DYNAMIC HETEROGENEOUS AGENT MODELS OF DEFAULT ON FARM REAL ESTATE LOANS

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INTRODUCTION

According to the USDA ARMS data, farm real estate values have increased almost threefold since 1987, but this trend is leveling off. The Federal Reserve Bank of Kansas City reported that both irrigated and non-irrigated farmland was trending negatively in the second and third quarters of 2015. This phenomenon not only happens in district 10, but reports from districts 11, 8, and 7 of the Federal Reserve are also indicate a downward trend in farmland value. It is likely that the value of farm real estate, especially in middle America, is just beginning a downward slide. This decrease in land value is correlated with low commodity prices and low expected returns from the agricultural sector. According to the USDA, net U.S. farm income tumbled 38% to $55.9 billion in 2015, the lowest in more than a decade (Newman, 2015). The futures price for corn, the nation's largest crop by value, fell nearly 8% in 2015. Prices for soybeans have dropped 15% in 2015 and are down by more than half since 2012. The strong dollar is stifling U.S. agricultural exports, worsening the strain on farmers already dealing with a collapse in prices and weaker demand.

Agriculture is by nature a cyclical industry. In the 1980s, the bust of the agricultural economy resulted in an increase in farmer defaults and agricultural bank failures. In 1985 and 1986, agricultural banks charged off $2.5 billion in loan loss, and 50 agricultural banks failed each year from 1985 to 1987. Therefore, banks and shareholders are very interested in whether the decline in farmland prices and weak agricultural profitability will cause another agricultural credit crisis. In a 2015 Agricultural Lender Survey conducted by Brewer et al. (2015), most respondents expected an increasing number of non-performing loans in the next 1-5 years. Respondents indicated that the low commodity price and rising input costs are the major reasons for this pessimistic expectation. The agricultural credit crisis in the 1980s and the current agricultural economy expectations highlight the importance of understanding the economic mechanisms triggering agricultural loan default and the rise in charge-off rates. Insights into these issues may then inform political debates on how to prevent future foreclosure crises or mitigate their impacts if they must happen. To date, a clear lack of structural theory on farm real estate loan default behavior exists. This paper contributes to this research agenda by developing a heterogeneous agent model to study the effects of a farmland price shock and commodity price shock on the default decisions of farmers. Findings from simulations of this structural model can help policy-makers understand the mechanisms of farmland loan default.

RELATED LITERATURE

There are very few structural studies on farmland loan default. However, existing empirical studies provide discussions of factors which might change a farmer's propensity to default. Peoples et al. (1992) gave a comprehensive review of the 1980s agricultural credit crisis in his book. Existing empirical studies provide evidence that risk of agricultural loans is dependent on a farmer's net income and the valuation of assets held as collateral. A farmland's value may have two channels for affecting the risk of agricultural loans. Firstly, because the land is the collateral of agricultural loans, the deteriorated value will decrease the loss reserves given default. Briggeman et al. (2009) analyzed the data of real agricultural land value and net charge-offs in agricultural banks from 1977 to 2008. Through a visual inspection, it appears that farmland values are a leading indicator for net loan charge-offs. Then, they estimated a simple vector autoregression (VAR) model to represent this complex dynamic system and imposed a land value shock to examine its impact on loan charge-off rate. They concluded that the past farmland values are negatively correlated with the current net loan charge-off rate.

On the other side, farmland value might have some effect on the Probability of Default (PD). Featherstone et al. (2006) estimated a probability of default model using 157,853 loans from the seventh Farm Credit District portfolio. Using this synthetic credit rating model and USDA's 2013 Agricultural Resource Management Survey data (ARMS), Burns et al. (2015) predicted that 1.7% of land-owning farmers move to the substantial risk category (CCC+ or lower) under a 35% drop in land prices. This predicted default probability is based on financial ratios, so it is relatively static and imperfectly measured. In a study conducted by Weber and Key (2014), a probit model was estimated using the Census of Agriculture from 1997, 2002, and 2007 to understand the factors which will affect farm survival probability. The nominal crop-land value in the United States doubled during that period. The farmers who had a larger ownership share were proven to have a higher probability of survival, but there is little evidence to show that the land appreciation rate has a direct effect on the survival rate. Intuitionally, the larger and more highly efficient farms also have a higher probability of surviving.

THE MODEL ECONOMY

According to the 2012 Census of Agriculture, 97% of the 2.1 million farms in the United States are family-owned farms. Thus, farm income is closely related to household consumption and utility. The economy is comprised of heterogeneous finitely lived farmers subject to uninsurable idiosyncratic productivity shocks and systemic price shocks in each period.

Representative Agents

The main elements of this model are set up as follows. Time is modeled discretely and indexed by t=0, 1, 2,…. This model comprises only non-farmers and farmers who have different farm sizes (k). It is assumed that a farmer cannot rent or lease the farmland. All agents are finitely-lived and face an aggregate path of farmland price (F), intermediate input price (M_t) and agricultural commodity prices (P_t). At the beginning of each simulation period, an agricultural intermediate input (x_t) and time allocation between farm work (n_t) are all endogenously determined to maximize the expected annual total income, based on the end of last period M_{t-1}, and expected current period P_t and productivity (A_t)[1].

$$\mathrm{E}_{t-1}y_t = \max_{n_t\, x_t}\{\tilde{y}(1-n_t), +\mathrm{E}_{t-1}(P_t A_t){k_t}^{\gamma_k}{n_t}^{\gamma_n}{x_t}^{\gamma_x} - \mathrm{M}_{t-1}x_t\} \qquad \textbf{(1)}$$

When $n_t < 1$, this farmer will work part-time off the farm and earn both farm income and non-farm income. When $n_t \geq 1$, this household will work on the farm full-time and hire (n_t-1) people to work on the farm. For simplicity, both the non-farm work and the farm hire wage rate are denoted by ỹ, which is normalized to 1. The base farmland price (F), the intermediate input price (M_t) and commodity prices (P_t) are all normalized to 1; thus, the farm size (k), intermediate input (x_t) and farm labor (n_t) all represent 1 unit of U.S. median household income.

[1] When farmers optimize their production, the intermediate input is purchased in the beginning of production, such as fertilizer, seed, animal feed, etc. However, they will never know their current year yield and sale price until the end of production. $\mathrm{E}_{t-1}(P_t) = P_{t-1}$ and $\mathrm{E}_{t-1}(A_t)$ will be explained in the following section of this paper.

At the end of each period, all agents receive their realized annual farm profit and their non-farm income as follows:

$$y_t(k_t, P_t, \mathrm{M}_t) = \max_{n_t\, x_t}\left\{\tilde{y}(1-n_t), +P_t\left(A_t {k_t}^{\alpha} {n_t}^{\beta} {x_t}^{\gamma}\right) - \mathrm{M}_{t-1} x_t\right\} \quad \textbf{(2)}$$

Value Function and Budget Constraints

The farmer in this model maximizes a state-contingent value function of a current state variable over an infinite time horizon. The agent's dynamic decision problem is characterized by a Bellman Equation which is subject to a budget constraint.

a. Worthy Non-farmer

Consider the problem of a worthy non-farm owner who does not own a farm. His/her value function is denoted by V^N:

$$V^N(s, j=0) = \max_{c}\{u(c) + \beta V^N(s', j'=0)\} \quad \textbf{(3)}$$

subject to

$$\frac{s'}{1+r} + c = s + y$$

$$s' \geq -b$$

$$r = \begin{cases} r_{credit} & s' < 0 \\ r_{saving} & s' \geq 0 \end{cases}$$

Note that s is the end of period net asset, k is the farm size, and j is used to denote how many years a foreclosure or bankruptcy agent has been in an unworthy state. Here s', k', j' are all next period state variables, c is the consumption in the current period, $\beta \in (0, 1)$ is the household's per-period discount factor, and r_{credit} and r_{saving} are the credit card debt and riskless savings interest rate. In the value function, $u(c)$ is the utility function with constant relative risk aversion (α), which is a twice continuously differentiable function of current consumption, with $u' > 0$, $u'' > 0$, $u'(0) = \infty$. To simplify this study, the annual income $\tilde{y}$ is constant, so it refers to a non-farmer who does not have income uncertainty and whose strategic consumption is approximately equal to his/her annual income.

b. Unworthy Non-farmer

After filing for bankruptcy, farmers will lose their farms and be excluded from the credit market for τ years with an unworthy flag ($j > 0$). Their value functions are denoted by V^U.

$$V^U(s,j) = \max_c\{u(c) + \beta V^U(s', j+1)\} \quad \forall j \in \{1,2,3,4,5,\dots,\tau-1\} \qquad \textbf{(4)}$$

When $j = \tau$, the unworthy agent will automatically go back to a worthy state in the next period.

$$V^U(s, j = \tau) = \max_c\{u(c) + \beta V^N(s', j' = 0)\} \qquad \textbf{(5)}$$

subject to

$$\frac{s'}{1 + r_s} + c = s + y$$

$$s' \geq 0.$$

c. Farmer

Given the farm land size and expected annual income, farmers will determine current period consumption to maximize lifetime utility.

$$V_k^F(s, j = 0) = \max_c\{u(c,k) + \beta[\omega\eta\Phi + (1-\omega)V_k^F(s', j' = 0)\} \qquad \textbf{(6)}$$

Subject to

$$c + \frac{s'}{1 + r} = s + \mathrm{E}_{t-1}y_t$$

$$s' > \max[0, \quad \mathrm{s}(1 + \mathrm{r}) - \Psi(k, D, r_{secure}, L)]$$

$$r = \begin{cases} r_{secure} & s' < 0 \\ r_{saving} & s' \geq 0 \end{cases}$$

If a farmer owes on a farmland loan ($s' < 0$), he/her has the obligation of the annual installment payment $\Psi(Loan, r_m, L)$. The annual installment payment is a function depending on total loan size ($Loan$), secured loan interest rate (r_{secure}), and length of the loan (ι). Upon making a secured loan for the farmland purchase, the lender requires all the borrower's total liability to be lower than $k\Lambda$. Λ is the required maximum loan to value ratio (LTV). To reduce the dimension of value function and save computation time, the total loan note size can only be approximated by $k\Lambda$.

$$\Psi(Loan, r_{secure}, L) = 12 \times \frac{k\Lambda \times {r_{secure}}/{12}}{1 - \left(\frac{1}{1 + {r_{secure}}/{12}}\right)^{\iota \times 12}}. \quad \textbf{(7)}$$

In each period, farmers are forced to sell their farm with probability ω for the death and change of the household head. The importance of the bequest motive is measured by parameter η. The non-foreclosure sale of the farm incurs a proportional cost χFk. The Φ is the total equity of the farmer, which depends on farm size (k), farm price (F), and riskless asset level (s).

$$\Phi(\mathrm{F}, \mathrm{k}, \mathrm{s}) = \max[0, \mathrm{s} + (1 - \chi)Fk] \quad \textbf{(8)}$$

Strategic Decision

a. Selling and Buying Farmland

At the beginning of each period, agents can change their farmland size by selling and buying. To simplify the problem, the farm size is discretized to m levels. Both farmers and non-farmers can buy farmland by obtaining farm real estate loans from a bank; meanwhile, farmers can sell the farmland at the sale discount ϕ and refinance their loan. At the loan orientation or refinance, lenders will restrict their total loan-to-asset value (LTV) ratio to lower than Λ. This implies that a lifetime utility of changing farm size from k to $\tilde{k}$ should be as follows:

$$\mathrm{W}_k^{\tilde{k}}(s) = V_{\tilde{k}}^F(\tilde{s}) \tag{9}$$

Subject to

$$s = \begin{cases} F \times \left(\tilde{k} - k\right) + \tilde{s} & when\ \tilde{k} > k \\ F \times (1 - \chi)\left(\tilde{k} - k\right) + \tilde{s} & when\ \tilde{k} < k \end{cases}$$

$$\frac{\tilde{s}}{1 + r} \geq \left(F\tilde{k}\right) \times \Lambda$$

$$r = \begin{cases} r_{secure} & \tilde{s} < 0 \\ r_{saving} & \tilde{s} \geq 0 \end{cases}$$

This model applies an uncertainty mechanism to the farmer's strategic decision-making concerning buying or selling the farm. Under this mechanism, farmers are reluctant to change from their current farm size until there is enough lifetime utility gain to stimulate those behaviors. The probability of changing a farm size from k to $\tilde{k}$ is decided by a multinomial distribution: $Pr[n = 1; \mathrm{P}(\tilde{k}_1), \mathrm{P}(\tilde{k}_2), \mathrm{P}(\tilde{k}_3), \dots, \mathrm{P}(\tilde{k}_m)]$. Mathematically, each farmer has m possible mutually exclusive farm size choices, with corresponding probabilities $\mathrm{P}(\tilde{k}_i)$ and just one trial. The corresponding probability is dependent on the utilities of other farm size increases compared with the utility of the current farm size. If the value function of the current farm size is higher than any other value function, then farmers will retain their farm size without buying or selling.

$$when\ V_k^F(s) \geq \mathrm{W}_k^{\tilde{k}_i}(s)\ \forall i, \qquad \mathrm{P}(\tilde{k}_i) = \begin{cases} 1, & \tilde{k}_i = k \\ 0, & otherwise \end{cases} \tag{10}$$

$$otherwise \qquad \mathrm{P}(\tilde{k}_i) \propto \max\left[0, \mathrm{W}_k^{\tilde{k}_i}(s) - V_k^F(s)\right]$$

b. Strategic Default

The farmers can allow foreclosure on their farm by stopping payment on their farmland loan at the beginning of the period. Because the farmland loans are usually semiannual or annual, the farmland will be foreclosed on at the end of the period. Therefore, farmers can use the free farmland for a year after they decide to default. The lifetime utility of the farm default is given by:

$$W_k^{defaut}(s) = \max_c\{u(c) + \beta V^U(\check{s}, j = 1)\} \tag{11}$$

subject to

$$c = s + \mathrm{E}_{t-1} y_t$$

$$s' \geq Fk\Lambda.$$

$$\check{s} = \max(0, s')$$

During this period, farmers can consume all their net income and raise their loan up to their borrowing limit ($Fk\Lambda$). After the farm foreclosure, the total loan will be discharged and their balance in the next period ($\check{s}$) will be equal to or higher than 0. When $W_k^{defaut}(s) > \mathrm{W}_k^{\tilde{k}}(s)$, the farmer will choose to default on their farms.

SOLVING THE MODEL

Because these value functions (3) and (6) in the Bellman Equations do not have closed-form solutions, they have to be solved numerically using dynamic programming in the MATALB platform (Aruoba and Fernández-Villaverde, 2015).

For the non-farmer value function, $V^N(s_t)$ is a function that depends on the net ending asset balance. The asset domain from –b to 1 is divided into 513 equally spaced grid points; then, a linear interpolation[2] was used to represent the value function (Garin, 2015). Given the farm size, the farmer's value function $V_k^F(s_t, A_{t-1})$ is a function that depends on both net asset balance and last period productivity. The asset domain from $-1.3k$ to $\min(200, 3k)$ is divided into 513 equally spaced grid points; the productivity domain from 0.5 to 2 is divided into 21 equally spaced grid points. This setting was proven to be effective and time efficient through the trial-and-error optimization. Then a two dimensional linear interpolation was used to represent the value function

The simple procedure to find a solution would be the following:

Step 1: Make an initial guess regarding the form of the value function V_0,

Step 2: Update the value of V iteratively using a single-variable function minimization algorithm which is based on the golden section search and parabolic interpolation[3]. The value at all grid points is independently updated in each iteration; then linear interpolation of the updated grid is used to approximate the V_{t+1}

$$V_{t+1}(\mathrm{s}) = \max_{\mathrm{s}'} \mathrm{F}[V_t]$$

Step 3: When it reaches convergence $V_{T+1} \approx V_T$, then the iteration is finished and the problem is solved.

CALIBRATION

Farm Land

The national average of farm real estate values from 2006 to 2015 is presented in Figure 2. Since 2010, the real estate value has been trending from 2000 up to 3000 dollars

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[2] The results do not change significantly when spline interpolation is used. Studies have shown that spline interpolation does not necessarily preserve concavity.

[3] $fminbnd$ function in MATLAB R2015 is a platform that is used to implement this optimization. To reduce the total time, the farmer's value function was solved by the multi-thread computation resource at the Georgia Advanced Computing Resource Center

per acre. As a base case, the farmland value in the model is set as $2200 per acre. As described above, the farm size (k) is normalized to 1 unit of U.S. median household income. The median household income in the 2013 Consumer Finance Survey was $46,700 per year. Therefore, 1 unit of k in the model represents ${}^{46700}/_{2200} = 21.23$ acre

The farm size distribution in the United States is given in Figure 1. It is rather clear that there is a large number of farms smaller than 100 acres. Owners of these small farms are typically called hobby farmers. Because this study is intended to help understand the farmland default behavior of farming households, small hobby farmers are usually not in the credit market and very large farms are not family-owned operations. For these reasons, only farms which are larger than 100 acres and smaller than 10,000 acres will be considered.

Because the USDA census provides only the interval data, the distribution of farm size can be estimated by assuming the underlying truncated distribution function. Through visual observation, the truncated log-normal function is selected to model the farm size distribution. The maximum likelihood method was used to estimate the log-normal distribution. The farm size in acre is presented as $21.23 \times k$, given 1 unit of k in the model represents 21.23 acre area. The farm size follows a Log normal distribution in equation (12).

$$21.23 \times k \sim lnN(3.1567, 2.229), \quad given\ 21.23 \times k \in [100, +\infty) \qquad \textbf{(12)}$$

Production Function

To simplify this problem, I assumed that the farming production function exhibits constant return to scales. Thus, $\gamma_k + \gamma_n + \gamma_x = 1$ and these three output elasticities are equal to their input shares, respectively. The Multifactor Productivity Table of Crop & Animal Production, which is provided by the Bureau of Labor Statistics, gives factor shares of capital, labor, and intermediate inputs. The average factor shares of capital, labor, and intermediate inputs from 2004 to 2013 are 0.3784, 0.118, and 0.5036, respectively.

Every farmer is subject to uninsurable idiosyncratic productivity shocks. In this study, productivity was designed to follow a stochastic process:

$$A_{l,t} = \widetilde{A_{l,t}} \times A$$
$$\ln \widetilde{A_{l,t}} = \lambda \ln \widetilde{A_{l,t-1}} + \epsilon_t \quad where\ \epsilon_t \sim N(0, \sigma) \quad \textbf{(13)}$$

Firstly, the productivity of each farmer in each period can be decomposed into two components. One is a constant productivity base case value A which is identical across time and agents; the other one is a shock component $\widetilde{A_{l,t}}$ whose average is 1. Therefore, the expectation of current period productivity at the beginning of the period is:

$$\mathrm{E}_{t-1}\left(A_{l,t}\right) = \mathrm{E}_{t-1}\left(\widetilde{A_{l,t}}\right) \times A = \exp(\lambda \ln \widetilde{A_{l,t-1}}) \times A \quad \textbf{(14)}$$

Given the farm size and price of labor and intermediate inputs, total net farm income (excluding interest payment) is a function of the productivity in this model. Therefore, the base case productivity value A is calibrated using the national data of average net agricultural income per farm in the 2012 USDA census. As shown in Figure 3, when A is calibrated to 0.83, the model output matches that census data in every farm size level. This idiosyncratic productivity stochastic process of $\widetilde{A_{l,t}}$ should be estimated using farm level yield data. Because we lack farm level production data, the county level survey data from the National Agricultural Statistics Service (NASS) was used to calibrate this stochastic process. In order to make the data homogenous and comparable, a total of 105 counties was selected from 10 states which produce the most corn in the United States. Their corn yields (Bu/Acre) from 1960 to 2014 were used to estimate the stochastic process. For time series yield data in every county, the productivity is defined by:

$$\tilde{A}_{county,t} \equiv \frac{\overline{yield}_{county,t}}{\overline{yield}_{state,t}} \quad \textbf{(15)}$$

As a result, the λ and σ were estimated as 0.5859 and 0.1564.

Preference

Weber and Key (2014) provided strong evidence to show that the wealth gain from the land appreciation can motivate farmers to purchase additional land. According to another work of Weber and Key (2015), the increases in wealth from farmland appreciation accompanied substantial increases of collateral-based lending supporting land acquisition. However, farmers make their production and land use decisions independent of the price of land. Therefore, it is clear that the farmer's land purchase behavior is not only from increased net income but also from wealth accumulation. Most farmers use their farmland equity as pension funds for future retirement. Thus, we employ an isoelastic flow utility function based on the Magill and Quinzii (2015) framework that is modified to account for farmers:

$$u(c,k,F) = \frac{c^{1-\alpha}-1}{1-\alpha} + \delta \frac{(\mathrm{Fk})^{1-\ddot{\alpha}}-1}{1-\ddot{\alpha}}\, I(own) \quad \textbf{(16)}$$

Here, $I(own)$ is an indicator variable which equals one if the agent owns a farm in a current period and zero otherwise. α and $\ddot{\alpha}$ are constant relative risk aversion parameter for consumption and farm wealth, respectively. Abdulkadri and Langemeier (2000) estimated that the coefficient of relative risk aversion ranged from 2.849 to 6.329.

For households producing both crops and livestock, their mean coefficients equal 2.849. In this study, the constant relative risk aversion α is set to 3, which also is standard in most consumer studies (Lopes, 2008; Wang and Miranda, 2015). $\ddot{\alpha}$ can only be internally calibrated in the simulation. More importantly, δ is the relative desirability of farm wealth. Agents in our economy have heterogeneous desirability of farm wealth. Apparently, δ must be a positive random value for each agent. For each agent in this study, δ is a positive random value that follows a truncated normal distribution in the equation (17).

$$\delta \sim N(0, \theta) \; given \; \delta \in [0, +\infty) \tag{17}$$

Financial Intermediary

The interest rate of unsecured credit debt (r_{credit}) and saving (r_{saving}) is set based on recent empirical averages ($r_{credit} = 12\%$ and $r_{saving} = 1\%$). The Federal Reserve Bank of Kansas City published three types of agricultural interest rate quarterly in their agricultural credit survey. Agricultural Resource Management Survey (ARMS) reports farmer's total liability and interest payment in the balance and income statement, respectively. The gross national average agricultural interest rate can be easily calculated. As shown in Figure 4, the interest rate in the agricultural credit survey is higher than the calculated interest rate in ARMS. It is reasonable, because sometimes farmers enjoy the very low interest rate when they purchase agricultural machinery and buy farmland from parents. Overall, the interest rate in the recent 5 years is lower than the historical value, because after the last recession, The Federal Reserve has kept their fed funds rate close to 0 to stimulate the economy. Because we want to model and predict default risk under the current economy, the secured farmland debt interest rate (r_{secure}) is calibrated to 5%. The

2009 Survey of Consumer Finance reported that the median credit limit per family on all credit cards combined is about $18,000, which is about 39% of the median family income. The credit limit of non-farmers (b) was set as 0.39. We set the credit exclusionary period as $\tau = 7$ in the base case, corresponding to the current average 7 years without access to the credit market as punishment for a credit default. Strictly speaking, filing for bankruptcy should not affect the credit score, but in practical terms, the credit reporting agencies are allowed to report bankruptcy history for up to 10 years. After the short survey of an auctioneer, the sale value in foreclosure (ϕ) and non-foreclosure cases (χ) are all at a 6% discount.

According to the standard in the practice, the average length of a farmland loan (ι) was set as $30yr$ and the required Loan-to-Asset ratio (Λ) was set as 90%. Farmers on average worked for 50 years; thus, the out of farm probability is calibrated as 0.02. The bequest motive η is set by 0 for simplicity.

Internal Parameter Calibration

The parameters whose values have been set so far are either fairly standard in the literature or can be estimated directly or indirectly from the data. I estimate the remaining structural parameter: discount factor (β), Standard deviation of truncated normal distribution of farm wealth desirability (θ), and Constant relative risk aversion for land wealth ($\ddot{\alpha}$) by minimizing the distance between empirical farm size distribution and model output. The farm size domain was divided into 24 non-equally spaced levels. As shown in Figure 5, the calibrated log-normal empirical farm distribution was discretized into these 24 levels. Then, farm size distribution in the model simulation was used to internally calibrate the above three parameters. The lower future discount means that the household is willing to lower current consumption for farmland investment. I estimate a value for $\beta = 0.96$, which is actually in the standard range. The values $\ddot{\alpha} = 0.8$ and $\theta = 0.02$ mainly shape the distribution of farm size in the simulation. A higher θ value and smaller $\ddot{\alpha}$ value will increase the farm desirability, while the change of $\ddot{\alpha}$ has a heavier effect on the desirability of big farms. After tuning these three parameters, the model output (Figure 5) matches the empirical data in the regions of both big farms (upper figure) and small farm (lower figure).

Another parameter social stigma of bankruptcy Θ is internally calibrated to match the long-run farmland loan default rate data in the United States. A steady state simulation is conducted under the constant prices of farmland, agricultural commodity, and intermediate input. Brewer et al. (2012) estimated that the probabilities of default for USDA ARMS farms from 1996 to 2010 ranged from 1% to 2%. Federal Reserve Bank of Kansas city published quarterly national and regional agricultural finance data in Ag Finance Databook. The average percentage of nonperforming farm real estate is 1.5% from 1991 to 2014. In this study, the base case default rate is reasonably set as 1.4~1.5%. To match this base case default rate target, the one period social stigma utility loss is estimated to be -0.2.

BASE CASE MODEL RESULTS

To estimate the model's solution given stochastic shocks, 1,000,000 representative agents were simulated until reaching a steady state and then for 200 periods afterwards. The average of 1,000,000 Monte Carlo experiments resulted in economic paths and aggregate distribution.

The average characteristics of farmers in different farm sizes are shown in Figure 6. As can been seen, the larger farmer has a relatively higher relative desirability of farm wealth, longer operation years, and higher productivity. However, these three factors do not equally affect every farm. Due to this budget constraint of smaller farms (under 1000 acres), the operation years and productivity is the leading causes of an increase in farm size. Farm size increase is a relatively slow process of wealth accumulation, and farmers with higher productivity can accumulate their equity quicker. Whereas it seems that big farmers are not subject to budget constraints, their propensity of farm increase is mostly coming from their business ambition. The decomposed default rate is also presented in Figure 6. The default rate in the smallest farm size level is high, because all beginning farms are in this farm size level. In this model, all non-farmers are only allowed to purchase land and to be farmers with the smallest farm size. Besides this, the overall trend of default rate increases with an increase in farm size. Previous literature provided evidence to support this finding (Brewer et al., 2012). Because a farmer's indebtedness is the important factor for strategic default behavior, the prevailing explanation is that the larger farmer has a higher Loan-to-Asset ratio in the current economy.

To fully understand the indebtedness of farmers and its relationship with farm size, the farmer's LTV value is regressed on some characteristics (Table 2). The farmers with higher relative desirability of farm wealth will have a higher propensity to purchase more land and enlarge their farm size. Therefore they tend to have higher indebtedness. The indebtedness is also negatively correlated with age and productivity, and the interaction effects of age and farm size are more significant in the smaller size farm. Compared with a bigger farm, the small farm's indebtedness is more dependent on the years of operation and the wealth accumulation, which is consistent with the wealth accumulation assumption above. Conditional on age (37 years), the average Loan-to-Asset Ratio in different farm sizes is presented in Figure 7. Obviously, the indebtedness of a large farmer is higher than that of small farmers. The LTV ratios are strictly monotonically increasing from 0.492 at a farm size of 100 acres to 0.675 at a farm size of 1,317 acres. Based on multiple comparison results of the general linear regression, LTVs of farms which are larger than 1,371 acres weakly monotonically increase with the farm size. It is noteworthy that the farm with 10,000 acres is an outlier, because a farmer with 10,000 acres cannot purchase more land but rather accumulate equity. As it is described in the last section, only farms which are larger than 100 acres and smaller than 10,000 acres will be considered.

The logistic regression results for the farmer defaults are found in Table 3. We find that most of the attributes identified in previous studies are significant with the expected signs. LTV and consumption on assets are positively correlated with default probability and higher income, and desirability of farm wealth significantly helps farmers keep their farms. The coefficients of farm size variables indicate that the larger farms are more willing to default than smaller farms, conditional on all other attributes. According to the assumption of this model, farmers can use the free farmland for a year after they decide to default. Therefore, bigger farms have more incentive to default because of this benefit. Another explanation is off-farm incomes. In the 1980s’ agricultural credit crisis, a small farmer’s off-farm income proved to be an effective substitute for weak farm earnings. However, the coefficient of LTV is almost 10 times bigger than that of the farm size. A deeper indebtedness is still the leading explanation of big farmers' strategic defaults.

DYNAMIC SIMULATION EXPERIMENTS

After calibrating the model to match the long-run features of the U.S. farm real estate loan default data, dynamic simulation experiences were also conducted to study the agricultural commodity price shock and farmland price shock.

Agricultural Commodity Price

The food price index increased from 80 in the beginning of this century up to around 180 in 2013. The PPI adjusted price increased more than 60% percent. However, since 2014, the food price has slid all the way down to 134 in February 2016. In this economy, we are interested in whether this boom-bust commodity price path will affect farmers' strategic default decisions. Also, predictions of farm real estate default rates for any future agricultural commodity price move are also very interesting for both bankers and the government. Instead of setting a constant price, paths of agricultural commodity prices are given in Figure 8. For all experiments, the prices increase from 1 to 1.6 in the four periods, which represent the price booming period in the last decade.

In the first column of Figure 8, there are price drops in three periods from the peak to the valley at five different levels (1, 0.9, 0.8, 0.7 and 0.6) and then back to 1, the base price level. During the high price period, the default rate declined to 0.5%. The elevated sales prices increased farmers' business and generated profit; in turn, this helped them pay off the loans. From the figure, we can see there is one period lag between the default peak and the price valley. This result is not surprising, because it is totally sensible that farmers would sell their products at the market price at the end of each period and default in the end of the next period. In reality, this lag can be longer, because banks tend to postpone some foreclosures on less troublesome loans to later years, because it is very costly to have many foreclosures in a short period of time[4]. It is easily found in the figure that the severity of a default explosion is strongly correlated with the lowest price level. If the commodity prices just drop back to the base level, there is no obvious bust of defaults, but the default rate rises to 1.85% before coming back to the normal level (1.4%). If the price drops below the base level, the peak of default will be observed at one period after the price valley. When the price drops to 90%, 80%, 70% and 60% of the base level, the default rate peaks at 1.93%, 3.31%, 4.27% and 7.79%, respectively. These sale price discounts make the farm operation very unprofitable or even cause it to lose money. Farmers cannot afford the annual payment and find the farming business unattractive; both reasons give rise to a peak in the default rate. Learning from this observation, it is very critical to keep the agricultural commodity price stable during this price adjustment period. Instead of letting the market volatility draw the price deep into a low level, if the government and organization can help to make it a soft landing to the long-run average level, a credit crisis in the financial section can be avoided.

In the second column of Figure 8, commodity prices in the four experiments stay at a low price level (0.8) for a different number of periods. According to this observation, the severity of the defaults not only depends on the lowest price levels, but also depends on the length of this state. Low agricultural sale prices have a negative impact on

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[4] In the farm crisis of the 1980s, the USDA's index of prices received by farmers for their crops fell 37% between 1981 and 1987. The default of real estate loans peaked in 1990 (Peoples et al., 1992).

farmers' incomes, and this negative income impact will accumulate across periods. The longer the economy stays in a low price level, the higher the chance that farmers become poor and are more likely to default. As shown in the figure, the economy, which stays in P=0.8 for 4 periods, faces the highest default peak and the longest effect. During the extended low price period, the subsidies and cash transfer might be effective for preventing a great credit crisis, because the farmers' profit loss can be alleviated.

To future understand the effect of commodity price on different farmers, the decomposed default rates of different farmers are presented in Table 4. In the first period of low commodity price, the default rate of whole population is still lower than that in normal state. The default rate of whole population peaked one year after the end of low commodity price periods. At the peak, the big farmers and young farmer has the highest default rate, 17.65% and 10.48% respectively. However, the default rate of median farmers increased about 8 times from 1.82% in the normal state to 14.20% at the peak. The default rate of middle age farmers increased about 20 times from 0.50% in the normal state to 9.86% at the peak. Therefore the median farmer and middle age farmer is the most sensitive to the commodity price shock. That is because that the smallest and youngest farmers' usually have large proportion of off-farm income. As descripted earlier, this off-farm income can help farm household make ends meet during the period of weak farm earnings. On the other side, older farmer are wealthier and bigger farmer might pay off loan by selling their land.

Farmland Price

From 2011 to 2015, the farmland price has increased from $2,178 to $3,020 per acre. Recently, farmland price started to slide down. It is interesting to study whether the farmland price is a major factor of the farm default. The economy experiment of three different farmland price shocks is found in Figure 9. All of the farmland prices increase from a base level (1) up to a high price level (1.6), then drop to three different price levels (1.2, 1 and 0.8). According to these results, the severity of the defaults not only depends on the commodity price, but also depends on the farmland price. In the period of farmland prices being high, there are very few beginning farmers, because they cannot afford the purchase price. The older farmers are very unlikely to default, because they enjoy a high capital gain. As described by Peoples et al. (1992), timing is the most important factor in making successful farmers. Farmers who bought the land in the late 1960 had accumulated wealth during the farmland booming period. The farmers who had "miss the train" were not able to afford the farmland. During the good time in this simulation experiment, the default rate is as low as 0.32% when the farmland price goes up to 1.6. The decomposed default rate in this valley is presented in the last column of Table 5. The older and median farmers have nearly 0% default rate. The default rate of big farmers is about 18 times less than that in the normal state. On the contrary, the default rate of young and small farmers is only half less. In short, owning more land before the farmland price booming brings more capital gain and discourages loan default. This finding is aligned with the facts in the agricultural expansion in 1970s.

However, when the farmland price starts to be adjusted to a lower level after the booming, there have been more and more beginning farmers because of this affordable price. When the farmland price has dropped to 1.2, the default rate goes up to a higher level gradually without significant peaks. If the farmland price drops back to 1 (the base case) and 0.8, the peak of default rises up to 3% and 5.69%. During the period when the farmland price is booming, all land owners have more and more credit, due to the increasing land property value. Instead of choosing default, the farmers of poor performance can lived by borrowing more debt or obtaining capital gain. When the farmland booming stops, the decreasing land price drives their loan underwater and incurs more strategic default. In Table 5, the decomposed default rates of farmers of different scales and ages at peak are all 4~5 times higher than those in the normal case. The bigger farmers are slightly more sensitive to this farmland shock and their default rates are as high as 18.78% at peak. The young farmers react to the farmland price drop more quickly than other farmers and their default rates are as high as 13.27% at peak.

According to the observation in the second panel of Figure 9, the long-term aggregate default rate under the higher farmland price is lower than that under the lower one. It is opposite to the short-term observation, but it tells an intuitive story. If the farmland price is low in the long run, all farmers pay lower cost of capital and are more likely to survive. As shown in the third panel of Figure 9, there are less new farmers under the price 1.2 in the long run compared to that in the base case, since this price is still higher than 1 - the base case price.

CONCLUSIONS

This paper provides a structural study on the impacts of the agricultural commodity price and the farmland price on farmland loan default in the recent United States. The result of the dynamic experiment on agricultural commodity price shocks suggests that the lower commodity price and the longer low price period will cause severer aggregate farmland loan default. The impact of the farmland price on default is more complex. In the short run, high farmland price will hold back beginning farmers but make existing farmers wealthier, and then the default rate will become low. In the long run, a higher farmland price means more capital cost and a thinner profit margin, and then the default rate will become higher. After serval periods of elevated farmland price, a plummeting price will follow an aggregate default peak. Given future expectations of lower commodity prices and lower farmland prices, agricultural banks should expect an increase in default rate. A short period cash transfer and a policy for market price stabilization will help alleviate the possible future credit crisis.

Table 1 The Calibrated Base Case Parameters

Parameter	Value	Description	Source
α	3	Constant relative risk aversion	Abdulkadri and Langemeier (2000)
$\ddot{\alpha}$	0.8	Constant relative risk aversion for land wealth	Internal Calibration
β	0.96	Discount factor	Internal Calibration
γ_k	0.3784	Output elasticities of capital	Bureau of Labor Statistics
γ_n	0.118	Output elasticities of labor	Bureau of Labor Statistics
γ_x	0.5036	Output elasticities of intermediate inputs	Bureau of Labor Statistics
η	0	Bequest motive	(Low, 2015)
θ	0.02	Standard deviation of truncated normal distribution of farm wealth desirability	Internal Calibration
ι	30	length of farmland loan	Rule of Thumb
λ	0.5859	Parameter of productivity stochastic process	NASS survey
σ	0.1564	Parameter of productivity stochastic process	NASS survey
τ	7	Credit exclusionary period	Rule of Thumb
ϕ	0.06	Foreclosure value discount	Survey of Auctioneer
χ	0.06	None-foreclosure value discount	Survey of Auctioneer
ω	0.02	Out of farm probability	Rule of Thumb
Θ	-0.2	Social stigma of farm bankruptcy	Internal Calibration
Λ	0.9	Required Loan-to-Asset value	Rule of Thumb
A	0.9	Base case productivity	2012 USDA Census
b	0.39	Credit limit of non-farmer	2009 Survey of Consumer Finance
r_{credit}	12%	The interest rate of unsecured credit debt	Market Quote
r_{saving}	1%	The interest rate of saving	Market Quote
r_{secure}	4%	secured farmland debt interest rate	ARMS

Table 2 Parameter Estimate from the Loan-to-Asset Ratio Linear Regression

Parameter	Estimate	t Value	p value
Intercept	0.685	116.92	<.0001
Productivity	-0.108	-60.83	<.0001
Relative desirability of farm wealth	0.225	185.55	<.0001
Age	-3.82E-03	-64.6	<.0001
Age*size 100	-9.90E-03	-117.49	<.0001
Age*size 200	-7.06E-03	-97.58	<.0001
Age*size 317	-4.92E-03	-71.7	<.0001
Age*size 433	-3.89E-03	-58.2	<.0001
Age*size 583	-3.29E-03	-48.43	<.0001
Age*size 733	-2.68E-03	-39.13	<.0001
Age*size 900	-2.45E-03	-35.13	<.0001
Age*size 1100	-2.11E-03	-29.53	<.0001
Age*size 1317	-1.85E-03	-25.16	<.0001
Age*size 1550	-1.49E-03	-19.88	<.0001
Age*size 1817	-1.34E-03	-17.28	<.0001
Age*size 2117	-9.61E-04	-12.06	<.0001
Age*size 2450	-9.10E-04	-10.94	<.0001
Age*size 2833	-6.88E-04	-7.85	<.0001
Age*size 3250	-7.36E-04	-7.8	<.0001
Age*size 3717	-2.81E-04	-2.86	0.004
Age*size 4233	-2.63E-04	-2.47	0.014
Age*size 4800	-1.48E-04	-1.3	0.193
Age*size 5450	-9.10E-05	-0.75	0.453
Age*size 6183	-5.63E-05	-0.42	0.671
Age*size 6983	-1.76E-05	-0.12	0.905
Age*size 7883	1.68E-04	1.07	0.284
Age*size 8883	5.91E-04	3.66	0.000

Note: only part of the result is presented in this table.

Table 3 Parameter Estimate from Logit Model of Default in Base Case

Parameter	Estimate	SE	Wald χ^2	Pr > ChiSq
Intercept	-31.22	0.41	5782.97	<.0001
LTV	32.15	0.41	6223.30	<.0001
Age	1.65E-03	7.74E-04	4.54	0.033
Income On Asset	-16.27	0.61	702.92	<.0001
Relative Desirability of Farm Wealth	-3.31	0.06	3576.78	<.0001
Consumption On Asset	50.44	1.51	1112.37	<.0001
Size 200	-7.83	0.36	480.05	<.0001
Size 317	-5.46	0.21	683.46	<.0001
Size 433	-5.98	0.36	269.38	<.0001
Size 583	-1.46	0.06	527.91	<.0001
Size 733	-1.02	0.06	245.31	<.0001
Size 900	-0.69	0.07	109.76	<.0001
Size 1100	-0.29	0.07	19.73	<.0001
Size 1317	0.01	0.07	0.04	0.8498
Size 1550	0.47	0.07	44.72	<.0001
Size 1817	0.79	0.07	121.94	<.0001
Size 2117	1.06	0.07	203.16	<.0001
Size 2450	1.22	0.08	236.69	<.0001
Size 2833	1.46	0.09	289.08	<.0001
Size 3250	1.75	0.09	378.00	<.0001
Size 3717	1.73	0.10	274.32	<.0001
Size 4233	2.11	0.10	409.62	<.0001
Size 4800	2.52	0.10	575.65	<.0001
Size 5450	2.63	0.11	542.94	<.0001
Size 6183	2.60	0.12	446.29	<.0001
Size 6983	2.89	0.13	524.52	<.0001
Size 7883	2.39	0.15	254.40	<.0001
Size 8883	3.06	0.12	613.92	<.0001
Size 10000	3.64	0.09	1670.42	<.0001

Note: Farm size 100 acre is set as baseline.

Table 4 The Decomposed Default Rate during agricultural commodity Price Shock

	Normal	Peak Period of Default Rate					
		Period 1	Period 2	Period 3	Period 4	Post-Period 1	Post-Period 2
Commodity Price	1.	0.80	0.80	0.80	0.80	1.00	1.00
Whole Population	1.43%	1.14%	3.21%	4.63%	7.62%	8.67%	6.74%
Small Farm (Farm Size<600 Acre)	1.19%	0.81%	2.71%	3.66%	5.06%	5.68%	3.86%
Median Farm (600≤Farm Size<5000Acre)	1.82%	1.48%	3.91%	5.77%	11.89%	14.20%	13.11%
Big Farm (Farm Size≥5000Acre)	3.52%	3.24%	4.44%	9.33%	13.64%	17.65%	15.99%
Young Farmer (Age of Farm<10)	3.32%	1.66%	5.80%	7.82%	10.23%	10.48%	5.30%
Middle Age Farmer (10 ≤ Age of Farm<30)	0.50%	0.82%	2.48%	3.70%	8.27%	9.86%	8.36%
Old Farmer (30 ≤Age of Farm<60)	1.16%	1.08%	1.96%	3.62%	6.15%	7.74%	7.43%
Multi-generation Farm (Age of Farm≥60)	0.97%	0.71%	0.95%	1.70%	2.83%	3.57%	4.24%

Table 5 The Decomposed Default Rate during Farmland Price Shock (dropped from 1.6 to 0.8)

	Normal	Pre-peak	Peak	Post-peak	Valley
Whole Population	1.41%	2.01%	5.69%	3.46%	0.32%
Small Farm (Farm Size<600 Acre)	1.19%	1.97%	4.79%	1.93%	0.34%
Median Farm (600≤Farm Size<5000 Acre)	1.88%	1.89%	7.73%	7.04%	0.01%
Big Farm (Farm Size≥5000 Acre)	3.44%	5.16%	18.78%	11.95%	0.19%
Young Farmer (Age of Farm<10)	3.26%	12.53%	13.27%	3.78%	1.57%
Middle Age Farmer (10 ≤Age of Farm<30)	0.52%	0.41%	1.99%	2.10%	0.21%
Old Farmer (30 ≤Age of Farm<60)	1.15%	0.48%	4.62%	4.72%	0.01%
Multi-generation Farm (Age of Farm≥60)	0.94%	0.91%	3.97%	4.28%	0.02%

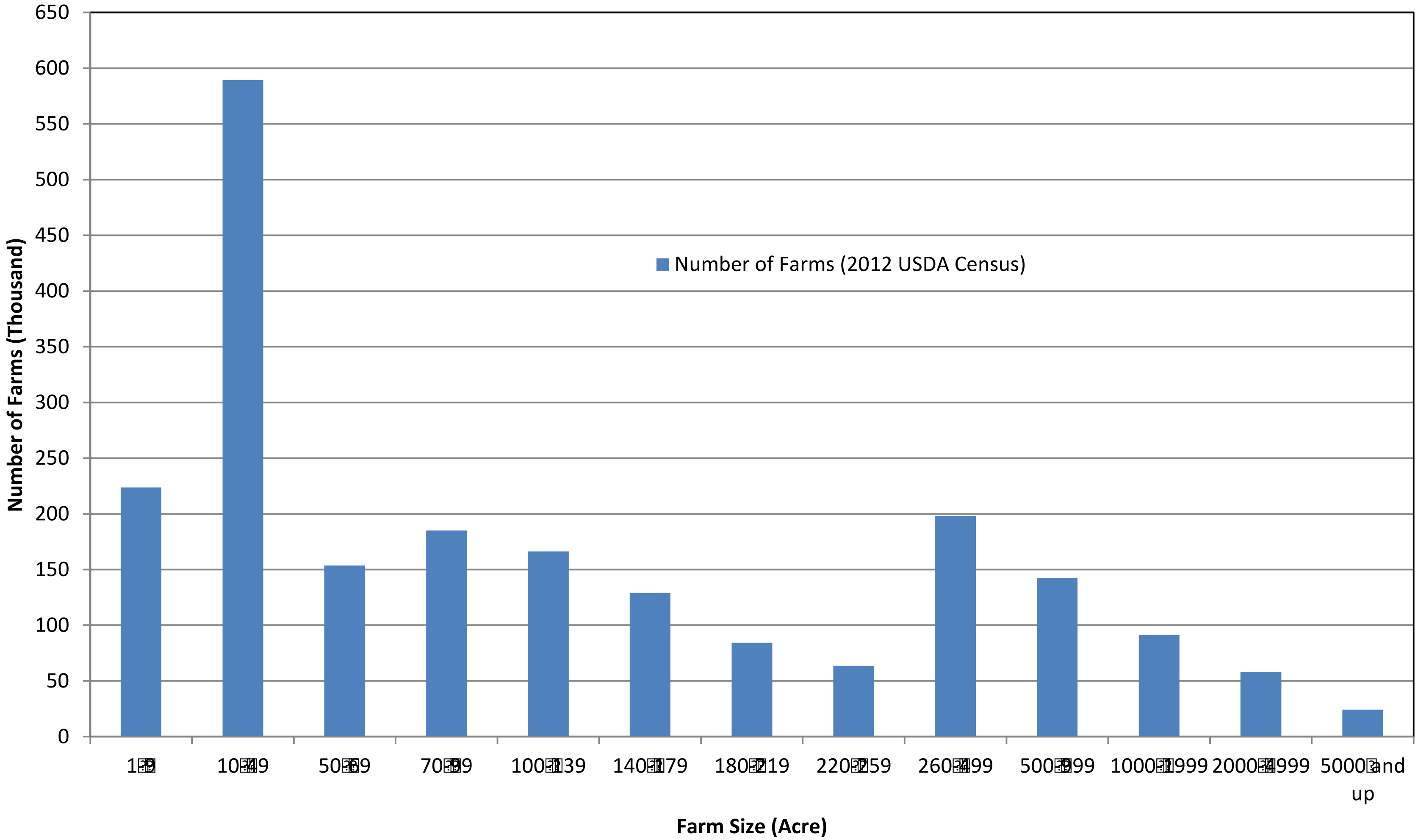


Figure 1 The size distribution of U.S. farms, 2012 USDA census

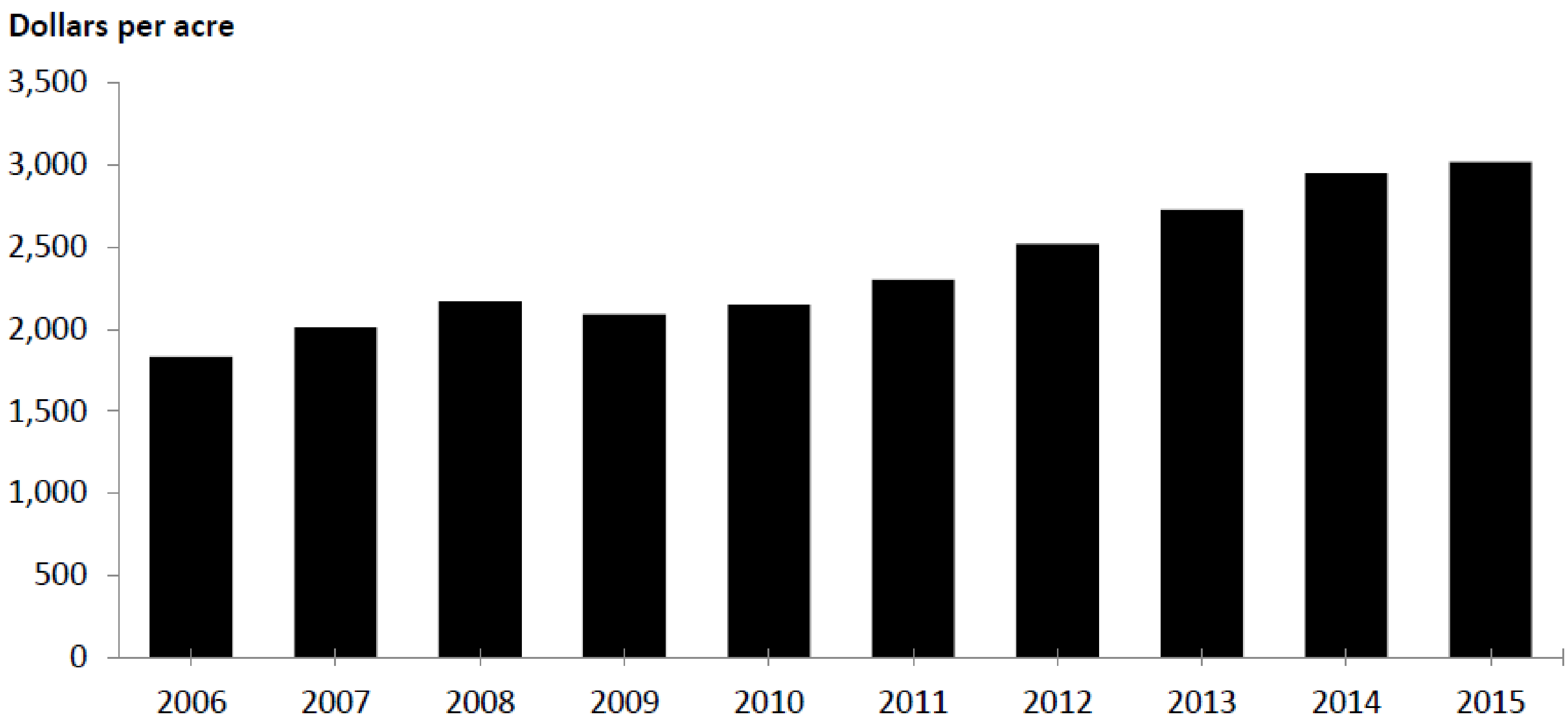


Figure 2 Average Farm Real Estate Value in the United States (USDA NASS 2015)

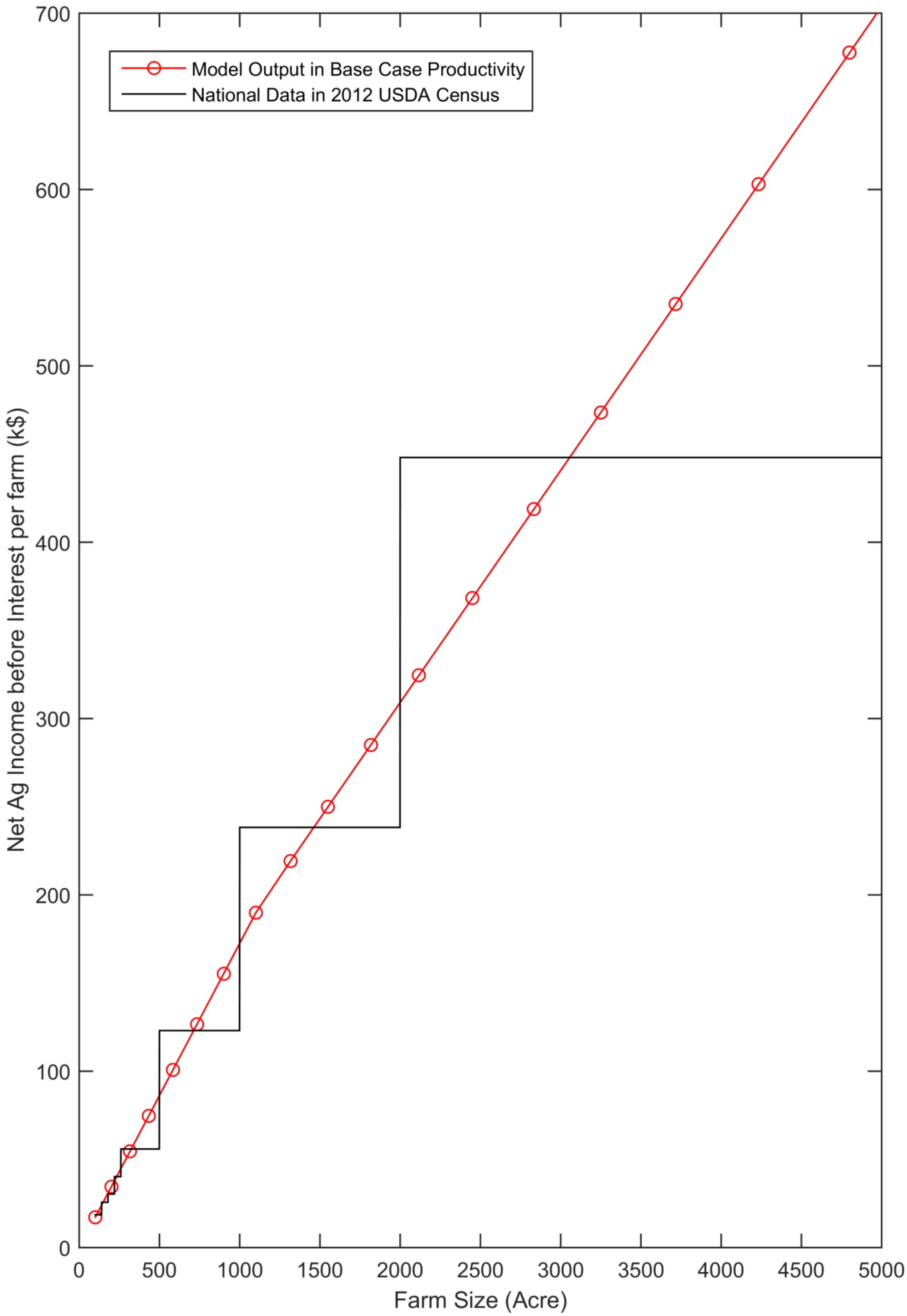
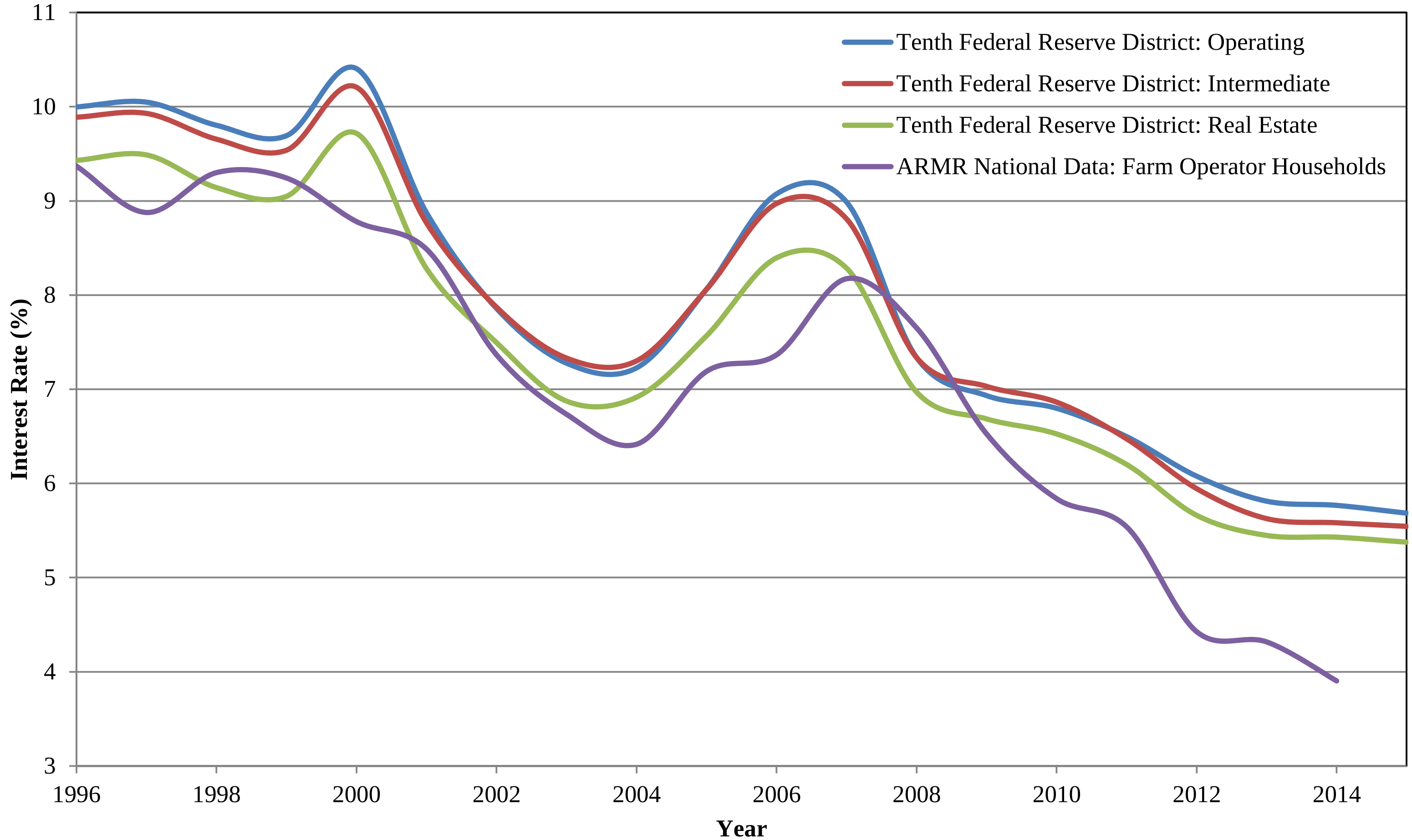
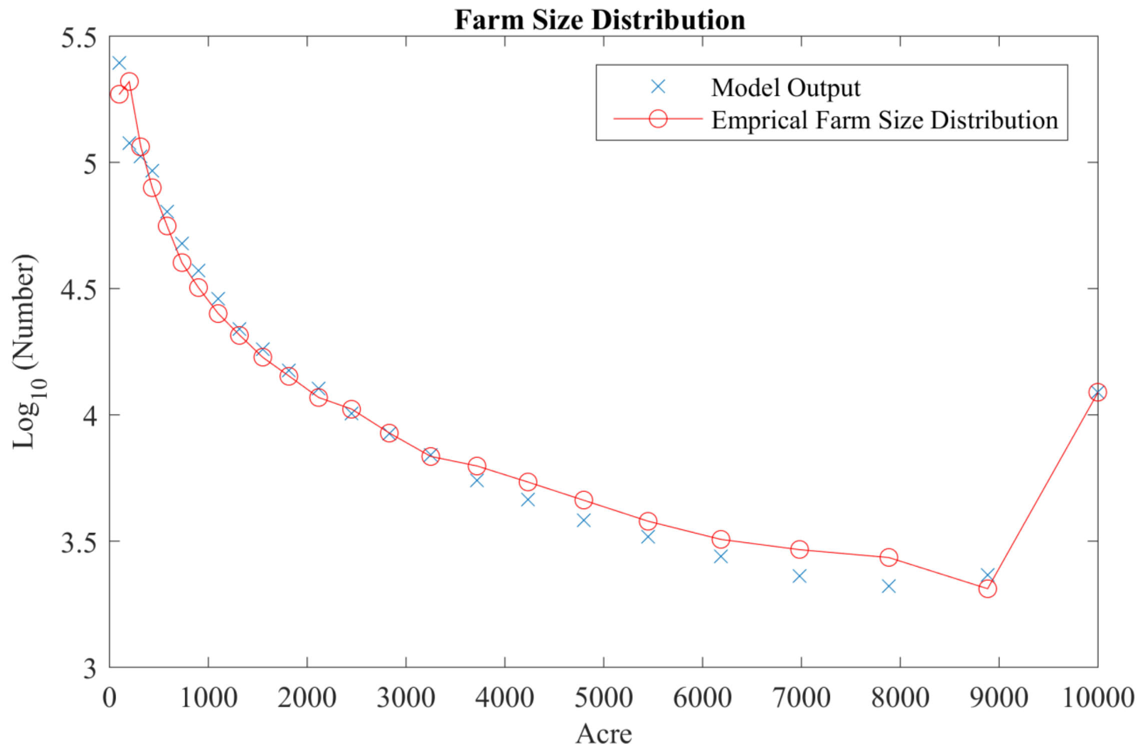


Figure 3 The Calibration of Productivity Based on Net Ag Income per Farm



Source: FRB of Kansas City-Quarterly Agricultural Credit Survey (http://www.kansascityfed.org/research/indicatorsdata/agcredit/)
Agricultural Resource Management Survey (ARMS) : $total\ liability/total\ interest\ payment$farm operator households

Figure 4The agricultural loan interest rates



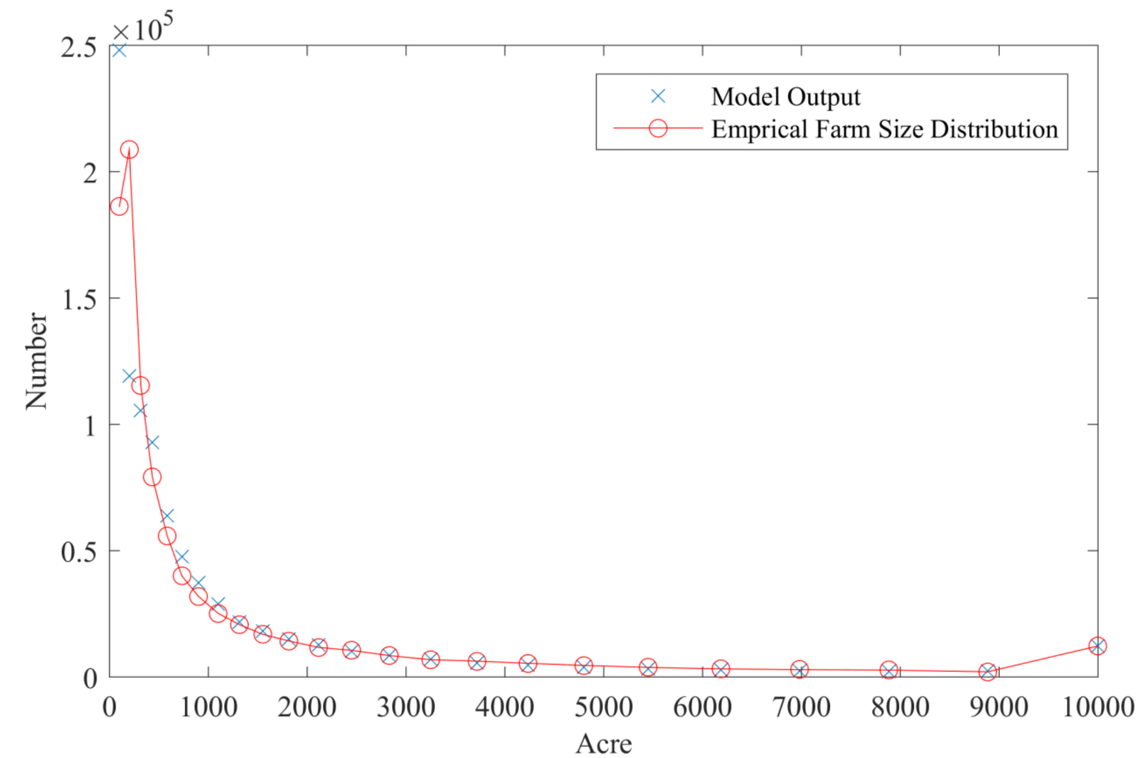


Figure 5 The Farm Size Distribution Calibration

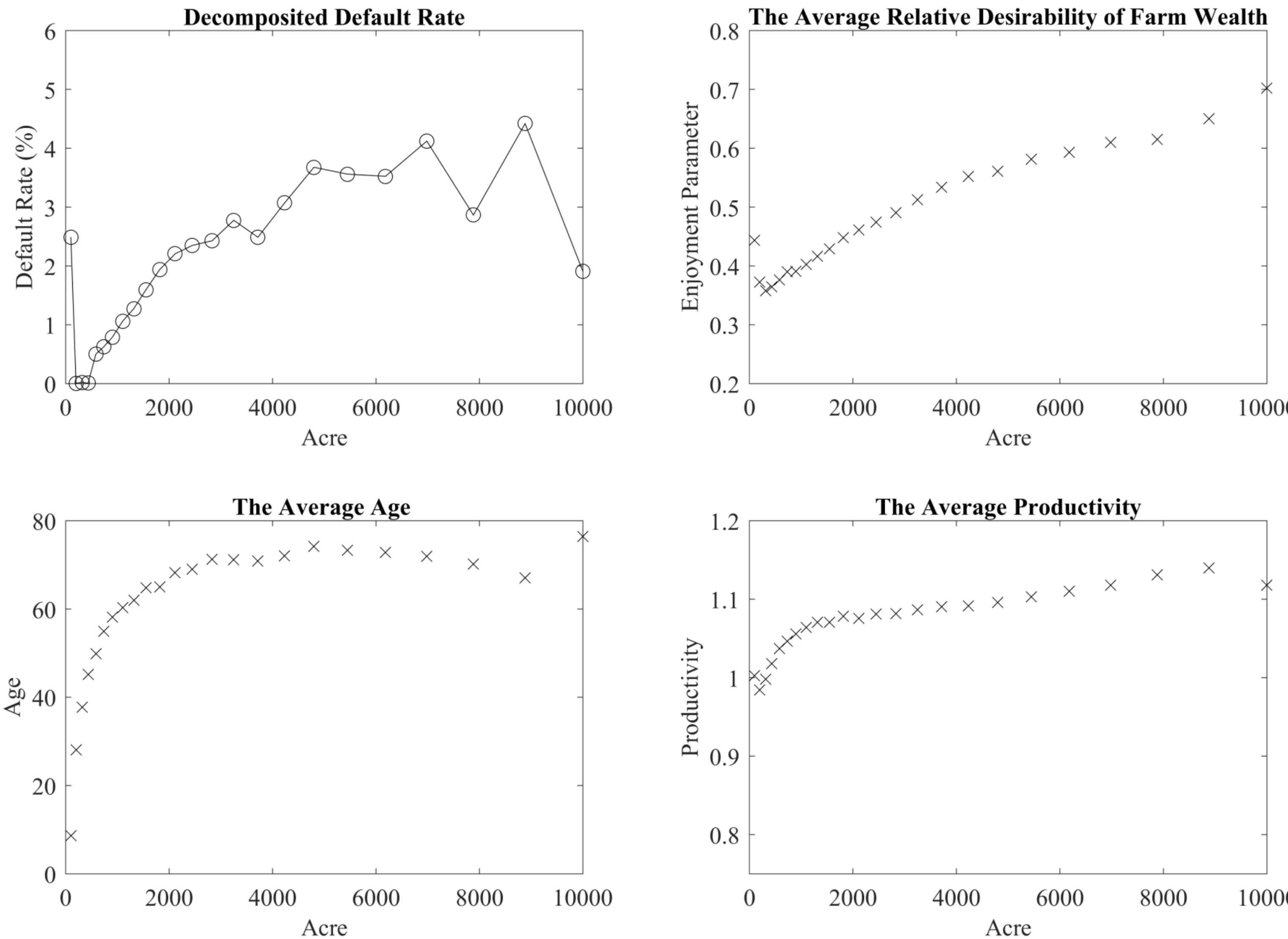


Figure 6 The Average Characteristics of Farms in Different Size Level

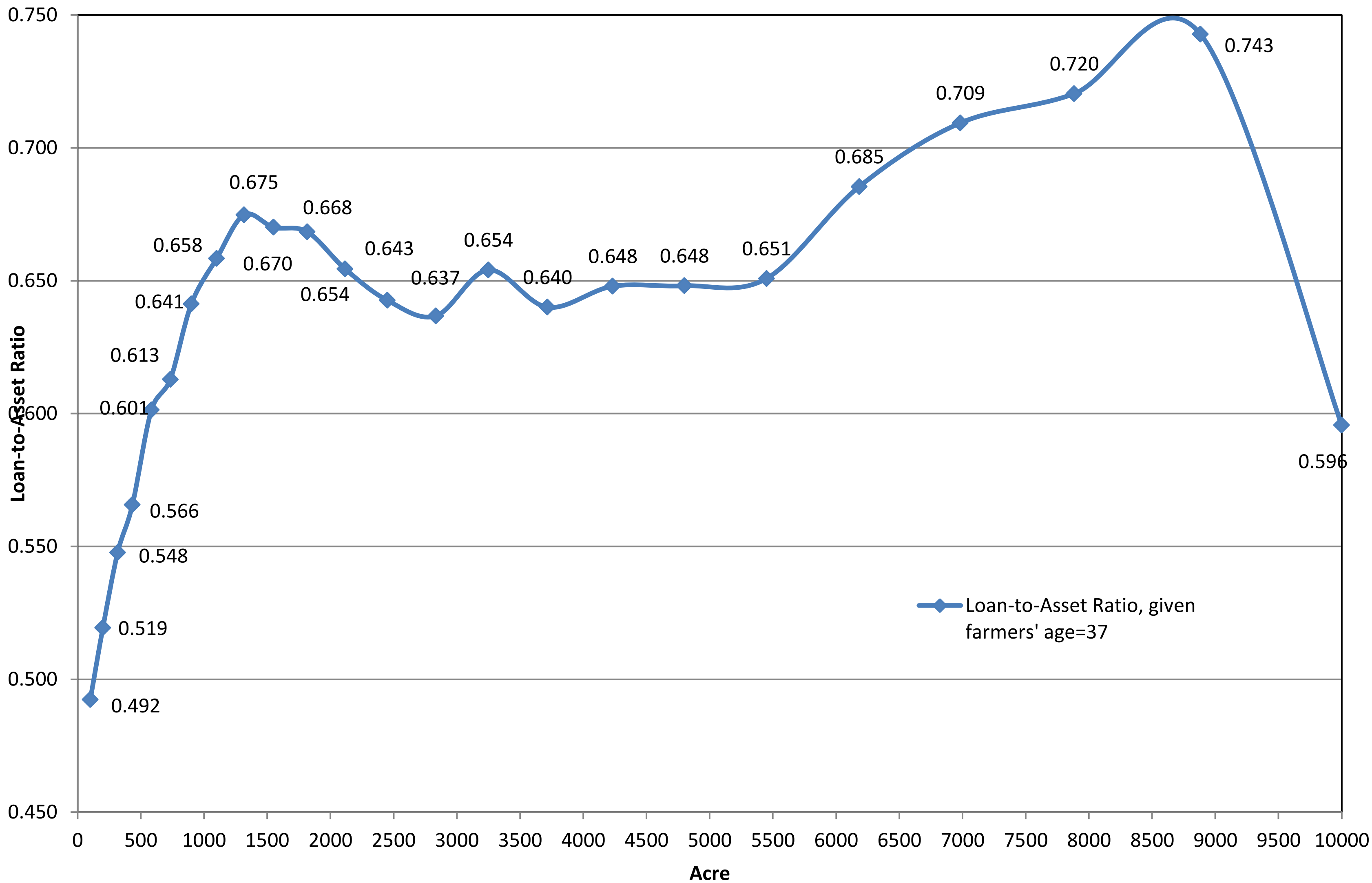


Figure 7 The Conditional Average Loan-to-Asset ratio, given Farmer's Age is 37 (The average age in this economy).

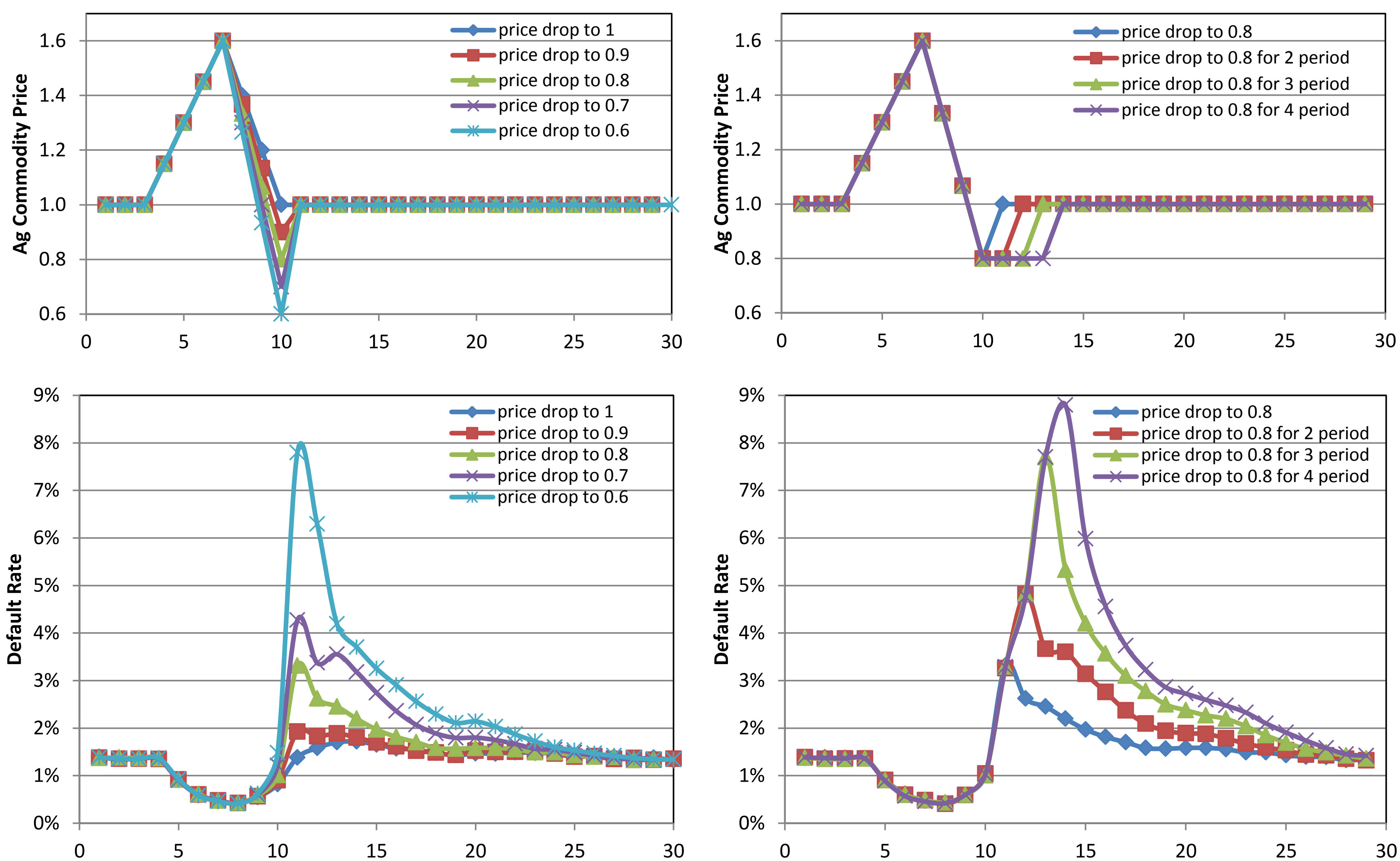


Figure 8 Dynamic Default Rate of Farmland Loan with Different Ag Commodity Price Shock

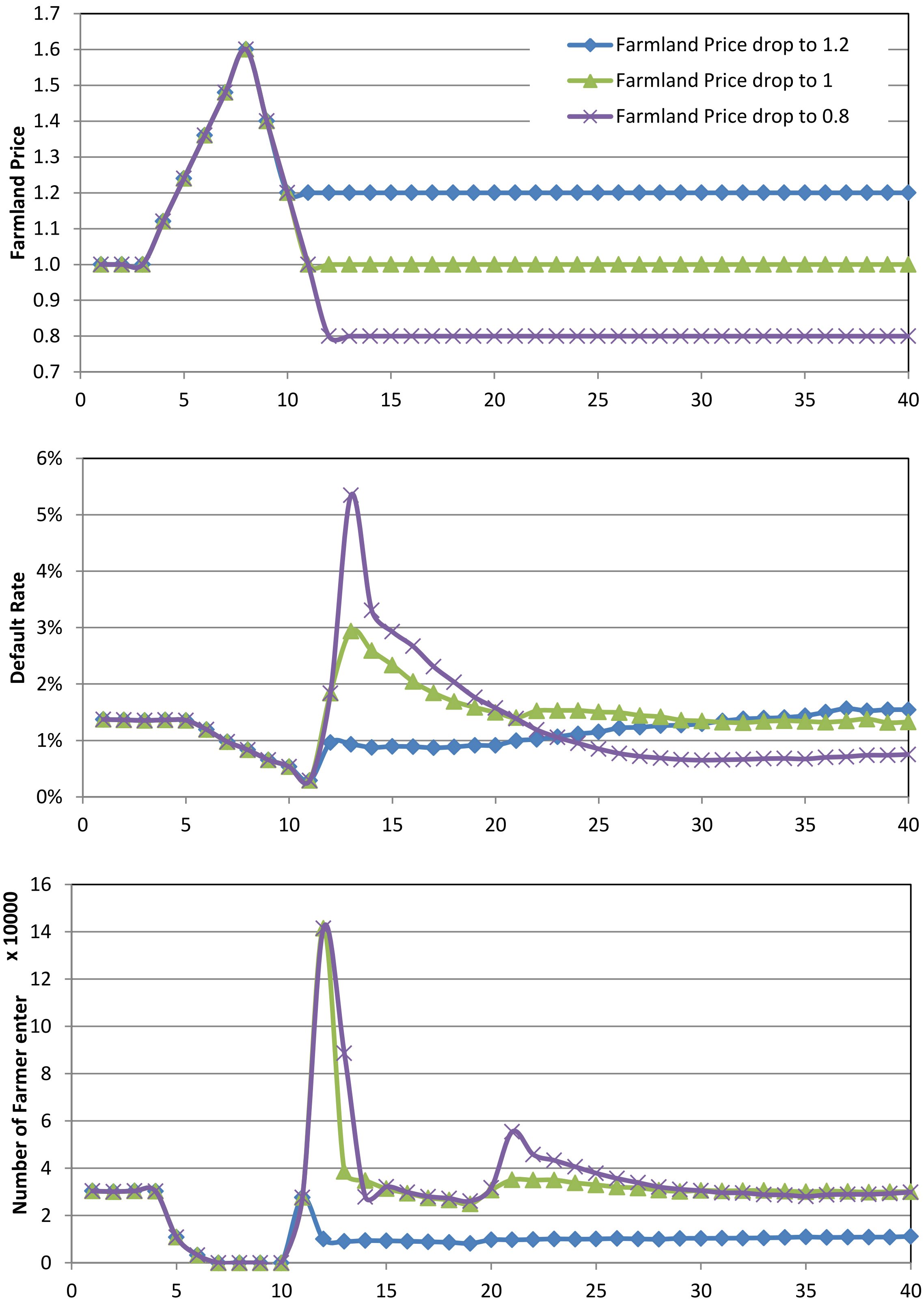


Figure 9 Dynamic Default Rate of Farmland Loan with Different Farmland Price Shock

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