	0.0665
	(0.239)	(0.150)	(0.0741)	(0.0513)
Land Value	-0.0258	-0.0359	0.00183	-0.0156
	(0.0223)	(0.0335)	(0.00735)	(0.0109)
Lagged Land Value	0.0662***	0.0596	-0.00197	0.0251*
	(0.0230)	(0.0372)	(0.0107)	(0.0134)
Lag RE Loans by FCS	6.737	28.90*	-4.998	-29.16
	(17.03)	(15.09)	(6.140)	(22.58)
Lag RE Loans by banks	-47.49	-45.35*	14.06	29.94
	(39.71)	(27.12)	(9.514)	(26.64)
Lag Number of Farms	-10006*	0	-882.4*	-1716**
	(5528)	(0)	(515.6)	(686.1)
Lag Value of Real Estate	0.159	0.147	-0.106	-0.114*
	(0.469)	(0.197)	(0.0871)	(0.0589)
Lag Debt/Equity Ratio	92.39*	-11.83	9.102	32.48
	(47.52)	(18.34)	(6.262)	(24.62)
Lag Value of Crops	23.79**	11.89***	0.0187	-6.756
	(11.97)	(4.488)	(1.531)	(7.819)
Dummy Financial Crisis	1058*	0	42.01	370.9**
	(594.3)	(0)	(72.47)	(152.7)
Mississippi (Alabama base)	321.0***	332.8***	17.21**	117.7***
	(22.26)	(16.59)	(8.085)	(8.163)
Constant	20589*	111.0	1545	3583**
	(11691)	(366.4)	(1054)	(1473)
Observations	2847	2867	2968	2968
R-squared	0.02	0.04	0.02	0.04
Number of id	448	451	473	473

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1