How Vulnerable Are Agriculturally Concentrated Banks to a Fall in Agricultural Land Values?

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Abstract:
The agricultural bank crisis that accompanied the Farm Crisis of the 1980s was preceded by a steep increase in agricultural land values. Agricultural land values are once again at all-time highs, both in absolute terms and relative to the income they generate. How would a fall in these land values translate into losses for banks with large agricultural concentrations and exposure? In this paper we model very large declines in land values and estimate the loan losses they would produce for banks with significant exposure to agricultural lending ("agricultural banks"). We find that the average agricultural bank would not suffer large loan losses. However, the subset of agricultural banks that are the most sensitive to land value declines would suffer substantial losses and have greatly reduced levels of capital.

The paper begins with background on the performance of the agricultural sector, current valuations of agricultural land, and agricultural lending by commercial banks. We then estimate the effect of a fall in land values on loan performance, bank equity-to-asset ratios, and the viability of agricultural banks. We end with a short summary.

[1] The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

Section 1. Motivation from Agricultural Production and Finance Cycles

Four factors motivate our analysis of how a fall in agricultural land values would translate into losses for agricultural banks. First, many community banks have a concentration in agricultural lending and there are signs of increased risk in this sector. Second, agricultural land in the United States has never been more highly valued in both nominal and real terms than it has in recent years. Third, the income that farm producers use to repay agricultural loans is falling and is expected to fall further in the future. Finally, a similar peak in land values was reached in the late 1970s but was followed by a significant fall and a large number of bank failures. We discuss each of these factors in turn.

Community banks throughout much of rural America are heavily exposed to agricultural loans. As of the second quarter of 2015, there were 1,889 agricultural banks out of a total of 5,412 community banks. [2] The median asset size of these agricultural banks was $104 million. Agriculturally concentrated banks were generally located in the Midwest. Iowa (258), Illinois (206), Kansas (189), Nebraska (163), and Minnesota (162) topped the list of states having the largest count of agricultural banks.

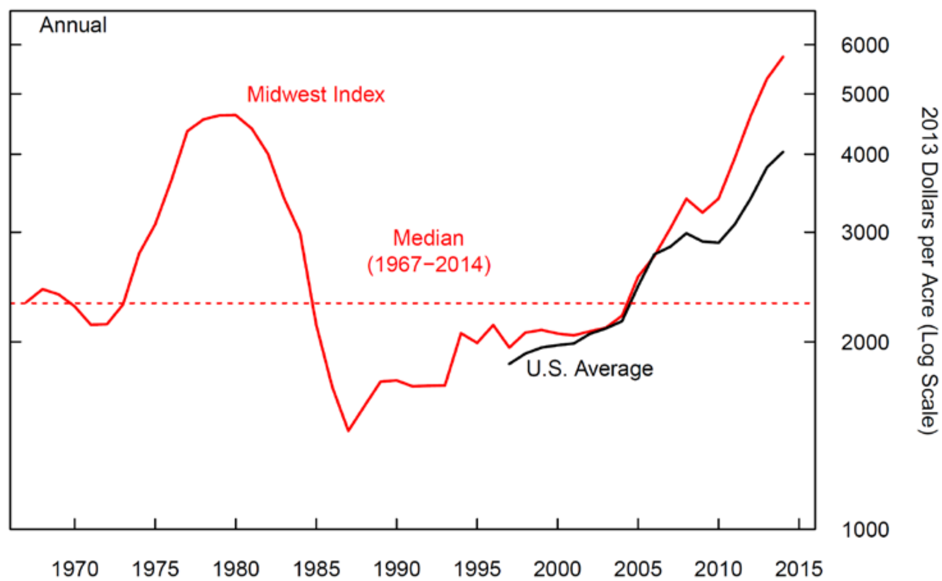
Contemporary agricultural banks show some signs of increased risk compared to other community banks. Since 2010, loan growth in agricultural banks has been significantly higher than in banks with low exposure to agricultural loans (2.9% annual growth rate over the period for the median agricultural bank, versus 1.5% for other banks). Further, lower-capital agricultural banks show higher loan growth than higher-capital agricultural banks. In addition to loan growth rates, capital levels at agricultural banks do not increase with concentration. The median tier 1 capital ratio for non-ag banks is 10.1%, versus 10.2% for banks with at least 25% of their loans in agriculture, and 10.4% for banks with at least 50% of their loans in agriculture. This is despite the higher risk that more concentration, all else equal, poses.

Agricultural land, the collateral for a sizeable proportion of the loan pool held at agriculturally concentrated banks, has reached extremely high values in both nominal and real terms. Domestically, farm real estate values averaged year-over-year gains of 8.4% during the period from 2004 to 2014, the highest 10-year average since 1984.[3] In the Midwest, cropland has become more expensive in real terms than at any time in the last half-century, including prior to the Farm Crisis (See Figure 1). Price-to-rent ratios are also at record levels, suggesting that valuation is high relative to the rental yield of the land.

[2] We define community banks as commercial banks that have assets below $10 billion. We define agricultural banks as those community banks whose proportion of agricultural loans to total loans is greater than the national average for commercial banks. This is the same definition found in the Federal Reserve's Agricultural Finance Databook. In the second quarter of 2015, this national average was 17.4%.

[3] The USDA's 2014 report is available at http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1446.

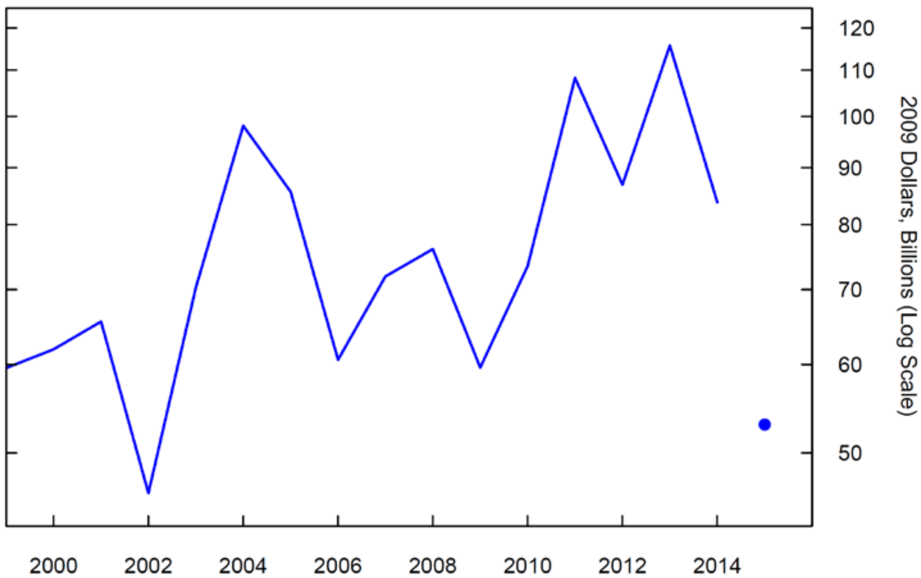
Figure 1
Cropland Value per Acre, Midwest Index and U.S. Average
Inflation-Adjusted Annual Series, 1967–2014



Source: USDA farmland and structures series with GDP-type deflator.

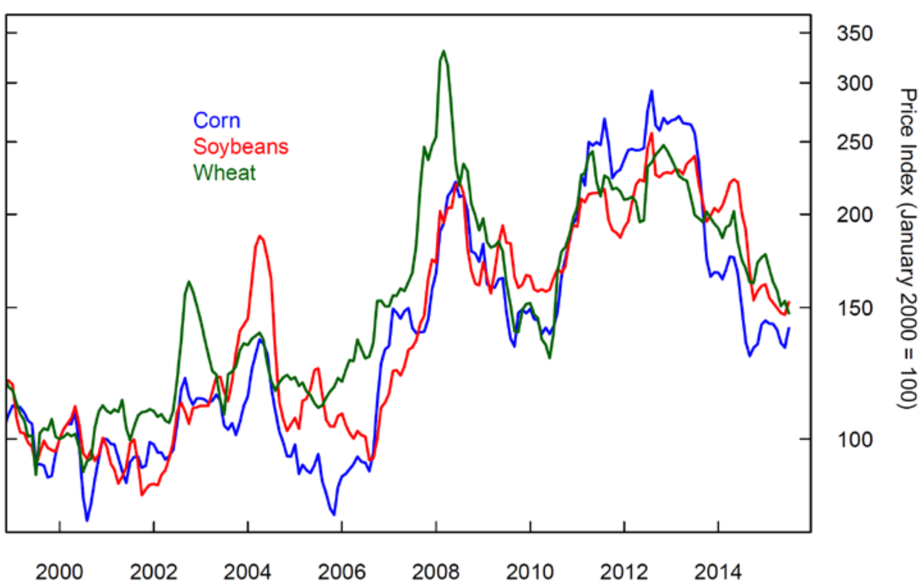
Increases in land prices during recent years have been associated with higher net incomes for agricultural producers, which hit historically high levels in the period from 2011 to 2014 (see Figure 2). Increases in crop commodity prices drove increases in producer income. Corn, soybean, and wheat prices saw a 2- to 2.5-fold increase in real prices from 2000 to 2013 (Figure 3). In addition, low interest rates contributed to increased investment in land and equipment.

Figure 2
Net Farm Income
Inflation-Adjusted Annual Series, 1999–2015 (forecast)



Source: USDA Farm Income and Wealth Statistics, CPI deflator. Note: 2015 is a USDA "forecast" estimate.

Figure 3
Crop Price Index
Inflation-Adjusted Monthly Series, 1999–2015



Source: USDA monthly prices received with CPI deflator.

Since their peak in 2013, however, commodity prices have fallen. The declines have been on the order of 40 to 50 percent peak-to-trough in real terms (see Figure 3). Despite declines in energy and other input-related costs for producers, net income has also declined markedly (see Figure 2). Agricultural real estate prices have flattened or even declined in some parts of the country, though they have been stickier than income and capital expenditures.

The United States has little recent experience with large-scale declines in agricultural land values. The only sustained and sharp period of decline in agricultural land values since the Great Depression occurred during the 1980s Farm Crisis period. The Farm Crisis period was characterized by the following land price dynamics:

- The pre-Farm Crisis period of the mid- to late-1970s had strong year-over-year growth, exceeding 10% at times—providing a close historical counterpart to recent events.
- Real national average land price declines were around 5% during the initial Farm Crisis period of 1980–81. Nominal declines began from 1982 to 1983 at 4%. The year-over-year declines in the national average during 1984–85 and 1985–86 were 11% and 10% in nominal terms, respectively. This 21% fall was the largest two-year drop during the Farm Crisis.
- The peak-to-trough fall in land values was 27% in nominal terms (1982–87), and 40% in real terms (1980–87).

The fall in agricultural land values during the Farm Crisis was associated with a crisis for agricultural banks. Sixty-five agricultural banks failed in 1985 alone, constituting half of all bank failures in that year. About 200 agricultural banks failed during the years 1982 to 1988 (FDIC, 1997). In general, the banks that failed were similar to those that survived, save in one important respect: Those that failed were, in general, more heavily concentrated in loans, particularly loans for agricultural production (Belongia and Gilbert, 1987).

We now describe how we model a very large decline in land values, and how that decline would translate into loan losses, capital losses, and changes in the probability of failure at agricultural banks.

Section 2. Vulnerabilities of Commercial Banks to a Fall in Agricultural Asset Values

In this section we analyze the effect of a fall in agriculture asset values on the condition of agricultural banks.[4] Specifically, we link a fall in agricultural land values to losses on loans made by these commercial banks, accounting for other relevant variables such as the financial leverage of producers.[5]

We analyze the association between land values, bank loan loss rates, and other variables using three "top-down" statistical models. These models rely on the long-term relationship between these variables across banks and geographic regions to forecast the increase in future loan loss rates.[6] The models vary in their complexity and focus, and as a result they generate a range of loss rate estimates.

We train the models on two sets of data. The first set is an unbalanced panel that is restricted to the Farm Crisis era, defined as the period from 1980 to 1987. We call this the "crisis" data set. The second set is an unbalanced panel stretching from 1980 to 2014. We call this the "full" data set.

We simulate three declines in nominal land values.[7] The first land decline shock we model we call "mild," and at 5% is consistent with the initial Farm Crisis period of 1980–81. The second shock is "severe," at 25%. This would be a severe one-period shock, more than twice as large as the largest one-year change during the Farm Crisis. (That said, recent increases in land values have been at the very high end of historical experience, both in magnitude and duration of trend.) Finally, to capture the effects of a "persistent severe" shock, we model a shock of two consecutive 25% declines.

The main results from the analysis are as follows:

- <u>Loan losses</u>: For the severe scenario, we estimate that average agricultural bank loan loss rates would increase from 0.2% before the shock to between 1.1% and 1.27% during the year of the shock, then 1.22% to 1.77% during the first year after the shock, and 0.95% to 1.14% in the second year after the shock.[8] For the persistent severe scenario, losses are the same in the concurrent year, then they increase to between 2.01% and 2.68% in the first year after the shock, and then to 1.68% to 2.3% in the second year.
- <u>Equity to assets</u>: For the severe scenario, the average impact on the equity-to-asset ratios for agricultural banks is a 45 to 54 basis point drop in the year of the shock, 103 to 164 basis point decline from pre-shock levels by the end of the first year after the shock, followed by a 134 to 183 basis point drop from pre-shock levels by the end of the second

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[4] We limit our analysis to banks with concentration of agricultural loans because the vast majority of banks have little to no agricultural loan exposure. The Federal Reserve Bank of Kansas City classifies banks as having an agricultural focus if their agricultural-loans-to-total loan ratio is greater than the mean of the same ratio for all banks nationwide. We use this definition of an agricultural bank in our analysis.

[5] Note that when we use the term "bank" we are referring to banks with a concentration in agricultural lending unless otherwise noted.

[6] These models are also "top-down" in the sense that they do not use individual loan level data as inputs. Instead, input data on loan loss rates is available only at the bank level.

[7] We emphasize nominal land values here because they are the driving variables in the loan loss models. We also shock farm debt-to-equity ratios and the portfolio vulnerability index as described in later sections.

[8] These loss rates are expressed in non-cumulative terms.

year. For the persistent severe scenario, the cumulative negative impact over two years ranges from 214 to 299 basis points. Losses among agricultural banks are heterogeneous and skewed such that banks in the high-loss end of the distribution suffer much higher losses than those in the middle.

- Probability of failure: Under the severe scenario, the probability of failure for the average bank increases by 24 to 30 basis points in the year of the shock from a pre-shock baseline of 1.00%; 63 to 102 basis points from the pre-shock baseline in the first year after the shock; and by another 101 to 165 basis points from the pre-shock baseline in the second year. For the persistent severe scenario, the mean impact is substantially larger, with an increase in the probability of failure of approximately 5.2 to 13.9 percentage points over the two-year post-shock period.

In the next section, we summarize the relevant stress testing literature. We then describe our data sources and variable selection. After the data section, we describe the three models used to estimate loan losses. Finally, we report stress test estimates for loan loss results, capital calculations, and changes in the viability of banks.

Background on Stress Testing Methodologies and Agricultural Finance

Briggeman, Gunderson, and Gloy (2009) represents the closest exercise to our own. They examine the link between land value and net loan charge-offs in a vector autoregression (VAR) framework, finding a strong relationship between the two. One of our models (the systems model, described below) is similar to their work.

We follow Hirtle and coauthors (2015) in developing our benchmark model (described below). They developed a generalized autoregressive framework—the Capital and Loss Assessment under Stress Scenarios (CLASS) Model—to examine banks' losses during adverse macroeconomic scenarios.

Finally, we base our distributional model (also described below) in large part on Covas, Rump, and Zakrajšek (2013). They examine capital shortfalls of bank holding companies under the Comprehensive Capital Analysis and Review macroeconomic scenarios using a quantile fixed-effect autoregression model.

Data Sources and Selection

We obtain data from three primary sources to estimate our models.

- We take state-specific nominal land values and national-level farm debt-to-equity ratios from the USDA's Economic Research Service's Quick Stats 2.0 application.
- We obtain the portfolio vulnerability index (described below) from the Agricultural Finance Databook and historic Tenth District agricultural bank survey data from the Federal Reserve Bank of Kansas City.

- We get bank-specific net loan charge-offs, as well as merger and acquisition history, from the Call Reports.[9] We also aggregate these data to generate a national average loan charge-off rate series.

We make a number of modifications to the farm and bank data prior to estimating our models.

- We include all banks that had, in one year of our sample period, an agricultural-to-total loan ratio greater than the national average for that year, and have existed for at least three years.[10] We use this as our working definition of an "agricultural bank."
- We aggregate the data into annual series, given that quarterly data on charge-offs and other variables have extremely strong seasonal variation.
- We merger-adjust the bank-specific data to remove the effects of step-jumps in balance sheet variables. Thus, all data are aggregated to the most recent top holder level.
- We analyze the bank data using both balanced and unbalanced panels. We present the results from the unbalanced panel analysis in this memo, as they are more conservative (higher loss) forecasts than those derived using the balanced panel.[11]
- As mentioned above, we train the models on data from two different periods: the "crisis" period (1980-1987) and the "full" period (1980-2014). The panels that result include data from 3,592 and 4,594 banks, respectively.

Models

We use three models to analyze how declines in agricultural asset values would increase bank losses on loans. First, we use a simple historical time-series model as a benchmark. This model largely assumes that the historical relationship between agricultural land values, farm-side financial health, and bank portfolio vulnerability holds in the current period and for the period over which we make our forecasts. We use this model to establish a baseline mean estimate for the industry.

Second, we use an approach (vector autoregression) that captures the interrelationships between factors that will determine bank loan losses given a fall in agricultural asset values. This systems model analyzes the interrelationships between (1) the nominal value of agricultural land, (2) farm sector debt-to-equity ratio, (3) a proxy for underlying portfolio vulnerability, and (4) agricultural loan losses.

Finally, we use a distributional time series model (i.e., quantile regression) to complement the other two models. The model estimates the distribution of the impact of land price changes on net charge-off rates conditional on other variables. This is in contrast to a traditional autoregressive model that only estimates a conditional mean impact. We use this model to determine whether potential losses are distributed equally across banks or are concentrated in a small subset of banks.

[9] Officially known as "Consolidated Reports of Condition and Income for a Bank with Domestic and Foreign Offices" or "Federal Financial Institutions Examination Council Form 031."

[10] We investigate entry and exit from the universe of agricultural banks and find that, excluding mergers/acquisitions and failures, there are a small number of institutions that make this transition.

[11] Output from these alternative specifications is available upon request to the authors.

Benchmark Time Series Model
Model selection for the benchmark, or fixed effects autoregression, model consists of the following steps:

- We start with a fully specified ordinary least squares model with the following variables included:
    - Variables that account for the fact that each bank has different characteristics than its peers that idiosyncratically affect its baseline loan loss rate (bank fixed effects)
    - Percent change in nominal agricultural land values on a state-by-state basis
    - Lagged annual net charge-offs as a percent of all loans (autoregressive effects)
    - Changes in the national average farm debt-to-equity ratio
    - A national proxy for the relative vulnerability of the loan portfolio to a loss-producing shock
    - A bank-specific proxy for the interest rate charged on agricultural loans
    - Differenced log(net farm income)
    - Differenced log(off-farm income)
    - Differenced farm debt repayment capacity utilization.
- We identify optimal lag length by minimizing Akaike and Bayesian Information Criteria (AIC and BIC).
- We choose the specification that minimizes AIC and BIC and produces economically reasonable coefficient signs.
- We test for fixed versus random firm-specific effects using the Durbin-Wu-Hausman test, finding that fixed effects are the most appropriate specification.

Once the model selection is complete, we have six variables to estimate the loan loss rate.[12] They are:

1. Bank fixed effects
2. The percent change in nominal agricultural land values on a state-by-state basis
3. A single autoregressive term (lagged one year)
4. Changes in the national average farm debt-to-equity ratio
5. The proxy for the relative vulnerability of the loan portfolio to a loss-producing shock
6. The bank-specific proxy for the interest rate charged on agricultural loans.

Variable five requires additional explanation. The goal of our exercise is to estimate loan losses at agriculturally-focused banks arising from a fall in agricultural asset values. We would expect loan losses to be higher if the existing loan portfolios of these banks are more vulnerable to a relevant shock (such as a fall in collateral value). Vulnerability of an existing portfolio might be related to past underwriting or the exposure of a bank's borrowers to a specific type of agricultural asset value shock. There is no direct measure of this vulnerability; however, bank loan officers, who have private information about their customers and the local economic environment, have insight into the likelihood of default on the various loans they hold on their books.

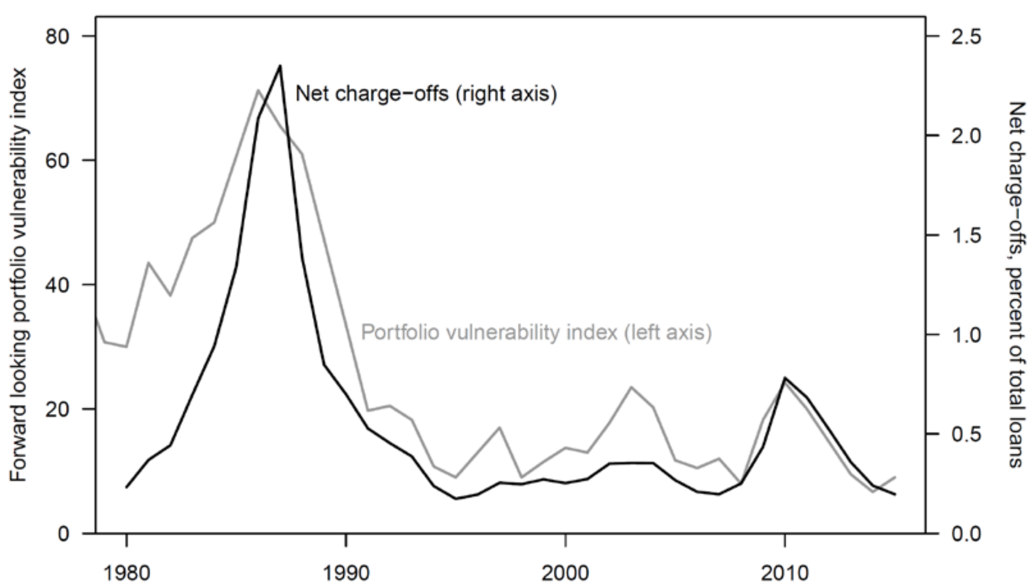
[12] We define the loan loss rate as annual net charge-offs on loans as a proportion of total loans. This is not limited to agricultural loans but is the loss rate on the entire loan book.

As a result, we proxy for changes in this portfolio vulnerability by using information from Federal Reserve Bank quarterly agricultural credit surveys that ask agricultural banks if they plan to increase or decrease their demands for collateral on agricultural loans.[13] Our proxy is the *net percent of loan officers increasing their demand for collateral*. Our intuition is that increased demand for collateral indicates a view that the bank is relatively more vulnerable to a shock and future losses. A decrease in the demand for collateral indicates that banks see a declining chance of loss.

To test our intuition, we examine the correlation between our proxy for relative loan portfolio vulnerability and our measure of loan losses (Figure 4). Data showing an increase in future losses following an increase in the request for collateral would be consistent with our intuition. That is, an increase in a bank's plan to increase its demands for collateral on agricultural loans in year T would be positively correlated with loan losses in year T+X. We test this hypothesis by examining this relationship when X equals 1 and 2 years. The data are consistent with our intuition. The correlation coefficient between the lagged proxy and loan losses is 0.81 with a one-year lag and 0.67 with a two-year lag.

Figure 4

Portfolio Vulnerability and Net Charge-Offs at Agricultural Banks



Sources: Net charge-offs: Federal Reserve Bank of Kansas City's Agricultural Finance Databook. Agricultural Bank Portfolio Vulnerability Index: The Agricultural Finance Databook and historic Kansas City (Tenth District) survey data.

[13] More precisely, the survey asks "What changes do you expect in non-real estate farm loans during the next [three] months compared to the same months a year ago…[In] the [a]mount of collateral required?" The answers can be "higher," "no change," or "lower."

The formal regression equation that describes the benchmark model is:

$$NCO_{i,t} = \alpha_i + \mu + \rho_1 NCO_{i,\,t-1} + \rho_2 NCO_{i,t-2} + \sum_{j=0}^{2} \beta_j \Delta \ln(LV)_{t-j} + \beta_4 \Delta DE_{t-1} + \beta_5 \Delta PVI_{t-1} + \varepsilon_{i,\,t}$$

where,

NCO = annual net charge-offs as a percent of total bank loans
i = bank-specific subscript
t = year-specific subscript
α = bank fixed effects
μ = regression intercept
ρ = coefficients on autoregressive terms
β = coefficients on non-autoregressive terms
LV = nominal agricultural land values, state average
DE = debt-to-equity ratio for farm producers, national average
PVI = loan portfolio vulnerability index
ε = error term.

Distributional Model

The distributional model estimates the conditional distribution of loan loss rates due to falls in nominal agricultural land values across the universe of agricultural banks.[14] A stylized version of the equation governing the model has the following features. The i^{th}-quantile of net charge-offs on agricultural loans as a proportion of total loans is explained by the percent changes in land values, previous net charge-offs, changes in debt-to-equity ratio of farms, and finally changes in the loan portfolio vulnerability variable. For reasons of computational tractability and because results are nearly identical, we remove the fixed effects variable from the distributional model.[15]

The specification for the distributional model is nearly identical to that of the benchmark model, aside from the fixed effects. All coefficients are estimated as conditional on the quantile of net charge-offs. We choose cutoffs for the distribution at every percentile, from the 1st percentile to the 99th percentile.

$$k^{th}\text{ quantile}(NCO_{i,t}) = \mu_k + \rho_{k|1} NCO_{i,\,t-1} + \rho_{k|2} NCO_{i,t-2} + \sum_{j=0}^{2} \beta_{k|j} \Delta \ln(LV)_{t-j} + \beta_{k|7} \Delta DE_{t-1} + \beta_{k|8} \Delta PVI_{t-1} + \varepsilon_{i,\,t}$$

The benchmark and distributional model coefficient estimates are given in Table 1 and 2 for models trained on the “crisis” and “full” datasets. As expected, decreases in land values have a strong

[14] The output of the distributional model does not identify specific problem institutions.

[15] Covas, Rump, and Zakrajšek (2013) find that there was considerable heterogeneity in loan charge-offs across institutions, and that distributional models did a better job of estimating losses than their benchmark counterparts.

association with the net charge-off rate at agricultural banks. In addition, there are strong autoregressive properties. Increases in the debt-to-equity ratio, portfolio vulnerability indicator, and the interest rate charged on loans are all associated with increases in the net charge-off rate. Models trained on the "crisis" dataset showed larger-magnitude coefficient estimates than those from models trained on the "full" dataset.

Table 1. Coefficients from Benchmark and Distributional Model, Crisis Sample [SEs]

	Benchmark (Mean)	Distributional (5th pctile)	(50th pctile)	(95th pctile)
NCO, t-1	0.127* [0.008]	-0.001 [0.006]	0.454* [0.011]	1.305* [0.059]
Δln(LV), t	-2.756* [0.163]	-0.064 [0.045]	-1.013* [0.075]	-4.819* [0.783]
Δln(LV) , t-1	-2.32* [0.144]	-0.063 [0.035]	-0.693* [0.072]	-4.322* [0.779]
Δln(LV) , t-2	-0.525* [0.151]	0.055 [0.046]	-0.289* [0.048]	-1.465* [0.654]
ΔDE, t-1	0.106* [0.012]	0.018* [0.004]	0.094* [0.005]	0.398* [0.051]
ΔIR, t-1	0.111* [0.007]	0.003* [0.002]	0.05* [0.002]	0.256* [0.028]
ΔPVI, t-1	0.015* [0.002]	0.001* [0.001]	0.006* [0.001]	0.019* [0.007]
Intercept	-0.141* [0.015]	-0.064* [0.008]	0.248* [0.007]	2.088* [0.084]

* Denotes statistical significance at the 5% level.

Table 2. Coefficients from Benchmark and Distributional Model, Full Sample [SEs]

	Benchmark (Mean)	Distributional (5th pctile)	(50th pctile)	(95th pctile)
NCO, t-1	0.289* [0.003]	0.013* [0.003]	0.423* [0.004]	1.123* [0.024]
Δln(LV), t	-2.407* [0.059]	-0.045 [0.03]	-0.801* [0.012]	-3.958* [0.198]
Δln(LV) , t-1	-1.096* [0.059]	-0.062* [0.028]	-0.215* [0.012]	-1.456* [0.233]
Δln(LV) , t-2	-0.362* [0.056]	0.235* [0.031]	-0.044* [0.01]	-1.416* [0.193]
ΔDE, t-1	0.053* [0.004]	0.023* [0.002]	0.028* [0.001]	0.187* [0.015]
ΔIR, t-1	0.092* [0.003]	0.006* [0.001]	0.031* [0.001]	0.169* [0.011]
ΔPVI, t-1	0.008* [0.001]	0.006* [0]	0.002* [0]	0.01* [0.002]
Intercept	0.207* [0.004]	-0.128* [0.003]	0.177* [0.002]	1.708* [0.026]

* Denotes statistical significance at the 5% level.

Systems Model

In our systems approach we estimate each of the variables as a function of the other variables to account for the complex interrelationships among them. Consider the following example: A shock to land values erodes farm equity positions and is associated with a reduction in income. The fall in collateral values and loan income causes an increase in loan losses. Banks become less willing to lend to agricultural producers, decreasing the supply of credit. A reduction in the supply of credit to finance land purchases causes a further deterioration in land values. The benchmark model, described above, would not capture such system feedback, while the systems model would.

Variable selection

- We first review the following variables for potential inclusion in the model:
    - Nominal national land value changes

- Net loan charge-offs
    - Debt-to-equity (DE) ratio of agricultural producers
    - Debt repayment capacity utilization (DRCU)[16]
    - Net farm income per acre
    - Bank capital levels
    - Loan portfolio vulnerability proxy variable
    - Proxy for interest rate charged on agricultural loans.
- Because of the mechanics of our research question, we automatically include net charge-offs and change in nominal land values.
- We use formal statistical tests to identify the optimal combination of other variables in the model.
    - We test predictive power using adjusted R^2.
    - We test for structural stability of the VAR.
    - We run the Portmanteau and Breusch-Godfrey tests for serial correlated errors.
    - We run the Jarque-Bera tests for normality, skewness, and kurtosis.
    - We test for Granger and rank causality.
    - We test for cointegration and construct an expanded VECM (all VAR variables plus debt repayment capacity utilization and net farm income). This results in a forecast that is little different from our reduced-form VAR.
    - We then adjust the model or reject model formulation based on results obtained in the above model performance tests.
- These tests lead us to include changes in nominal land values, the net loan charge-off rate, changes in the DE ratio of agricultural producers, and changes in the portfolio vulnerability index.

The system model is an unrestricted vector autoregression with four endogenous variables and three lags. The final VAR model is described by the following set of equations:

Land values

$$\Delta\ln(LV_t) = \alpha + \sum_{j=1}^{3} \rho_j \Delta\ln(LV_{t-j}) + \sum_{j=1}^{3} \beta_j NCO_{t-j} + \sum_{j=1}^{3} \beta_{j+3} \Delta DE_{t-j} + \sum_{j=1}^{3} \beta_{j+6} \Delta PVI_{t-j} + \varepsilon_t$$

Net charge-offs for agricultural loans

$$NCO_t = \alpha + \sum_{j=1}^{3} \beta_j \Delta\ln(LV_{t-j}) + \sum_{j=1}^{3} \rho_j NCO_{t-j} + \sum_{j=1}^{3} \beta_{j+3} \Delta DE_{t-j} + \sum_{j=1}^{3} \beta_{j+6} \Delta PVI_{t-j} + \varepsilon_t$$

[16] DRCU is a ratio of current debt obligations to maximum debt repayment capabilities. We use the DRCU derived from debt and income data associated with the mean farm household. The maximum repayment capability is based on a coverage ratio of 1.25, which requires that no more than 80% of the loan applicant's income be used for repayment of principal and interest on loans. See the USDA's Economic Research Service (http://ers.usda.gov/) for more information about the measure.

Debt-to-equity ratio

$$\Delta DE_t = \alpha + \sum_{j=1}^{3} \beta_j \Delta \ln(LV_{t-j}) + \sum_{j=1}^{3} \beta_{j+3} NCO_{t-j} + \sum_{j=1}^{3} \rho_j \Delta DE_{t-j} + \sum_{j=1}^{3} \beta_{j+6} \Delta PVI_{t-j} + \varepsilon_t$$

Portfolio vulnerability index

$$\Delta PVI_t = \alpha + \sum_{j=1}^{3} \beta_j \Delta \ln(LV_{t-j}) + \sum_{j=1}^{3} \beta_{j+3} NCO_{t-j} + \sum_{j=1}^{3} \beta_{j+6} \Delta DE_{t-j} + \sum_{j=1}^{3} \rho_j \Delta PVI_{t-j} + \varepsilon_t$$

where

t = year-specific subscript
LV = nominal agricultural land values, national average
NCO = net charge-offs on agricultural loans as a percent of total bank loans
DE = debt-to-equity ratio for farm producers, national average
PVI = portfolio vulnerability index
ε = error term.

The systems model coefficient estimates are given in Table 3 for models trained on the aggregated "full" dataset.

Table 3. Regression Coefficients from Systems Model, Full Sample [SEs]

	Δln(LV)	**NCO**	**ΔDE ratio**	**ΔPVI**
Δln(LV) , t-1	0.057 [0.192]	1.032 [1.093]	0.383 [6.561]	43.36 [27.06]
Δln(LV) , t-2	0.093 [0.176]	0.201 [1.002]	0.368 [6.017]	-23.36 [24.82]
Δln(LV) , t-3	-0.157 [0.16]	0.167 [0.91]	8.428 [5.464]	52.53* [22.54]
NCO, t-1	-0.061 [0.045]	1.105* [0.254]	-0.442 [1.522]	8.41 [6.28]
NCO, t-2	0.019 [0.065]	-0.567 [0.371]	-1.752 [2.227]	-3.72 [9.19]
NCO, t-3	-0.051 [0.047]	0.491' [0.267]	1.99 [1.603]	-4.14 [6.61]
ΔDE ratio , t-1	-0.015' [0.007]	0.116* [0.042]	0.386 [0.251]	1.74 [1.03]
ΔDE ratio , t-2	-0.012 [0.009]	-0.003 [0.049]	-0.171 [0.294]	-1.49 [1.21]
ΔDE ratio , t-3	0.01 [0.008]	0.071 [0.044]	0.387 [0.262]	2.28* [1.08]
ΔPVI , t-1	-0.002' [0.001]	0.012 [0.007]	0.012 [0.043]	-0.02 [0.18]
ΔPVI , t-2	0 [0.001]	-0.001 [0.007]	0.001 [0.04]	-0.25 [0.16]
ΔPVI , t-3	0 [0.001]	-0.002 [0.006]	-0.01 [0.037]	-0.15 [0.15]
Constant	0.087* [0.024]	-0.029 [0.137]	-0.453 [0.82]	-4.05 [3.38]
Adjusted R^2	0.7	0.87	0.24	0.53
p-value	<0.01	<0.01	0.11	<0.01

* Denotes statistical significance at the 5% level.

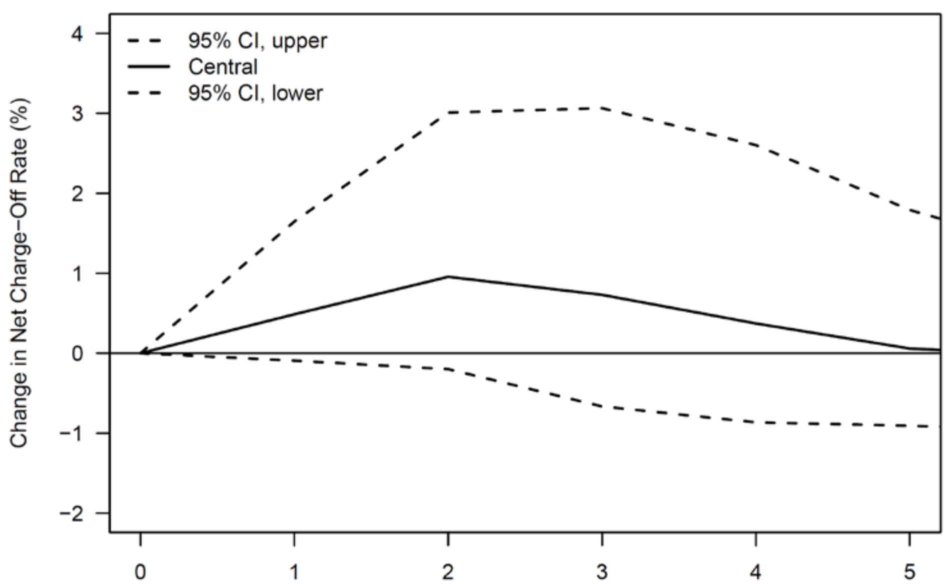
As is common with vector autoregression or other endogenous variable model frameworks, the coefficients from the systems model are not easy to interpret directly. For this reason, we generate impulse response function (IFR) graphs to test the direction and magnitude of impacts from shocks to one or more variables. IRFs are functions describing the evolution of endogenous variables over time after exposure to exogenous shocks. Below, we show the responses to a 25% shock in land values for net charge-offs, the farm debt-to-equity ratio, and the portfolio vulnerability index.[17]

The IRFs show that net charge-offs increase in the first and second years after the shock, and then move towards baseline after that (Figure 5). Farm debt-to-equity ratios increase in the first year after the shock as a result of the land value shock impacting the equity side of the ratio, and then begin to decline (Figure 6). The portfolio vulnerability index jumps up in the first year after the shock as banks tighten standards, but then loosens over time (Figure 7). Land values decrease for three years and then begin to recover in the fourth year (Figure 8).

Figure 5

Response of Net Charge-Offs to a
25% Decrease in Nominal Land Values

Systems Model



[17] We model this as an orthogonal shock to nominal land values.

Figure 6

Response of Farm Debt-to-Equity Ratio to a 25% Decrease in Nominal Land Values

Systems Model

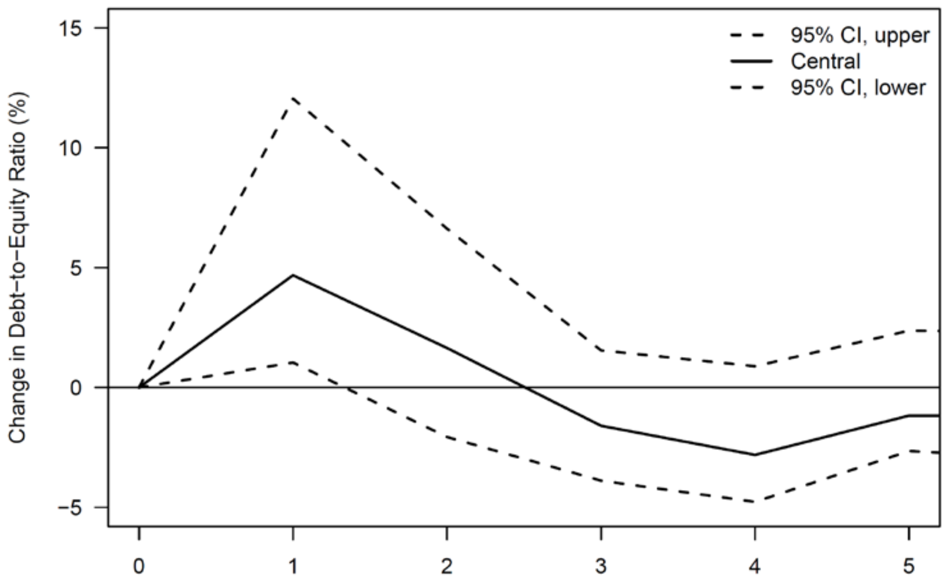


Figure 7

Response of Portfolio Vulnerability Index to a 25% Decrease in Nominal Land Values

Systems Model

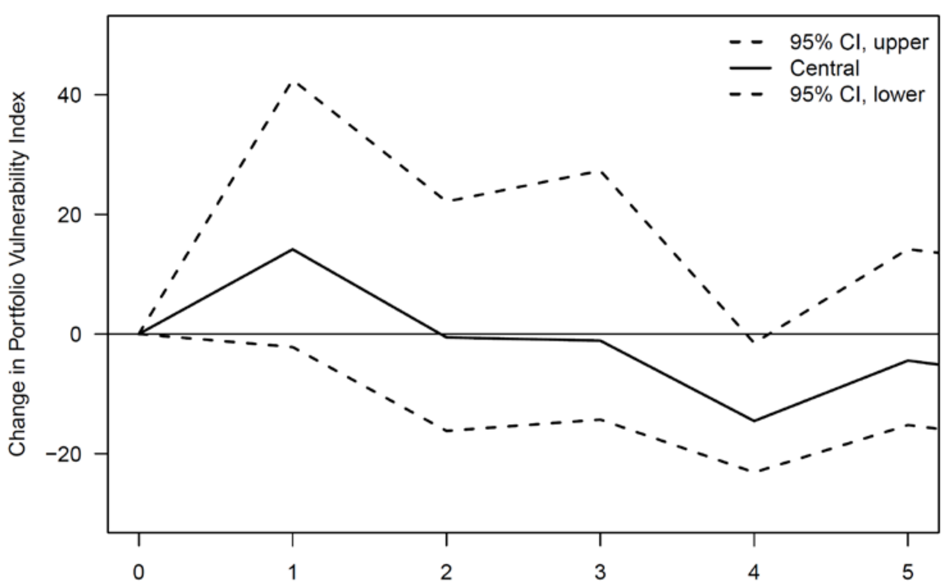
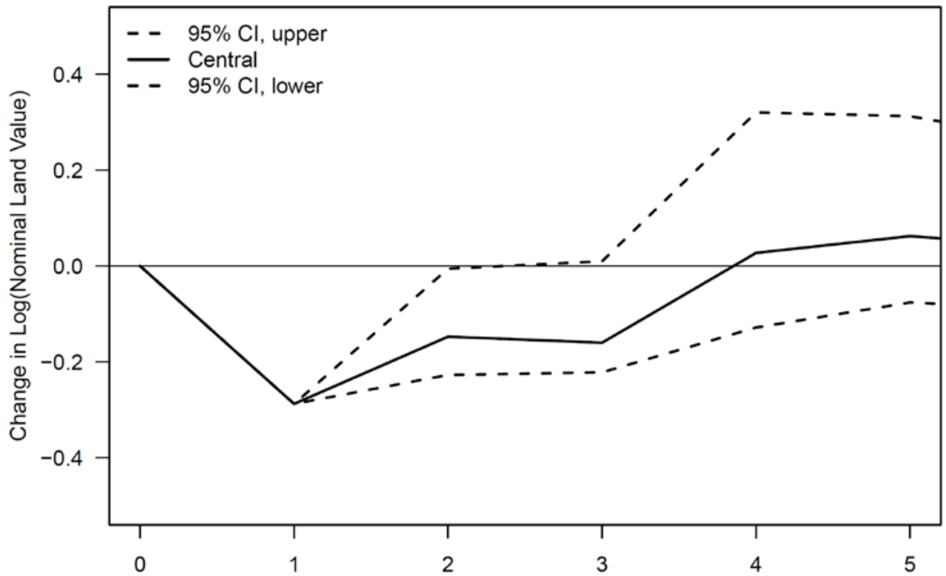


Figure 8

Response of National Average Nominal Land Values to a 25% Adverse Shock

Systems Model



<u>Capital Calculation Methods</u>

We estimate the effect of increases in bank loan loss rates on bank capital using a mechanical "pass-through" from loss to capital reduction. We calculate changes to capital at both one and two years after the shock. We use our net charge-off increase projections to infer corresponding changes to bank equity-to-asset ratios. We estimate changes to equity-to-asset ratios as follows.

We assume for simplicity that

- all "excess" charge-offs (i.e., charge-offs beyond the 2014 baseline) will reduce income and thus equity by an equivalent amount,
- assets fall by the same amount as equity, and
- all else stays the same at the bank.

The formula for this calculation in the benchmark model is:

$$\Delta \mathrm{EtA}_{\mathrm{year}\ 1} = \frac{\mathrm{EtA}_{\mathrm{year}\ 0} - \left(\mathrm{NCO}_{\mathrm{year}\ 0} - \mathrm{NCO}_{\mathrm{baseline}}\right) * \mathrm{LtA}}{1 - \frac{\left(\mathrm{NCO}_{\mathrm{year}\ 0} - \mathrm{NCO}_{\mathrm{baseline}}\right)}{100} * \mathrm{LtA}}$$

where

EtA = equity-to-asset ratio

LtA = loan-to-asset ratio

Calculation of the results of the second year after the shock uses the same basic framework.

<u>Forecasting Changes in the Viability of Banks</u>

We use the Federal Reserve Board's Supervision and Regulation Statistical Assessment of Bank Risk Model (SR-SABR) to assess changes in the viability of individual institutions. The output of the model is the probability of bank failure over the next two years. It is a probit model that uses 11 bank-specific factors to estimate the probability of failure. Model details are considered confidential supervisory information. Our procedure, in general, is as follows.

For each bank we

- adjust credit-related variables in SABR and variables related to other real estate owned upward, consistent with the increase in loan losses forecast by our models,
- decrease earnings and asset-related variables in SABR consistent with the loan losses forecast by our models,
- do not adjust other variables in the SABR, and
- recalculate the probability of failure for each bank.

<u>Framework for Reporting Loan Loss Results</u>

In this section, we introduce the scenarios used to stress test the agricultural banks. We report the loan loss rate results from the models. We also report the results of our simple bank capital calculations as well as bank viability assessment.

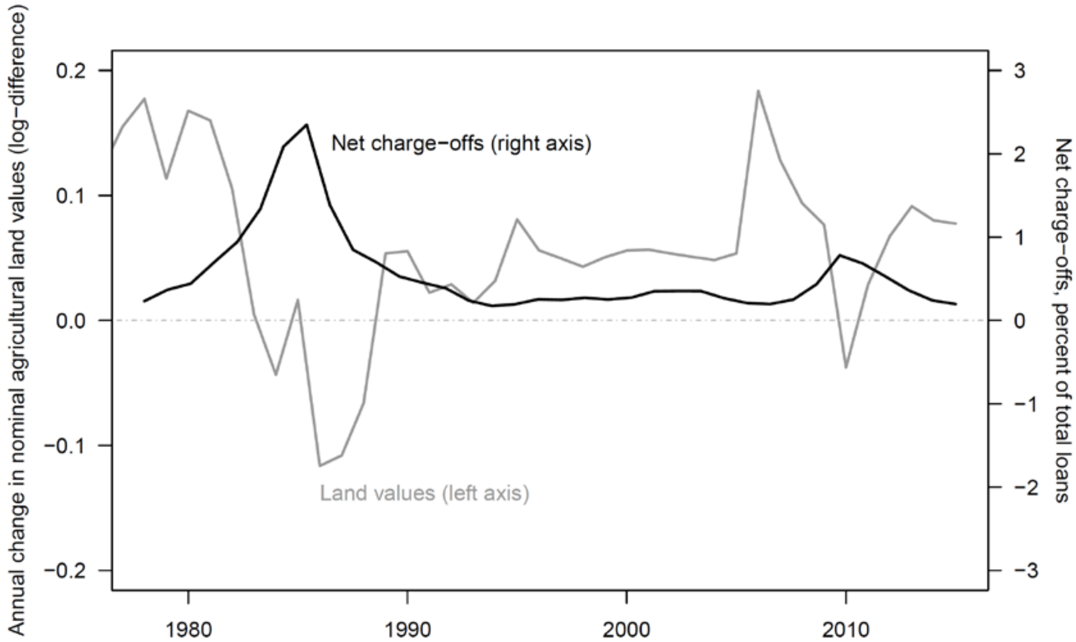
<u>Scenario Design</u>

To provide context for scenario design as well as forecast declines, Figure 9 shows net charge-off rates at agricultural banks and year-over-year changes in nominal land prices before, during, and after the Farm Crisis of 1980–87. During the Farm Crisis, the average net charge-off rate at these banks remained well above its historical average, peaking in 1986 at above 2% and not coming down to "normal" levels (0.2% to 0.4%) until 1990. The annual average net charge-off rate exceeded 1% from 1984 to 1987.

Figure 9

Net Charge-Offs at Agricultural Banks and Changes in Nominal Land Values

National Aggregates 1978–2014



Sources:

Net charge-offs: Federal Reserve Bank of Kansas City's Agricultural Finance Databook.

National average nominal land values: USDA ERS Quick Stats 2.0.

We designed the scenarios in which we shock real agricultural variables with the express purpose of bookending mild and severe states of the world. In addition, we wanted to examine the dynamics of loan losses with shocks persisting over multiple years. We used the land value series from Figure 9 as a benchmark for our design. We create the three distinct scenarios summarized in Table 4.

Table 4. Shocks by Scenario and Model Type

Model \ Scenario	Mild	Severe	Persistent Severe
Benchmark	Land (nominal): -5% Farm DtE: +0.43 ppt PVI: +5 point	Land(nominal): -25% Farm DtE: +2.13 ppt PVI: +10 point	Land(nominal): -25% Farm DtE: +2.13 ppt PVI: +10 point Same the following year
Systems	NA	NA	Land(nominal): -25% Farm DtE: endogenous* PVI: endogenous*
Distributional	Same as Benchmark	Same as Benchmark	Same as Benchmark

Notes: DtE = debt-to-equity ratio (percent); PVI = portfolio vulnerability index; ppt = percentage points

* The persistent severe scenario is analyzed with the benchmark and distributional models; we are not able to model two subsequent years of exactly 25% land value drops in the systems model because of variable endogeneity. It should be noted that for the systems model in year 2, land value declines by approximately the same amount once again. Thus, the forecasts from this model represent a sort of quasi-persistent severe scenario.

The first scenario, we label as "mild." With a 5% drop in nominal land values, it is consistent with the initial Farm Crisis period of 1980–81. The farm debt-to-equity ratio and PVI changes are also consistent with this period's data. The second shock is severe, containing a nominal land value decline of 25%. This would be a severe one-period shock, more than twice as large as the largest one-year change during the Farm Crisis. (That said, recent increases in land values have been at the very high end of historical experience, both in magnitude and duration of trend.) Finally, to capture the effects of a persistent shock, we model a persistent severe shock of two consecutive 25% declines.

Mechanistically, we model the land value shocks as entering the models in 2015. For the benchmark and systems models, we model farm DtE ratio and PVI shocks as entering in 2016, given their one-year-lag specification in the final models. Post-shock, we force all variables to zero, equivalent to saying that nominal land values, farm DtE ratios, and PVI all stay flat. In the systems model, we introduce the land value shock as orthogonal to the other variables.

<u>Stress Test Results: Loan Loss Rates</u>

Table 5 reports the loan loss results from the mild, severe, and persistent severe scenario declines, and Figure 11 illustrates the loan loss rates in the severe scenario for the average and high-loss agricultural banks. We estimate that a 25% fall in nominal land values would cause the loan loss rates at the average agricultural bank to jump from 0.2% to between 1.1% and 1.27% during the year of the shock, 1.22% to 1.77% in the first year after the shock, and 0.95% to 1.14% in the second year after the shock. If that initial shock is followed by another 25% drop, losses are expected to jump to 1.68% to 2.3% by the second year after the initial shock. Mean losses forecast with the benchmark and systems models produce two-year-out estimates that are considerably higher than means from the distributional model.

The distributional model indicates that loss rates jump considerably higher in agricultural banks in the high-loss percentiles. Additionally, according to the distributional model, a smaller subset of banks will show losses for longer periods of time rather than quickly moving back to baseline loan loss numbers. Both phenomena can be seen in the forecasts in Figure 10.

Table 5. Forecast of Total Loan Net Charge-Off Rate (%) for Three Scenarios [5th/95th Percentiles]

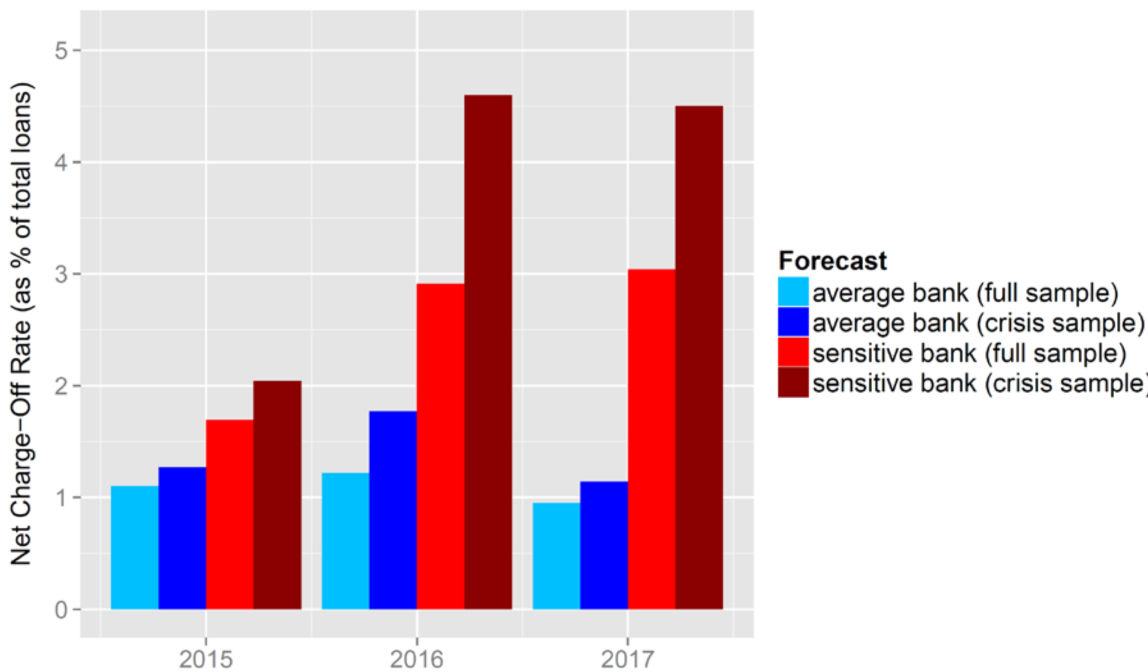
Scenario	Estimation Data	Measure	2014 (pre-shock)	2015	2016	2017
Mild	Full	Mean	0.21	0.48 [0.47, 0.49]	0.65 [0.64, 0.66]	0.7 [0.69, 0.71]
Mild	Full	95th Percentile	1.12	0.96 [0.93, 0.99]	1.9 [1.77, 2.07]	2.26 [2.11, 2.41]
Mild	Crisis	Mean	0.21	0.57 [0.52, 0.62]	0.88 [0.85, 0.91]	0.91 [0.88, 0.94]
Mild	Crisis	95th Percentile	1.12	1.01 [0.97, 1.04]	2.4 [2.23, 2.6]	2.95 [2.74, 3.15]
Severe	Full	Mean	0.21	1.1 [1.06, 1.13]	1.22 [1.19, 1.25]	0.95 [0.92, 0.97]
Severe	Full	95th Percentile	1.12	1.69 [1.61, 1.78]	2.91 [2.7, 3.14]	3.04 [2.83, 3.26]
Severe	Crisis	Mean	0.21	1.27 [1.17, 1.38]	1.77 [1.69, 1.85]	1.14 [1.08, 1.21]
Severe	Crisis	95th Percentile	1.12	2.04 [1.93, 2.16]	4.6 [4.29, 4.96]	4.5 [4.21, 4.77]
Persistent Severe	Full	Mean	0.21	1.1 [1.06, 1.13]	2.01 [1.97, 2.04]	1.68 [1.64, 1.73]
Persistent Severe	Full	Mean (systems)	0.21	0.68 [0.06, 1.17]	1.64 [-0.32, 2.84]	2.37 [-0.71, 4.31]
Persistent Severe	Full	95th Percentile	1.12	1.69 [1.61, 1.78]	4.09 [3.8, 4.4]	4.42 [4.12, 4.72]
Persistent Severe	Crisis	Mean	0.21	1.27 [1.17, 1.38]	2.68 [2.59, 2.76]	2.3 [2.19, 2.42]
Persistent Severe	Crisis	95th Percentile	1.12	2.04 [1.93, 2.16]	6.05 [5.62, 6.51]	7.26 [6.82, 7.71]

* The forecast scenarios that we fed into the systems model are orthogonal shocks to nominal land values. As a result, the evolution of the debt-to-equity and portfolio vulnerability variables is allowed to take place endogenously. This means that we are not able to externally impose a second land value shock and preserve orthogonality. However, the endogenous second year land value shock is approximately equal to the first. As a result, we report results from the systems model under the persistent severe scenario.

Figure 10

Net Charge-Offs in Average and "Sensitive" Agricultural Banks

Severe Scenario



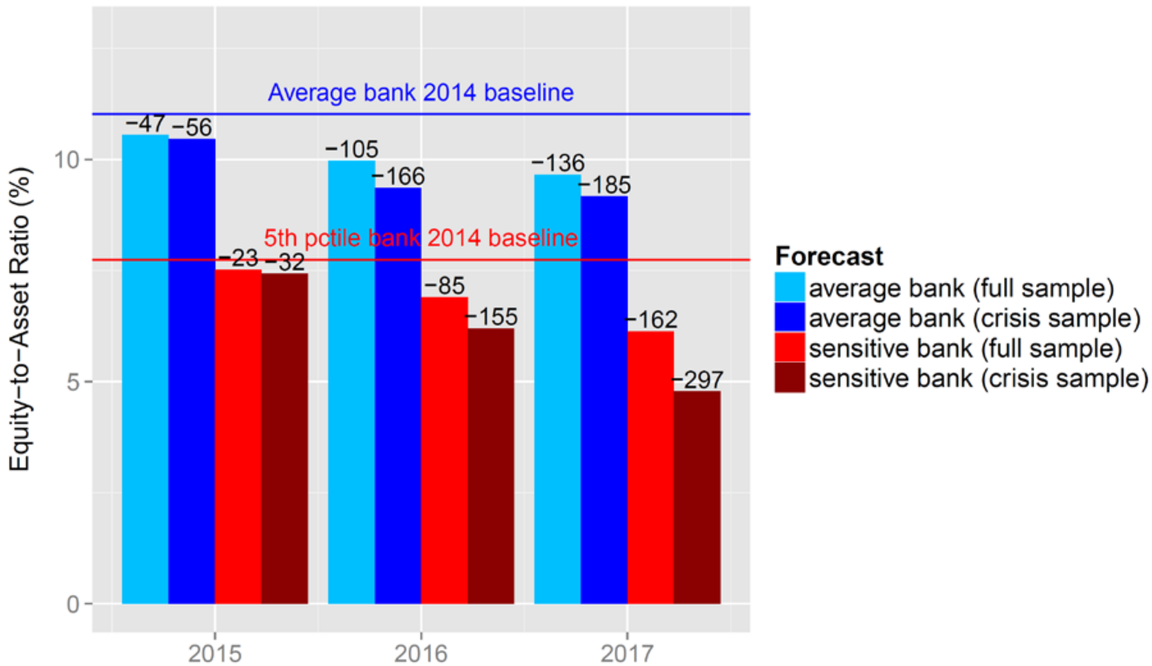
<u>Effect on Capital and Viability</u>

We calculate the impact on bank equity-to-asset ratios of these simulated loan losses in Table 6. To do this we use the loan loss results from all three of our models. Using loss estimates for the severe scenario, the average reduction in capital is a 45 to 54 basis point drop in the year of the shock, a 103 to 164 basis point decline from pre-shock levels by the end of the first year after the shock, followed by a 134 to 183 basis point drop from pre-shock levels by the end of the second year. We focus on the severe scenario in Figure 11. The persistent severe scenario results in larger equity-to-asset ratio reductions over two years, ranging from 214 to 299 basis points. There is significant variation across firms.

Figure 11

Changes in Equity-to-Asset Ratios in Average and "Sensitive" Agricultural Banks

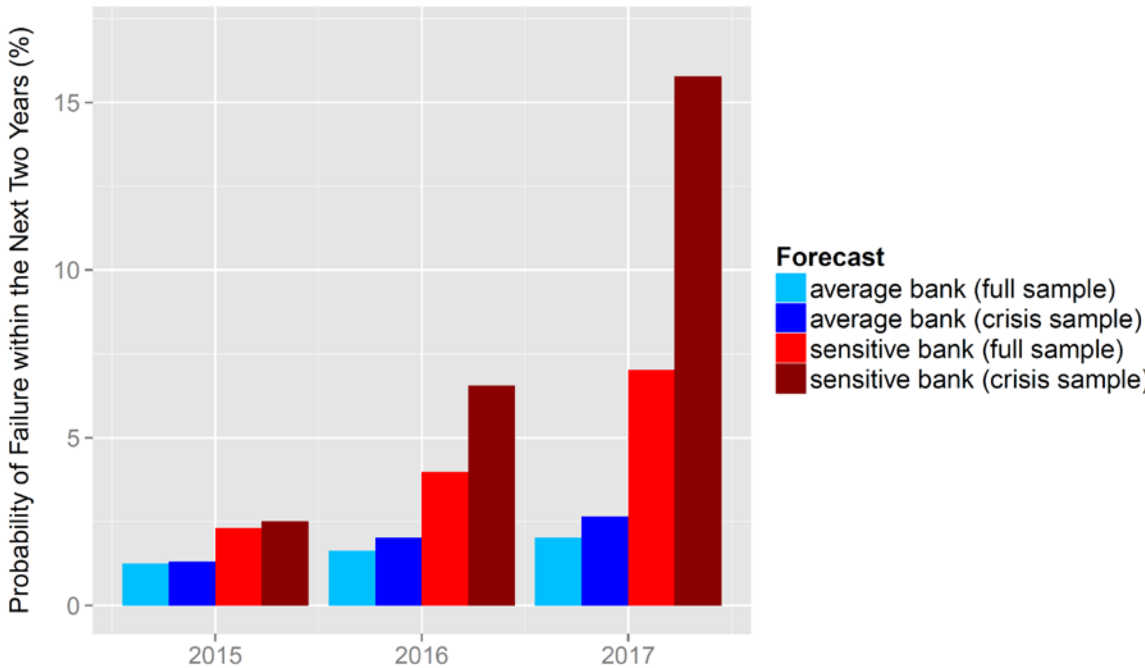
Severe Scenario



Our distributional model forecasts that, during the severe scenario, equity-to-asset ratios for the worst-off 5% of banks will fall to 4.78% to 6.13% by the second year after the shock; whereas, for a sizeable minority of banks, we forecast negligible impacts on equity capital. During the persistent severe scenario, the capital impacts are larger, resulting in a drop to 2.84% to 5.17% two years after the initial shock for the most "sensitive" banks.

Figure 12

Average and High-Percentile Likelihood of Failure for Agricultural Banks
Severe Scenario



The increase in loan losses should translate into a higher chance of bank failure over a two-year period, but those changes in failure probabilities are highly skewed (Table 7). The change in probability of the mean bank in the severe scenario increases by 101 to 165 basis points over the two years after the shock. We show the skewed nature of the failure probabilities and their post-shock evolution in Figure 12. Finally, from the distributional model, we find that agricultural banks whose loan losses are worse than 95% of their peers see a large increase in their probability of failure, from a 1.84% baseline to 7.04–15.8% over two years.

Table 6. Forecast of Bank Equity-to-Asset Ratios (%) for Three Scenarios [5th/95th Percentiles]

Scenario	Estimation Data	Measure	2014 (pre-shock)	2015	2016	2017
Mild	Full	Mean	10.99	10.87 [10.87, 10.88]	10.56 [10.55, 10.57]	10.42 [10.41, 10.43]
		5th Percentile	7.76	7.72 [7.7, 7.74]	7.44 [7.36, 7.52]	6.98 [6.85, 7.09]
	Crisis	Mean	10.99	10.83 [10.83, 10.83]	10.32 [10.31, 10.32]	10.15 [10.14, 10.15]
		5th Percentile	7.76	7.7 [7.67, 7.72]	7.28 [7.19, 7.36]	6.58 [6.4, 6.75]
Severe	Full	Mean	10.99	10.55 [10.55, 10.56]	9.97 [9.96, 9.97]	9.66 [9.66, 9.67]
		5th Percentile	7.76	7.52 [7.46, 7.57]	6.9 [6.79, 7.01]	6.13 [5.93, 6.29]
	Crisis	Mean	10.99	10.46 [10.46, 10.47]	9.36 [9.35, 9.37]	9.17 [9.16, 9.18]
		5th Percentile	7.76	7.43 [7.36, 7.49]	6.2 [5.98, 6.36]	4.78 [4.4, 5.06]
Persistent Severe	Full	Mean	10.99	10.55 [10.55, 10.56]	9.09 [9.08, 9.1]	8.85 [8.84, 8.85]
		5th Percentile	7.76	7.52 [7.46, 7.57]	6.49 [6.31, 6.63]	5.17 [4.82, 5.43]
	Crisis	Mean	10.99	10.46 [10.46, 10.47]	8.34 [8.33, 8.35]	8.04 [8.03, 8.05]
		5th Percentile	7.76	7.43 [7.36, 7.49]	5.61 [5.36, 5.81]	2.84 [2.35, 3.22]

Table 7. Forecast of Failure Probability over Next Two Years (%) for Three Scenarios [5th/95th Percentiles]

Scenario	Estimation Data	Measure	2014 (pre-shock)	2015	2016	2017
Mild	Full	Mean	1.00	1.06 [1.05, 1.1]	1.18 [1.17, 1.22]	1.34 [1.32, 1.38]
		95th Percentile	1.84	1.95 [1.9, 2]	2.49 [2.29, 2.71]	3.77 [3.36, 4.3]
	Crisis	Mean	1.00	1.08 [1.07, 1.12]	1.28 [1.27, 1.32]	1.54 [1.52, 1.58]
		95th Percentile	1.84	1.98 [1.93, 2.04]	2.88 [2.59, 3.24]	5.15 [4.53, 5.86]
Severe	Full	Mean	1.00	1.24 [1.23, 1.28]	1.63 [1.61, 1.68]	2.01 [1.98, 2.05]
		95th Percentile	1.84	2.31 [2.19, 2.47]	3.97 [3.57, 4.47]	7.04 [6.07, 8.13]
	Crisis	Mean	1.00	1.3 [1.29, 1.35]	2.02 [1.99, 2.06]	2.65 [2.62, 2.7]
		95th Percentile	1.84	2.5 [2.32, 2.71]	6.56 [5.67, 7.59]	15.77 [13.42, 18.4]
Persistent Severe	Full	Mean	1.00	1.24 [1.23, 1.28]	2.05 [2.03, 2.1]	3.18 [3.15, 3.23]
		95th Percentile	1.84	2.31 [2.19, 2.47]	5.41 [4.8, 6.23]	12.84 [11.03, 14.71]
	Crisis	Mean	1.00	1.3 [1.29, 1.34]	2.65 [2.62, 2.69]	4.96 [4.92, 5.03]
		95th Percentile	1.84	2.5 [2.32, 2.71]	9.74 [8.36, 11.51]	34.77 [30.32, 39.74]

Robustness Testing

We run a number of robustness tests. These include but are not limited to

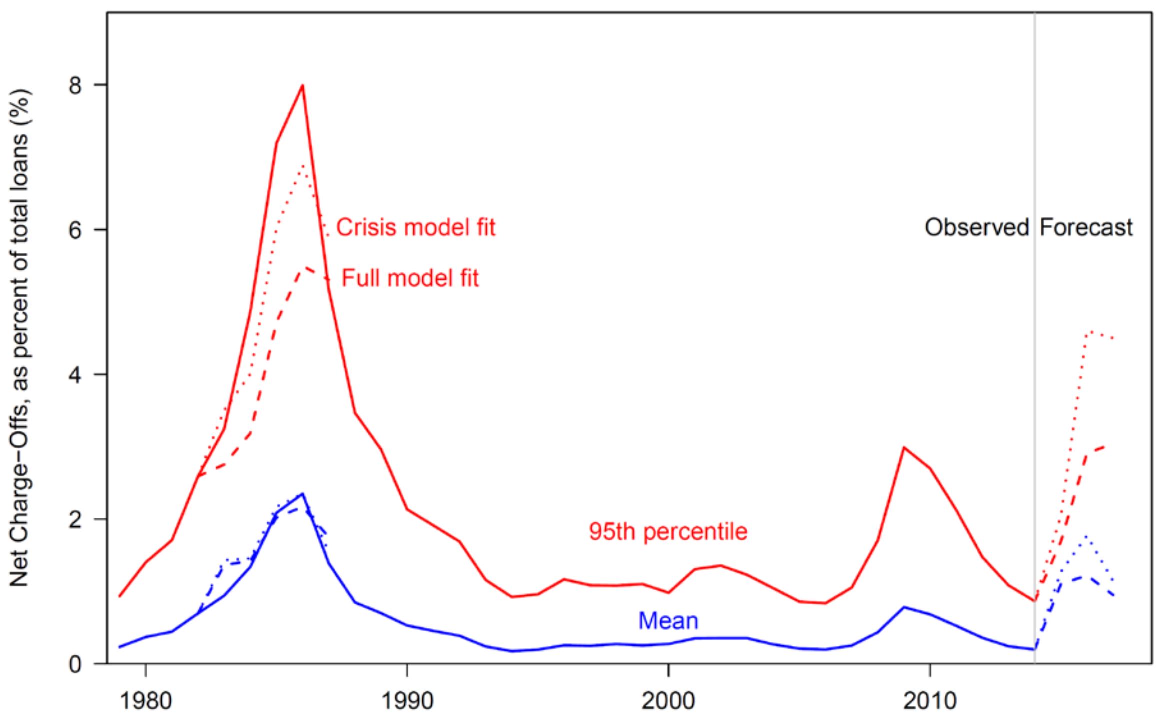
- Back-testing of the models against the Farm Crisis data,
- Using alternative model specifications, and
- Modeling alternative data sets.

First, we examine the model fit over the Farm Crisis period of 1982 to 1987 (Figure 13). We find that the benchmark and distributional models trained on the "crisis" data provide a respectable fit of loan loss rates for both the average and sensitive, or high-loss, banks. When trained on the "full" data, the distributional model does a poorer job fitting the Farm Crisis era.

Figure 13

Farm Crisis Model Fit

Severe Scenario, Benchmark and Distributional Models



The difference in outcomes due to the underlying estimation period has significant implications for interpreting our results. Loan losses will be relatively small, even if the drop in land values is large, if banks are fundamentally less susceptible to a Farm Crisis-type event. Losses will be large if the vulnerability to a Farm Crisis-type event remains.

In addition to back-testing the final set of models, we also specify the model in a number of different ways.

- We use different variable combinations during the model selection process. Variables not selected include net farm income, non-farm income, and debt repayment capacity utilization.
- We interact variables where it makes sense economically (e.g., interest rate and differenced land value).
- We vary lag structures.
- We test the use of the log-transformed net charge-off rate as a dependent variable.
- We create a charge-off rate specific to agricultural loans rather than using the broader rate.

None of these modifications improve the metrics used to judge model accuracy (e.g., in-sample fit, coefficient stability, etc.).

In addition to changes in model specification, we use alternative data sets to perform robustness checks on the models. We use a balanced panel approach to estimate the model coefficients, but find that the resulting models does a poor job in back-testing and results in low forecast losses. We change the inclusion criteria for agricultural banks, using a definition of 25% agricultural loan-to-total loan ratio. The results are very similar to those obtained with the definition of greater than the national average agricultural loan-to-total loan ratio.

Conclusions

Agricultural land values have increased at near-record rates over the last several years and have reached record highs in nominal and real terms. These high values likely reflect recent high commodity prices, very strong agricultural producer income, and low interest rates. All of these factors either have already reversed or likely will reverse soon. It is reasonable to expect the value of agricultural land to fall; some recent readings suggest that a decline has already started (or at least the rapid rate of increase has stopped).

We review the implications of this potential reversal in agricultural land values. We examine how a fall in farmland values might reduce the capital position of commercial banks. We find that the capital position of the vast majority of banks that specialize in agricultural lending would not materially decline. We find that a subset of agricultural banks would be subject to sizeable losses and impact on capital.

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