DYNAMIC HETEROGENEOUS AGENT MODELS OF DEFAULT ON RESIDENTIAL HOUSING MORTGAGES AND FARM REAL ESTATE LOANS

by

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(Under the Direction of Jeffrey H. Dorfman)

ABSTRACT

The first chapter of the dissertation examines two possible approaches to reducing residential mortgage default using a dynamic model of heterogeneous infinitely-lived agents acting optimally subject to uninsurable idiosyncratic earnings shocks and systemic house price shocks. We find higher down payments are very effective in minimizing residential mortgage foreclosures, even in periods of house price declines and recessions. In contrast, the length of the credit exclusionary period for people who experience bankruptcy or foreclosure has a much smaller impact on mortgage defaults. It suggests that a major aspect of credit scores and credit policy is non-productive and punitive, harming people in return for little societal gain.

The second chapter of the dissertation assesses the impacts of agricultural commodity prices and the price of farmland on farmland loan default in the United States. This study solved a dynamic model of a family-owned farm that can purchase farmland with a farmland loan or sell its farmland and must simultaneously decide how much to consume in each period. We find that lower agricultural commodity prices and, a longer period of low prices will cause severer a higher level of farmland loan defaults. Meanwhile, the impact of farmland prices on default is more complex. In the short run, high farmland prices hold back beginning farmers but make the existing farmers wealthier, leading to a low default rate. In the long run, higher farmland prices increase the capital requirement of farming result in a thinner profit margin, and then the default rate will become higher. The dynamic simulation experiment tells a compelling story. After several 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. The study also suggests that a short period of cash transfer and a policy for market price stabilization will help alleviate the possibility of a future credit crisis.

INDEX WORDS: Foreclosures, Bankruptcy, Down payment, Home prices, Farmland Price, Agricultural Commodity Price

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A Dissertation Submitted to the Graduate Faculty of the University of Georgia in

Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2017

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May 2017

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my advisor, Dr. Jeffrey H. Dorfman, who offered me not only the best academic advice but also the most patient mentorship. Every day in the past years, I feel so grateful to have you in my life, the best mentor one can ask for. We discuss not only technical problems in the dissertation but also the difficult question in my future career and the economic phenomena in the world. You set an excellent example that I want to make myself be: a scholar with wisdom, a teacher with patience and a father with love.

I would also like to thank my committee members, Dr. Cesar Escalante and Dr. Brady E. Brewer, without whose help this work cannot be smoothly finished. Dr. Cesar Escalante has been offered lots valuable and insightful advice to me ever since I know him. Dr. Brady E. Brewer is such a kind professor who is always ready to help others, and thanks for your help on the paper we work together. I also want to say thank you to Laura Clark, Greg Timmons and Katherine Klimt from UGA writing center who provide precious proofreading on my dissertation.

Thank you to all of my family for their support in everything I do. To my loving parents, Ning Wu and Rong Hua. Thank you for teaching me to work hard. To my wife and my best friend, Xiaojie He. Thank you for your unconditional love and encouragement.

Finally, the utmost thanks to God Father in heaven. I am so grateful that Lord revealed himself to me more and more. God sanctified all great difficulties I met and all serious mistakes I made, and then "cause all things to work together for good to those

who love God" (Roman 8:28). "Even though I walk through the darkest valley, I will fear no evil, for you are with me; your rod and your staff, they comfort me" (Psalms 23:4). All glory of my dissertation was from God and should be for God.

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CHAPTER 1

A DYNAMIC HETEROGENEOUS AGENT MODEL OF RESIDENTIAL MORTGAGE DEFAULT DURING REAL ESTATE MARKET BOOM-BUST CYCLES

1.1 INTRODUCTION

During the Great Recession of 2008, GDP contracted by 5.1%, and the national unemployment rate jumped from 4.7% in November 2007 to 10% in October 2009. This devastating economic recession was closely related to a nationwide banking emergency, which was mainly precipitated by the subprime mortgage crisis. The U.S. banking system suffered a substantial number of both mortgage foreclosures and household bankruptcies due to the housing downturn of the late 2000s. For example, in 2010 alone there were more than 1 million houses that went into foreclosure and 1.5 million households filed for bankruptcy (Mitman, 2015). The tremendous devastation of the subprime mortgage crisis highlights the importance of understanding the household incentives on mortgage foreclosure and bankruptcy during a house price bust period. This paper studies these two default behaviors using a new heterogeneous agent model of rational utility-maximizing households. We solve a dynamic model of a household who can purchase a house with a mortgage and must decide how much to consume and borrow from credit cards in each period. Under uninsurable idiosyncratic earnings shocks and systemic house price shocks, homeowners have two channels for default: file for bankruptcy or go into mortgage foreclosure. Understanding the linkage and interaction between these two default behaviors is crucial for explaining the observed aggregate empirical data and evaluating the possible policies to prevent future "mortgage crisis".

Our model can dynamically simulate household behavior from 1985 to 2014 given the historical data on economic conditions and house prices. The aggregate mortgage charge-off rate from the simulation can be compared with the empirical evidence to understand the foreclosure mechanism dynamically during the recent aggregate house price drop and the high unemployment rate. Then this structural model can be used to quantitatively understand how factors, such as down payment ratio and the credit exclusionary period, affect default behaviors. A growing literature in macroeconomics investigates the problem of mortgage foreclosure in a general equilibrium setting in which interest rates are determined endogenously of (Jeske et al., 2013). Because the interest rate is not within the scope of this study, we fixed their values to the average empirical observation. We begin with the framework developed by Wang and Miranda (2015) to study strategic credit card default and modify it by introducing housing, mortgage, and bankruptcy elements to study mortgage default.

The remainder of the paper is structured as follows. In part 1.2, I review the existing related literature. In part 1.3, I provide the theoretical structure of our model. A brief description of the computational method for solving is given in part 1.4. The model is calibrated to empirical data in part 1.5. The evaluation of the model by comparing it to empirical data is given in part 1.6. The result of the steady state simulation and sensitivity analysis is discussed in part 1.7. In part 1.8, we discuss the results of policy experiments under conditions similar to the recent real estate market collapse. Finally, Part 1.9 concludes the paper.

1.2 RELATED LITERATURE

The prior studies use two mainstream competing theories to understand mortgage default behavior.

In some early studies (Deng et al., 2000; Kau et al., 1994), models are structured based on option theory, in which the default option will be exercised if it is deeply in the money. This traditional “strategic default” theory assumes that borrowers default on their mortgage to maximize their financial gains, even though they still have enough liquidity to pay the mortgage. According to this theory, negative home equity is a necessary but not sufficient condition for default; rather there exists a threshold level which, the homeowner will go into foreclosure when his home equity drops below.

The other strand of literature believes that foreclosure behavior is triggered not only by negative home equity but also by other factors. This is referred to as the “double trigger” theory. This theory is well accepted among mortgage scholars. Campbell and Cocco (2015) argue that both negative home equity and a household liquidity constraint “double trigger” mortgage foreclosures. Low (2015) points out that more than 80% of mortgage defaulters were above water in the 1998 and 2001 SCF data, so the default behavior is not only caused by income shocks and negative home equity. He provides evidence that many defaults are also driven by the family size factor and divorce in his lifecycle cash in advance model. In contrast, Laufer (2013) argues that the foreclosure homeowners might have extracted their home equities through cash-out refinancing, second mortgages and home equity lines of credit which are not tracked in commonly used mortgage data. It has also been debated whether a change in policy towards more recourse leads to an aggregate lower mortgage foreclosure rate (Corbae and Quintin, 2015; Garin, 2015; Laufer, 2013; Quintin, 2012). Related papers include Chatterjee and Eyigungor (2015), who studied the effect of the tax code and inflation rate on mortgage foreclosures. Jeske et al. (2011), who study the effect of the mortgage interest rate subsidy on foreclosure rate. Corbae and Quintin (2015) directly investigated the effect of low-downpayment on the rise of foreclosure rate in the late 1990s. However, their model abstracts from unsecured debt and bankruptcy and are primarily based mortgage loan. For the first time, Mitman (2015) jointly analyzed foreclosure and bankruptcy with a one-period mortgage and unsecured debt. However, most of his analysis is discussed in the context of a steady state house price, not a period of house price decline. Agents are exposed to only idiosyncratic house price shocks, and there is no aggregate house price shock. Despite the enormous contribution to the mortgage foreclosure study, his discussion may not be able to explain the cause of the mortgage crisis directly.

In addition to the studies of structural models, existing empirical studies provide a discussion of more factors which might change homeowners' propensity to default on mortgages. Guiso et al. (2013) claimed that the cost of a strategical default is driven by both pecuniary and nonpecuniary factors, such as view about morality, fairness and bank regulation. Using loan-level data, Zhu and Pace (2011) tests the impact of foreclosure duration on default behavior.

1.3 THE MODEL ECONOMY

The main elements of this model are set up as follows. Time is modeled discretely and indexed by t=0, 1, 2, etc. The economy is comprised of infinitely-lived agents facing both exogenous employment uncertainty and house price shocks in each period.

1.3.1 Representative Agents

At the end of each period, all households possess a net saving s, with $s < 0$ indicating carrying debt and $s > 0$ indicating liquid saving. Every household has access to unsecured debt and can borrow up to a certain credit limit b. If the household is at an employed state, $i = 1$, it will receive normalized income $\overline{y} = 1$; if at an unemployed state, $i = 0$, it will receive an unemployment benefit $\underline{y} < 1$.

Those households without house ownership are called renters ($k = 0$). Renters can choose to buy a house, declare bankruptcy, or continue renting. As mentioned earlier, agents are exposed to a house market price shock (H). In a different time period, they may purchase a house at different prices (h). To simplify, all agents can only purchase one house and must finance the housing purchase with a 30 year fixed rate mortgage. Also, neither early mortgage payoff nor refinance are allowed. Therefore, for 30 years after the housing purchase, the household will have an installment payment obligation, during which it is referred to as homeowner ($0 = k \leq 30$). In each period, this homeowner can choose to declare bankruptcy, default on the mortgage, shortsale the house, or continue paying the mortgage. All unsecured debt will be discharged in the bankruptcy, but the household will immediately be flagged as an unworthy one which will be barred from borrowing for some years (τ) as penalty. After non-recourse mortgage foreclosure, all unworthy agents will also be barred from buying a house for τ years.

After 30 years, those who own a house and are finished with mortgage payments are called homeowners with no mortgages ($k > 30$). In the following year, they will have a certain probability to sell the house at market value due to death resulting in a change in the household head. Though the households, as families, have infinite life in this model, their houses are not assumed to be inherited by the next generation.

1.3.2 Value Function and Budget Constraints

The household 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 budget constraint.

1.3.2.1 Worthy Renter

Consider the problem of renters who do not own a house. Their value function is denoted by V^R:

$$V^R(s, i, j = 0) = \max_c \left\{ u(c) + \beta \sum_{i'} p_{i,i'} V^R(s', i', j' = 0) \right\} \qquad \textbf{(1.1)}$$

subject to

$$\frac{s'}{1+r} + c + \xi \widehat{H} = s + y(i)$$

$$s' \geq -b$$

$$r = \begin{cases} r_b & s' < 0 \\ r_s & s' \geq 0 \end{cases}.$$

Note that s is the end of period net asset, i is the employment state, and j is used to denote how many years a foreclosure or bankruptcy agent has been in an unworthy state. Here s', i', 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_b and r_s are the borrowing and saving interest rate. In the value function, $u(x)$ is the utility function with constant relative risk aversion (α), which is a twice continuously differentiable function of current consumption, with $u' > 0$, $u'' > 0$, $u'(0) = \infty$. $\xi\widehat{H}$ is the annual rent cost which is proportional with the underlying value of housing ($\widehat{H}$).

Most importantly, the annual income $y(i)$ is a function of the employment state in both a recession and the normal economy. In this setting, ex ante homogenous households are all facing the ex post heterogeneous income shock from the employment states. The employment state of each household independently and stochastically follows a two states discrete time Markov chain. The transition probability matrix of this Markov chain is a function depending on the underling economy.

$$\wp(econ) = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}$$

$p_{i,i'}$ is the probability that the agent's employment state will be i' in the next period, given the employment state is i in the current period.

1.3.2.2 Unworthy Renter

After filing for bankruptcy, a renter will be excluded from the credit market and mortgage market for τ years with an unworthy flag ($j > 0$). His value function is denoted by $V^{R,B}$.

$$V^{R,B}(s,i,j) = \max_{c}\left\{u(c) + \beta \sum_{i'} p_{i,i'} V^{R,B}(s',i',j+1)\right\} \quad \forall j \in \{1,2,3,4,5,\dots,\tau-1\} \tag{1.2}$$

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

$$V^{R,B}(s,i,j=\tau) = \max_{c}\left\{u(c) + \beta \sum_{i'} p_{i,i'} V^{R}(s',i',j'=0)\right\} \tag{1.3}$$

subject to

$$\frac{s'}{1+r_s} + c + \xi\widehat{H} = s + y(i)$$

$$s' \geq 0.$$

1.3.2.3 Worthy Homeowner with No Mortgage

Now, consider the problem of homeowners who have paid off their mortgages. They will live in their own houses until the shock of forced sale. Denote the value function by V_k^h $(k > 30)$:

$$V_k^h(s, i, j = 0)$$

$$= \max_c \left\{ u(c) + \beta \left[\omega\eta \sum_{H'} q_{H,H'} u\big((1-\chi)H' + s' + y(i)\big) + (1+\omega) \sum_{i'} p_{i,i'} \, V_{k+1}^h(s', i', j' = 0) \right] \right\}$$

$$\forall k > 30 \,, \forall j \in \{1,2,3,4,5, \dots, \Gamma - 1\,\}$$

(1.4)

subject to

$$\frac{s'}{1+r} + c + \kappa\widehat{H} = s + y(i)$$

$$s' \geq -(1+\mathrm{r})b.$$

Here, H and H' are house market prices in the current and next period. In this model, the agent's house price state follows the nine states discrete time Markov chain, whose transition probability matrix $\mathbb{Q}$ is empirically calibrated to the historical house prices. The price values in each state are a certain percentage higher or lower than the underlying value of housing ($\widehat{H}$). Thus $q_{H,H'}$ represents the probability of the next period house market price at H', given the current market price is H. The benefit of homeownership is the avoidance of rental costs, but this ownership also incurs an extra annual maintenance cost $\kappa\widehat{H}$. In each period, homeowners with no mortgages are forced to sell their house 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 house incurs a proportional cost $\chi H'$.

1.3.2.4 Bankrupt Unworthy Homeowner with No Mortgage

Similarly to the unworthy renter, after filing for bankruptcy, homeowners with no mortgage will also be excluded from the credit market for τ years with an unworthy flag, $j > 0$. The value function is denoted by $V^{h,B}$.

$$V_k^{h,B}(s,i,j)$$
$$= \max_c \left\{ u(c) + \beta \left[\omega\theta \sum_{H'} q_{H,H'} u\big((1-\phi)H' + s' + y(i)\big) + (1+\omega) \sum_{i'} p_{i,i'} \, V_{k+1}^{h,B}(s', i', j+1) \right] \right\}$$
$$\forall k > 30, \forall j \in \{1,2,3,4,5, \dots, \tau - 1\}$$

(1.5)

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

$$V_k^{h,B}(s,i,j=\tau)$$
$$= \max_c \left\{ u(c) + \beta \left[\omega\theta \sum_{H'} q_{H,H'} u\big((1-\phi)H' + s' + y(i)\big) + (1+\omega) \sum_{i'} p_{i,i'} \, V_{k+1}^{h}(s', i', j'=0) \right] \right\}$$
$$\forall k > 30$$

(1.6)

subject to

$$\frac{s'}{1+r_S} + c + \kappa \widehat{H} = s + y(i)$$

$$s' \geq 0.$$

1.3.2.5 Worthy Homeowner

Now, let us consider once more the problem of homeowners who live in their own home but have not paid off their mortgages. Denote their value functions by V_k^h $(0 < k \leq 30)$

$$V_k^h(s,i,j=0) = \max_c \left\{ u(c) + \beta \sum_{i'} p_{i,i'} \, V_{k+1}^h(s',i',j'=0) \right\} \quad \textbf{(1.7)}$$

$$\forall\, 0 < k \leq 30$$

subject to

$$\frac{s'}{1+r} + c + \kappa\widehat{H} + \Psi(h,D,r_m) \ = s + y(i)$$

$$s' \geq -(1+r)b.$$

In addition to paying annual maintenance cost $\kappa\widehat{H}$, if homeowners want to keep their house, they have the obligation of the annual mortgage installment payment $\Psi(h,D,r_m)$. Upon making a mortgage loan for the home purchase, the lender requires all borrowers to make a downpayment, which is expressed as a percentage (D) of the house value. Besides this downpayment ratio, the annual mortgage installment payment is also dependent on the house price when purchased (h) and the mortgage interest rate (r_m). It is noteworthy that the mortgage interest is actually compounded by the month:

$$\Psi(h,D,r_m) = 12 \times \frac{h(1-D) \times {}^{r_m}/_{12}}{1 - \left(\frac{1}{1+{}^{r_m}/_{12}}\right)^{30\times 12}}. \quad \textbf{(1.8)}$$

1.3.2.6 Bankrupt Unworthy Homeowner

The homeowner will be excluded from borrowing unsecured debt after filing for bankruptcy. If the bankruptcy trustee does not sell his house, the unworthy homeowner will keep paying the mortgage until the end of the repayment plan. The value function is denoted by $V_k^{h,B}$ $(0 < k \leq 30)$

$$V_k^{h,B}(s,i,j) = \max_c \ \left\{ u(c) + \beta \sum_{i'} p_{i,i'} \, V_{k+1}^{h,B}(s',i',j+1) \right\} \quad \textbf{(1.9)}$$

$$\forall\, 0 < k \leq 30, \forall j \in \{1,2,3,4,5,\dots,\tau-1\,\}$$

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

$$V_k^{h,B}(s,i,j=\tau) = \max_c \left\{ u(c) + \beta \sum_{i'} p_{i,i'} \, V_{k+1}^{h}(s',i',j'=0) \right\} \quad \forall\, 0 < k \leq 30 \tag{1.10}$$

subject to

$$\frac{s'}{1+r} + c + \kappa\widehat{H} + \Psi(h,D,r_m) \;= s + y(i)$$

$$s' \geq 0.$$

1.3.2.7 Foreclosed Unworthy Renter

The renter, who has a history of foreclosure within the last τ years, is not allowed to buy a house nor get a new mortgage. In other words, if a homeowner defaults on his non-recourse mortgage loan he will be barred from the mortgage market for τ years. Meanwhile, this renter cannot accumulate more unsecured debt, which means he has to use his current income to pay his interest expense and consumption in each period. The value function is denoted by $V^{R,F}$.

$$V^{R,F}(s,i,j) = \max_c \left\{ u(c) + \beta \sum_{i'} p_{i,i'} V^{R,F}(s',i',j+1) \right\} \quad \forall j \in \{1,2,3,4,5,\dots,\tau-1\} \tag{1.11}$$

When $j = \tau$, the agent will be automatically return to a worthy state in the next period and solve

$$V^{R,F}(s,i,j=\tau) = \max_c \left\{ u(c) + \beta \sum_{i'} p_{i,i'} V^{R}(s',i',j'=0) \right\} \tag{1.12}$$

subject to

$$\frac{s'}{1+r_s} + c + \xi\widehat{H} = s + y(i)$$

$$s' \geq min(0\,,s).$$

1.3.3 Strategic Decision and Structure of Uncertainty

1.3.3.1 The Strategic Decision of the Worthy Renter

The worthy renter has three options. First, he can continue to be worthy, the value function of which is V^h in the equation (1.1). Secondly, the renter can also buy a house by obtaining the mortgage. Although this decision would be made at the beginning of each period, because the time it takes to find a house, buy it, and obtain a mortgage is lengthy, the house is assumed to be purchased at the end of the period (Figure 1.1); Therefore, in that period he is liable for both the mortgage downpayment and one period rent. In the beginning of the next period, this renter will become a first year homeowner. His lifetime utility value if he decided to buy the house is denoted by $W^{R,buy}$.

$$\mathrm{W}^{R,buy}(s,i,j=0)=\max_{c}\left\{u(c)+\beta\sum_{i'}p_{i,i'}\,V_{k=1}^{h}(s',i',j'=0)\right\} \qquad \textbf{(1.13)}$$

subject to

$$\frac{s'}{1+r}+c+\xi\widehat{H}+DH=s+y(i)$$

$$s'\geq -b.$$

Finally, when a worthy renter is trapped deeply in debt, he can also declare bankruptcy. In this model, it is assumed that all households can only file bankruptcy under Chapter 7, primarily because bankruptcy filing under chapter 7 far exceeds any other type of filing. Specifically, in 2012 the number of Chapter 7 bankruptcy filing accounted for 69.12% of the total number of personal bankruptcy filings. According to Chapter 7, there is no reason for households to save money or repay the debt during the bankruptcy filing period because they expect the unsecured debt to be discharged at the beginning of the next period. As a matter of fact, it is assumed that they will spend as much as they can and begin with a zero balance in the next period. To avoid being accused of fraud, renters are assumed not to accumulate their debt by more than σ in that period. The value of parameter σ is calibrated internally by this model. The value function if bankruptcy is chosen is given by

$$W^{R,bankrupcy}(s,i,j=0) = u(c) + \Theta + \beta \sum_{i'} p_{i,i'} V^{R,B}(s'=0,i',j=1) \qquad \textbf{(1.14)}$$

subject to

$$c + \xi \widehat{H} = max(s,0) + y(i) + min(\sigma, b+s).$$

Here in the equation, bankruptcy behavior incurs a pure utility loss, referred to as social stigma Θ.

1.3.3.2 Strategic Decision of the Worthy Homeowner with Mortgage

The worthy homeowner has four options: (1) stay worthy, (2) declare bankruptcy, (3) default on the mortgage, (4) sell the home.

Firstly, if a homeowner stays worthy, his value function V_k^h is already given by the equation (1.7).

Secondly, similar to the bankrupt renter mentioned before, if choosing to declare bankruptcy under Chapter 7 while paying the mortgage, the homeowner will consume as much as he can access and the unsecured debt will be discharged in the next period. The bankruptcy trustees' interest in selling the house depends on the homestead exemption (Ξ) and the amount of home equity at the time of bankruptcy filing. According to Chapter 7, if the home equity is higher than the homestead exemption, the bankrupt trustee will sell the house, pay off the mortgage, and reimburse the household a check for the exemption; otherwise, the homeowner can keep his house and mortgage contract. All houses are assumed to be auctioned at the beginning of the next period which is the end of the bankruptcy process. There are some uncertainties concerning the house market price in the next period; hence, the current market house price is used to estimate the probability of the next period price. The implies a value function of

$$W_k^{h,bankrupcy}(s,i,j=0) = u(c) + \Theta + \beta \sum_{H'} q_{H,H'} \tilde{V}_{k+1}(H) \quad \forall\, 0 < k \leq 30 \qquad \textbf{(1.15)}$$

subject to

$$c + \kappa \widehat{H} + \Psi(h,D,r_m) = max(s,0) + y(i) + min(\sigma, b+s).$$

The contingent value function of the house market price is given by:

$$\tilde{V}_{k+1}(H') = \begin{cases} \sum_{i'} p_{i,i'} V_{k+1}^{h,B}(s'=0,i',j'=1) & (1-\chi)H' - \Omega \leq \Xi \\ \sum_{i'} p_{i,i'} V^{R,B}(s'=\Xi,i',j'=1) & \Xi < (1-\chi)H' - \Omega \leq \Xi - s(1+r) \\ \sum_{i'} p_{i,i'} V^{R,B}(s',i',j'=1) & s' = (1-\chi)H' - \Omega + s(1+r) \leq \Xi \end{cases}$$

$$\Omega = \Omega(h,D,r_m,k+1) \qquad \textbf{(1.16)}$$

Here, $\Omega(h,D,r_m,k+1)$ represents the outstanding mortgage debt in year k+1 of the mortgage. In some very rare cases (the third $\tilde{V}_{k+1}$equation), the bankrupt trustee sells the house, pays off the mortgage debt in full, sends the household a check for the homestead exemption, and pays off the unsecured debt with cash left over to reimburse to the household again.

Thirdly, the homeowner can allow foreclosing on his home by stopping payment on paying the mortgage and maintenance cost at the beginning of the period (Laufer, 2013). In 3~6 months, they will be flagged as a foreclosure unworthy renters, but they can still live in their home until the house auction sale at the end of this period. The lengthy foreclosure process saves 1 year of rent for this household (Figure 1.1). The lifetime utility of the foreclosure homeowner is given by:

$$W_k^{h,foreclosure}(s,i,j=1)=\max_c\left\{u(c)+\beta\sum_{i'}p_{i,i'}V^{R,F}(s',i',j'=2)\right\} \quad \textbf{(1.17)}$$

subject to

$$\frac{s'}{1+r_s}+c=s+y(i)+max[0,(1-\phi)H-\Omega(h,D,k+1)]$$

$$\frac{s'}{1+r_s}\geq min(0,s).$$

Finally, instead of just walking away from their foreclosed home, the homeowners can also choose to short sell the house himself. Because supply and demand in the housing market are out of the scope of this study, the homeowner selling a house is only used as an alternative given the previous decision of mortgage foreclosure. If the homeowner chooses to short sell the house, he will have a double housing cost, because he needs to move out of the house, get it ready for sale, and rent another house at the beginning of the period. At the end of the period, the house will be sold, and the mortgage debt will be paid off. When the homeowner decides to terminate this mortgage contract, the current period's cost and benefit will be directly compared as follows. The homeowner will choose foreclosure when the condition in the equation (1.18) holds; otherwise, he will short sell the house and extract this home equity.

$$\begin{aligned} &max[0,(1-\chi)H-\Omega(h,D,r_m,k+1)]-\kappa\widehat{H}-\Psi(h,D,r_m) \\ &\qquad < max[0,(1-\phi)H-\Omega(h,D,r_m,k)\times(1+r_m)\,]+\xi\widehat{H} \end{aligned} \quad \textbf{(1.18)}$$

1.3.3.3 Strategic Decision of the Worthy Homeowner with No Mortgage

The worthy homeowners with no mortgage have two options. First, they can continue to be worthy with the value function V_k^h $(k>30)$ which is shown in the equation (1.4). Second, they can declare bankruptcy under chapter 7. It is similar to the homeowner's bankruptcy utility function

$$W_k^{h,bankrupcy}(s,i,j=0)$$

$$= \max_c \left\{ u(c) + \Theta + \beta \sum_{H'} q_{H,H'} \left[\omega\theta u\big((1-\chi)H' + s' + y(i)\big) + (1+\omega)\tilde{V}_{k+1}(H') \right] \right\}$$

$$\forall k > 30$$

$$\text{Where } c + \kappa\hat{H} = y(i) \quad \textbf{(1.19)}$$

The house market price contingent value function $\tilde{V}_{k+1}$ is given by:

$$\tilde{V}_{k+1}(H') = \begin{cases} \sum_{i'} p_{i,i'} V_{k+1}^{h,B}(s'=0,i',j'=1) & (1-\chi)H' \le \Xi \\ \sum_{i'} p_{i,i'} V^{R,B}(s'=\Xi,i',j'=1) & \Xi < (1-\chi)H' \le \Xi - s(1+r) \\ \sum_{i'} p_{i,i'} V^{R,B}(s',i',j'=1) & s' = (1-\chi)H' + s(1+r) > \Xi \end{cases} \quad \textbf{(1.20)}$$

1.3.3.4 Decision under Uncertainty

This model applies an uncertainty mechanism onto the household strategic decision making. Under this mechanism, worthy households are reluctant to change from their current state to other strategic behavior, such as housing purchase, foreclosure, and bankruptcy, until there is enough lifetime utility gain to stimulate those behaviors. Therefore, it is sensible to assume that as utility increases, there is a higher probability for a corresponding strategic decision.

The probability of a strategic decision is assumed to be determined by a cumulative distribution function depending on the difference between the lifetime utility of this strategic decision and the worthy state. The cumulative distribution function is a good candidate to model the uncertainty of an agent's decision because it is non-decreasing and right-continuous on its domain.

Furthermore,

$$\lim_{x \to -\infty} F_X(x) = 0 \quad and \quad \lim_{x \to +\infty} F_X(x) = 1$$

To simplify the problem, the underlying distribution of this cumulative function is an exponential distribution with only one mean parameter μ.

$$Probably\ of\ Decision\ A = F_X(x = W^A - V) \quad where\ X \sim exp(\mu) \quad \textbf{(1.21)}$$

Firstly, the procedure of a worthy renter's decision is given by

Step 1: Accept two actions independently according to the following probability:

Probability of bankruptcy=$F_X(x = W^{R,bankrupcy} - V^R)$;

Probability of house purchase=$F_X(x = W^{R,buy} - V^R)$.

Step2: If neither action is accepted, then the agent keeps renting;

If both of the actions are accepted, the action with the higher lifetime utility is chosen;

If only one of the actions is accepted, then that one is chosen.

Secondly, the procedure of a worthy homeowner's decision is given by:

Step 1: Accept two actions independently according to the following probability:

Probability of bankruptcy=$F_X\left(x = W_k^{h,bankrupcy} - V_k^h\right)$;

Probability of foreclosure=$F_X\left(x = W_k^{h,foreclosure} - V_k^h\right)$.

Step2: If neither of the actions is accepted, then the agent continues being worthy;

If both of the actions are accepted, the one with a higher lifetime utility is chosen;

If only one of the actions is accepted, then that one is chosen.

Step 3: If the foreclosure action is accepted in step 2, the equation (1.18) is used to compare the current period's cost and benefit, and then either a short sale action or a foreclosure action will be accepted.

Finally, the decision procedure of a worthy homeowner with no mortgage is given by:

Step 1: Accept bankruptcy actions according to the following probability:

Probability of bankruptcy= $F_X\left(x = W_k^{h,bankrupcy} - V_k^h\right)$;

Step2: If this action is not accepted, then the agent keeps being a worthy homeowner with no mortgage;

If this action is accepted, then the agent files for bankruptcy.

1.3.4 Current Housing Price Prediction

Housing is very different from most financial assets and commodity goods, which are universally priced and comparable across regions. Before selling their house, homeowners can only predict the market value of their house from the National House Price Index or from a neighborhood sale. According to the study by Davis and Quintin (2014), this uncertainty about current house market price proved to be important in alleviating the aggregate foreclosure rate in the mortgage crisis. As we know, the House Price Index is a normalized house price, which represents nothing but the change of aggregate house prices. Therefore, all households in this model are assumed to predict their current market house price solely from the change of aggregate house price index in the last three periods. Additionally, each household's prediction is stochastically selected according to the current house price conditional probabilities. In order to obtain these probabilities without loss of generality, the house price was simulated over 100,000,000 periods using discrete time Markov chain with the transition probability matrix Q. Then, the probability of the current house price level, given three-period changes, is estimated by the sample proportion. For example, in last 3 years, if the house price index increased

2 levels, dropped 1 level and then dropped 2 levels again, the estimation of the probability of current price in level 5 is given by the following formula (1.22).

$$\hat{P}_{[+2,-1,-2],\ 5} = \frac{n_{[+2,-1,-2],5}}{\sum_{k=1}^{9} n_{[+2,-1,-2],k}} \quad \textbf{(1.22)}$$

Here, the denominator, $\sum_{k=1}^{9} n_{[+2,-1,-2],k}$, is the total number of simulation data observations which meets the above 3 year change condition, and the numerator, $n_{[+2,-1,-2],5}$, is the number of them which are currently in price level 5.

1.4 SOLVING THE MODEL

Because these value functions (1.1) and (1.4) in the Bellman Equations do not have closed form solutions, they have to be solved numerically using dynamic programming on the MATLAB platform (Aruoba and Fernández-Villaverde, 2015). The riskless asset domain from –b to 4 is divided into 200 equally spaced grid points; then, a linear interpolation[1] was used to represent the value function (Garin, 2015). The simple procedure to find a solution would be the following:

Step 1: make an initial guess on the form of the value function V_0(s)

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[2]. The value at all grid points are independently updated in each iteration, then linear interpolation of the updated grid is used to approximate the V_{t+1}

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

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

[2] $fminbnd$ function in MATLAB R2015 is a platform that is used to implement this optimization.

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

1.5 CALIBRATION

1.5.1 Model Economy

In this study, two economic states are considered: the normal and the recession economy. Because the expected duration of a recession economy is about 2 years (Wang and Miranda, 2015), all households in the recession economy have a prior probability for the economy to return to a normal state when it's in a recession of 0.33. Thus, the value functions of the recession economy are dependent on corresponding value functions of the normal economy, as shown in the equation (1.23).

$$V_t^{recession} = u(c) + E(33\% \times V_{t+1}^{normal} + 67\% \times V_{t+1}^{recession}) \qquad \textbf{(1.23)}$$

Three recent recession periods have been recorded by the National Bureau of Economic Research. The first one was from July 1990 to March 1991, the second was from March 2001 to November 2001, and the third was from December 2007 to June 2009. The historical national unemployment rate and unemployment duration data were obtained from the Bureau of Labor Statistics and are shown in Table 1.1 and Table 1.2. Based on these tables, we assume that the unemployment rate (γ) in the normal and recession economy is 5% and 9%, respectively.

Besides the unemployment rate, there are two other parameters used to differentiate the two states of the economy: the unemployment carryover rate p_{00} and the annual income expectation of the unemployed agents. As a part of the transition probability matrix of the employment Markov chain, p_{00} represents the probability of an unemployed agent staying unemployed in the next period. Given the unemployment carryover rate and the unemployment rate, the transition probability matrix can be determined by the equation set (1.25).

As mentioned earlier, the annual income of employed agents in both the normal and the recession economy is normalized to 1; meanwhile, the unemployed agents expect their annual income to be $\underline{\boldsymbol{y}}$. In the United States, unemployment benefits generally pay eligible workers between 40-50% of their previous pay. That is the major reason why Wang and Miranda (2015) assumed the unemployed annual income expectation to be 0.4. However, the standard time-length of unemployment compensation is 6 months; once this 6-month time period elapses, payment ceases. In order to precisely estimate the annual income expectation of the unemployed agents as well as the unemployment carryover rate, the distribution of unemployment duration should be approximated from the BLS data (Table 1.2). After visually inspecting the unemployment rate in Table 1.1, the duration data from 2009 to 2012 is used to estimate distribution in the recession economy. Excluding the data from the ambiguous small recession period, the data ranged from 2005 to 2007 and from 1994 to 1999 are used to approximate the distribution in the normal economy. Two histograms are drawn to depict both the density distribution and the cumulative distribution of unemployment duration in both the normal and the recession economy (Figure 1.2). Matching the histogram shape, the gamma distribution is selected to fit the data and its two parameters are estimated by the numerical method of maximum likelihood. Then, the unemployed annual income expectation in both economies can be computed by the equation (1.24).

$$\underline{y} = \int_0^{26} \left[0.4\frac{x}{52} + 1(1-\frac{x}{52})\right] f_X(x)\,dx + \int_{26}^{52} \left[0.4\frac{26}{52} + 1(1-\frac{x}{52})\right] f_X(x)\,dx \qquad \textbf{(1.24)}$$

$$
\begin{cases}
p_{00} = \int_{52}^{+\infty} f_X(x)\, dx \\
p_{01} = 1 - p_{00} \\
p_{10} = {}^{\gamma p_{01}}\!/_{(1-\gamma)} \\
p_{10} = 1 - p_{11}
\end{cases}
\tag{1.25}
$$

The results of the parameter estimation are given in

Figure 1.2. In the normal economy, the unemployment carryover probability is 7.87%, which is more than 3 times lower than 25.27% in the recession economy. The unemployed annual income expectation is reduced from 0.7317 in the normal economy to 0.5507 in the recession economy.

1.5.2 Aggregate House Price

This study leaves out the factor of housing size choice and simply assumes that there is only one house size available. All the underlying values of housing ($\widehat{H}$) are normalized to 3 in respect to the annual income of an employed household. This is according to the median household income and the median income household house price data in the 2013 Consumer Finance Survey, which were $ 46,700 and $125,000, respectively.

As mentioned earlier, the house market price fluctuation is the second major shock in this model. This study models the house market price shock using nine states discrete time Markov chain. The transition matrix $\mathbb{Q}$ of this Markov chain is calibrated using the real U.S. Case-Shiller Home Price Index, without being seasonally adjusted, from 1890 to 2013. First of all, the log of Home Price Index is decomposed to the trend component and the cyclical component, by a nonparametric method called the Hodrick–Prescott filter (HP filter). The HP filter is a commonly used tool in Real Business Cycle theory and was first proposed by E. T. Whittaker in 1923. Specifically, the log home price series variable z_t is composed of a trend component x_t and a cyclical component w_t, which $z_t = x_t + w_t$. Given an adequately chosen, positive value of λ, there is a trend solution by minimizes:

$$\min_{x}\left\{\sum_{t=1}^{T}(z_t - x_t)^2 + \lambda\sum_{t=2}^{T-1}[(x_{t+1} - x_t) - (x_t - x_{t-1})]^2\right\}. \qquad \textbf{(1.26)}$$

The multiplier λ represents the sensitivity of the trend component to short term fluctuations. The higher the λ value, the smoother the trend component is and the longer the term fluctuations are that are captured by the cyclical component. The objective of this mortgage study requires that the stochastic process captures a longer period price cycle. For this reason, λ is set to 3×10^7 by trial and error, which is relatively higher than Ravn and Uhlig (2002) who used 129,600 for monthly data. As a result, the log home price series, trend component series, and cyclical component series are modeled as presented in Figure 1.3.

The stochastic house price process is discrete, with the cyclical part modeled with discrete levels, namely -20%, -15%, -10%, -5%, 0%, 5%, 10%, 15% and 20% of the underlying house value. After discretizing the cyclical time series data, the transition probability can be estimated by the sample proportion:

$$\hat{q}_{ij} = \frac{n_{ij}}{\sum_{k=1}^{9} n_{ik}} \qquad \textbf{(1.27)}$$

Here, the denominator, $\sum_{k=1}^{9} n_{ik}$, is the total number of data observations in state i, and the numerator, n_{ij}, is the number of state i values which moves to state j in the next period.

1.5.3 Rent and Other Costs Related to Housing

Figure 1.4 shows the price index of house transactions and rent from the 1980s to 2015. As can been seen, rent did not follow the house price cycle in the recent recession. Thus, it would appear that the rent cost ($\xi\widehat{H}$) tends to be proportional to the underlying value of housing ($\widehat{H}$), not the market house price (H). The Price-to-Rent ratio was estimated to be 12 from two datasets of Zillow Research: the median of the value of all homes per square foot and the median of the estimated monthly rent price of all homes per square foot. The rent cost proportion parameter, which is reciprocal to the Price-to-Rent ratio, is approximately 8.33%.

It is also reasonable for the maintenance cost ($\kappa\widehat{H}$) to be proportional to the underlying value of housing. we assume the proportion parameter κ to be 0.035, which includes the maintenance cost (~2%), property tax (~1%), furniture replacement cost, pest control, etc.

Campbell et al. (2011) show that the houses in foreclosure are sold at an average 28% discount, meanwhile other forced sales only have a 3% ~7% discount. In this study, the sale value discounts are set to $\phi = 0.28$ and $\chi = 0.06$ in foreclosure and non-foreclosure cases, respectively.

1.5.4 Preference

The utility function of a household with respect to the consumable durable goods is taken to be lies in the CES family. In housing and renting studies, a commonly used utility function is the constant relative risk aversion function nested with Cobb-Douglas preferences over consumption and housing services (Mitman, 2015):

$$u(x, H) = \frac{(c^{\pi} h^{1-\pi})^{1-\alpha} - 1}{1-\alpha} \quad \textbf{(1.28)}$$

Here, α is constant relative risk aversion, δ is relative desirability of housing, and H is house price. In this function π is calibrated to match the share of annual housing expense in total consumption. It is worth noting that the h in this function does not denote the housing price, but the annual housing expenses.

Magill and Quinzii (2015) gave a general homeowner's utility function in their study:

$$u(c, H) = \frac{c^{1-\alpha} - 1}{1-\alpha} + \delta \frac{\widehat{H}^{1-\alpha} - 1}{1-\alpha} \quad \gamma > 0 \quad \textbf{(1.29)}$$

However, in this study, the utility derived from the housing is fixed, because both the income and house size are normalized for either renter or homeowner. Thus, I constructed an isoelastic flow utility function based on the Magill and Quinzii (2015) framework:

$$u(c) = \frac{c^{1-\alpha} - 1}{1-\alpha} + \delta \frac{H^{1-\alpha} - 1}{1-\alpha} I(own) \quad \textbf{(1.30)}$$

$I(own)$ is an indicator variable which is one if the agent owns a home in a current period and zero otherwise. This utility flow only accounts for the emotional utility gain of housing ownership depending on the current house market price H. Schelkle (2015) described δ as a homeowner's emotional attachment to the house, which is internally calibrated in this work. The constant relative risk aversion α is set as 3, which is standard in this field (Lopes, 2008; Wang and Miranda, 2015). The bequest motive η is set by 0 for simplicity.

1.5.5 Financial Intermedia

The interest rate of unsecured debt (r_d), mortgage debt (r_m), and saving (r_s) are directly identified in the data by the observation of the general market interest levels ($r_d = 12\%$, $r_m = 6\%$ and $r_s = 3\%$). 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 36% of median family income. I set credit exclusionary period $\tau = 7$ in the base case, corresponding to the average 7 years without access to the credit market as the punishment for default. Strictly, filing 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. For simplicity, this study assumes that both bankruptcy and mortgage default will cause τ years of credit exclusionary period. Bankruptcy homestead exemption varies a lot in different states, and it is set equal to one year median income in the base case, $\Xi = 1$. In the base case, the downpayment ratio D is set at 10%, which is very standard in the literature.

1.5.6 Internally Parameter Calibration

Besides the aforesaid parameters whose values either are standard in literature or can be estimated directly or indirectly identified from the data (Table 1.3), the remaining parameters will be set to match a set of empirical macroeconomic evidence (Table 1.4). These parameters are discount factor β, social stigma Θ, death rate of household heads ω, emotional attachment to the house δ and exponential mean parameter μ.Theoretically speaking, all five parameters jointly determine simulation outputs due to the complexity of this heterogeneous agent model. However, to reduce the optimization dimension, the discount factor β, social stigma Θ, and death rate of the household head ω are independently calibrated first.

Firstly, in the mortgage foreclosure literature, the discount factor β is either calibrated or borrowed from the literature value. Its values generally range from 0.9 (Schelkle, 2015) to 0.94 (Laufer, 2013) and 0.96 (Low, 2015). Iacoviello and Pavan (2013) separate households to be either "patient" and "impatient" with discount factors of 0.995 and 0.925, respectively. If rational agents in the model are more impatient, then they will smooth their current period consumption by accumulating more unsecured debts during periods of unemployment. Thus, I calibrate the time discount factor to match the average credit debt per household in the recent empirical dataset. The Federal Reserve Bank published the percentage of families holding credit cards (38.1%) and the mean value of their credit card balance ($5,700) in the 2013 Survey of Consumer Finance. After a back-of-the-envelope calculation, the average credit card debt in the whole population is $2,172 which accounts for about 5% of annual income. Secondly, the value of bankruptcy stigma was set to -0.57 so that the annual average charge-off rate of credit card debt is 5%, which is very standard in related literatures (Wang and Miranda, 2015). The death rate of the household head is a parameter whereby the fraction of homeowners with a mortgage in model matches that in the average empirical data (0.67) which is also provided by the Survey of Consumer Finance (1987~2013).

In addition, agents with higher emotional attachment to the house, δ, will be more likely to purchase or keep their house; on the other hand, the worthy agents with higher exponential mean parameter μ are more reluctant to make any strategic decisions, as described before. Because the mortgage foreclosure behavior is the primary goal of our study, these two parameters which are closely related to housing strategic decision are calibrated jointly using an on-line multi-objective optimization. This on-line optimization keeps adjusting and updating both parameters when the simulation is running, until both mortgage charge-off rate and homeownership rate meet their objectives. The average homeownership rate from 1989 to 2013 is 66%. The Federal Reserve Bank published the charge-off rate on single family residential mortgages quarterly since 1991. The historical average of this rate from 1991 to 2006 is 0.145.

1.6 MODEL FIT

Using the Monte Carlo method, the representative agents are simulated for 200 periods after reaching the steady state. Aside from prior calibrated parameters, other untargeted aggregate results are compared with empirical data in Table 1.5.

Bahchieva et al. (2005) approximated the total homeownership rate of the debtors in bankruptcy in 2001 to be 58.3%, by including both the current homeowner and past homeowner. According to (Zhu, 2011), the homeownership rate approached 50% in Chapter 7 bankruptcy. As can been seen, the homeownership rate of bankrupt households matches perfectly to the data. The total number of the bankruptcy filing in post-Bankruptcy-Reform and the pre-recession period (2006 and 2007) is very close to the average steady state output from the model in the normal economy; however, the steady state output in the recession economy is considerably less than the real data in the Great-Recession of 2008. This discrepancy tends to indicate that not only the unemployment but also the bust house price and distressed mortgage loan cause the elevated bankruptcy rate during the recent recession. The model slightly overpredicts the fraction of households with credit card debt. This result is not surprising because the only unsecured consumer loan that households can access in the model is the credit card loan. Additionally, the foreclosure rate output from the model is 50% higher than national data from 2004 ~2006, but the house market price in that period was climbing instead of keeping constant as assumed in the steady state. This model under-predicts home equity of bankrupt households at 0.14 compared to 0.21 in Miller (2011) which included bankruptcy cases under any Chapters. In reality, households with low home equity tend to declare bankruptcy under Chapter 7; meanwhile, those with high home equity can still file under Chapter 13 to keep their properties. In the theoretical sense, Mitman (2015) proved that if a household has only the exempt asset, then it will never choose to file for Chapter 13 bankruptcy. Because our model only allows Chapter 7 bankruptcy, it is not surprising that the home equity is smaller than reality. Last but very importantly, the aggregate output of the credit card charge-off rate in the recession economy absolutely matches the charge-off data in recession, which strongly supports the soundness of the setting and assumptions of the model economy.

Overall, the model performs well accounting for non-targeted moments in the data. The above model fit test provides an important source of model validation before proceeding to the following analysis.

1.7 ANALYSIS OF STEADY STATE

Table 1.6 provides the net carryover saving per household in various states and under different strategic decisions. This table separates both the renter and homeowner into four different states according to their employment status and worthy state. As can be seen, the unworthy renters on average have more than seven times as much saving per capita as worthy renters do; meanwhile, unworthy homeowners have more than four times the saving as do worthy homeowners. This may be because the unworthy agents with stricter borrowing constraints need higher precautions saving to self-insure against possible future income shocks. Also, the slightly lower saving rate of unemployed agents is contributed by those agents who have been unemployed for more than one period.

As it can be seen, unemployed renters are about four times more likely to declare bankruptcy than employed renters. This finding is comparable with other empirical studies of non-business bankruptcy. 65% of bankrupt households reported a job problem in 2007 (Warren and Thorne, 2012). This strong correlation between the loss of income and bankruptcy is also reported Sullivan et al. (1999; 2001) and Warren and Tyagi (2003). In addition, among all bankrupt debtors, the net carryover saving of unemployed renters is significantly higher than that of employed renters. It is also interesting to see that the net saving levels of bankrupt renters are lower than the average levels for all renters. These two findings support the existence of two trigger factors of the bankruptcy of renters: the heavy indebtedness and the job loss. These similar behaviors are also reported in a study of credit card default (Wang and Miranda, 2015).

In terms of other results, it is reasonable to see that renters tend to purchase a house when they are better off financially and have a job. The bankruptcy behavior of homeowners is similar to that of renters. Compared to renters, the lower bankruptcy filing rate of homeowners can probably be accounted for by the availability of the house sale and mortgage foreclosure options which can also help a household alleviate their financial distress. The homeownership year, carryover saving level and house price observation are all at play in the homeowner's strategic decision. Figure 1.5 illustrates the homeowner's stochastic strategic decision mechanism. It uses the color saturation level to represent the probability of mortgage foreclosure and bankruptcy. In any year, the bankruptcy probability is higher for an unemployed homeowner. Similarly, the probability of mortgage foreclosure is also slightly higher among unemployed homeowners, which is consistent with the result in Table 1.6 and other empirical studies (Gerardi et al., 2012; Gerardi et al., 2015). Notice that the expected house price level has very limited effect on bankruptcy probability. On the contrary, the mortgage foreclosure probability is high when the homeowner predicts a low house price. It indicates that the expectation of home equity, which is dependent on the house price prediction, would be a crucial determinant of a homeowner's mortgage foreclosure. It is commonly believed that negative home equity is a necessary condition for mortgage default (Kau et al., 1994). It is also very interesting to notice that homeowners are less likely to go through foreclosure, but have a very limited reduction of their bankruptcy probability when they have paid their mortgages for more years and been with higher home equity. Figure 1.6 illustrates that the homeowners will not choose foreclosure after 10 years of paying their mortgage, but still file for bankruptcy after 15 years. After 20 years, there are infinitesimal numbers of bankruptcy cases, because the home equity is higher than the exemption, and the net gain from bankruptcy is squeezed very small. In reality, a household usually can borrow against their home equity again.

Li and White (2009) show the relationship between homeowner bankruptcies and mortgage default/foreclosure is described as a substitution in some contexts and complementary in others. It is not hard to explain the complimentary relationship between bankruptcy and mortgage default because they share two common causes: unemployment and hefty indebtedness. On the other hand, the substitution effect may be due to a household's rationality of choosing one between these two strategic behaviors. Another empirical study (Lindblad et al., 2014) shows that homeowners in foreclosure who file for bankruptcy are 70% less likely to go into a foreclosure auction state, and the time to foreclosure auction is significantly prolonged. All in all, compared to bankruptcy, the mortgage is more house price sensitive and home equity sensitive. Thus, a rational homeowner will tend to go towards a foreclosure instead of filing for bankruptcy when home equity is low, house price is low, or bankruptcy cost is high. This substitution effect can be used to explain several findings in the following discussion.

1.7.1 Downpayment ratio ($\boldsymbol{D}$)

Table 1.7 summarizes the steady state statistics of model simulation using different downpayment ratios (D). Besides the base case (10%), the downpayment ratios are set to 20%, 5%, and 0%. As can been seen, when $D = 20\%$, the mortgage charge-off rate declined 24 times from that in the base case. Meanwhile, when $D = 5\%$ and $D = 0\%$, the mortgage charge-off rate increased three times and seven times from that in the base case. The annual foreclosure rate and total foreclosure numbers in the model follow the same trend and change even more dramatically. The above observation is the evidence that mortgages with a low downpayment ratio increase the probability that homeowners voluntarily go into foreclosure even when the actual house market value is stable. This conclusion is consistent with the finding of a recent life-cycle model study (Garin, 2015), which argues that a decrease in downpayments generates an increase in default rate across both recourse and nonrecourse environments.

The most straightforward side effect of the low downpayment is stimulating the home purchase because less upfront cash is needed. As shown in Table 1.7, the annual home purchase ratio is increased with a decrease in the downpayment ratio. Also, the renters who purchase a house have a lower average saving level when the downpayment required is low. The higher homeownership in a low downpayment requirement environment is also reported in Iacoviello and Pavan (2013)'s general equilibrium model.

Finally, the behavior of bankruptcy is also very interesting. On the one hand, the number of bankrupt renters is reduced when D is decreased, but there is no obvious trend of their bankruptcy ratio. There is a strong possibility that the high purchase ratio increases the homeownership ratio and reduces the total number of renters in the simulation. On the other hand, the homeowner bankruptcy ratio was significantly decreased with a decrease in downpayment ratio D. It is worthy to note that the homeowner's bankruptcy ratio and mortgage foreclosure ratio move in the opposite direction while downpayment ratio decreases. This can be explained by the aforementioned substitution relationship between foreclosure and bankruptcy. Because the lower downpayment cash reduced the cost of foreclosure, the financially distressed homeowner will more often choose mortgage foreclosure rather than the bankruptcy. This behavior was directly supported by both theory studies (Campbell and Cocco, 2015) and empirical results (Mayer et al., 2009; Schwartz and Torous, 2003).

1.7.2 Credit Exclusionary Period (τ)

The simulation results in Table 1.8 presents the household response to the different lengths of credit exclusionary period (3, 5, 7, 10, 15 yrs.). As this penalty year decreases four times from 15 years to 3 years, the mortgage charge-off rate was marginally increased by 28%. Correspondingly, the foreclosure rate and number both increase less than 30%, when the number of years in the credit exclusionary period decreases. Unlike the downpayment ratio, the bankruptcy rate follows the same trend of mortgage foreclosure as the penalty years decrease. The intuition for the result is straightforward. Both mortgage foreclosure and bankruptcy behavior will give rise to the stricter liquidity constraint to the unworthy household in the following credit exclusionary period, which imposes a cost on these two strategic behaviors. Intuitively, this cost is positively related to the length of this penalty. Increasing the penalty years will surely reduce the foreclosure rate and bankruptcy rate because the increased cost will make these strategic decisions less desirable. However, the prolonging of the credit exclusionary period is not only beneficial; on the contrary, this will profoundly incur the social cost. We argue that if the length of credit exclusionary period has a trivial effect on the average foreclosure and bankruptcy rate, it should be reduced to the minimum due to its hefty social cost. Most of the literature only selected the credit exclusionary period based on empirical data and their assumption: 4 years in mortgage foreclosure (Chatterjee and Eyigungor, 2015), 7 years in credit card default (Wang and Miranda, 2015), etc.. However, very few existing studies have investigated its effect on mortgage foreclosure and bankruptcy (Garin, 2015).

1.8 DYNAMICS OF AGGREGATE MODEL

1.8.1 Recent U.S. Experiment

In this section, we examine the dynamics of mortgage charge-off rate when the model economy and house market price replicate the United States' recent economic condition (1985~2014). In a prior study, Corbae and Quintin (2015) assumed three levels of house prices and simulated the history of the housing market by increasing the house price to a high level from 1999 to 2006 and setting back to the medium level in 2007 in their model. As a more precise and elaborate simulation, we set the house market price process in our model to the discrete cyclical component of the historical US Case-Shiller Home Price index (Figure 1.4). Then, according to the historical monthly unemployment rate in Table 1.1, those years with any months whose rate was higher than 7% was defined to be in recession. Following this standard, in our simulation the years 1991-1993 and 2008-2013 are set to the recession state. Using the Monte Carlo Method, we simulate the stochastic model with these two exogenous variable series and plot the simulated history of the aggregate mortgage charge-off rate in the first panel of Figure 1.8. To compared with the model output, two quarterly time series data sets of all U.S. commercial banks were obtained from the database of Board of Governors of the Federal Reserve System (FRB). The most straightforward data is the "Charge-off rate on single-family residential mortgages". We also add the "Charge-off rate on loans secured by real estate" data set, because the first one begins in 1991 which means that it fails to cover the period from 1985-1990. As it can be seen from Figure 1.8, house price starts to drop from the end of 2007, and the charge-off rate from both sources starts to rise in the same year.

The mortgage charge-off rate in my model starts to rise slightly beginning 1 year ago. This result is not surprising because it is totally sensible that homeowners would not choose to default their mortgage strategically until they firmly believe that house prices have declined dramatically. Also, banks slowed foreclosure because of legal issues and costs associated with it. After the peak, the model value declines quicker than the historical value. During the explosion of foreclosures, banks tend to postpone some foreclosures on less troublesome mortgages to later years, because it is very costly to have many foreclosures in a short period of time. Meanwhile, it is very interesting to see that both the time and value of the charge-off rate peak from our model matches those of the historical data in the late 2000s. Furthermore, the earlier house price decline from 1989 to 1994 was also accompanied by an elevated charge-off rate on loans secured by real estate. The peak of mortgage charge-off rate in the 1990s also can be observed in our model simulation output. As a comparison, in the early 1990s, the house price inflation only fell from +10% to -10%, whereas the house price inflation in the late 2000s plummeted from +20% to -15%. It is very probable that the almost three times higher mortgage charge-off rate in the recent crisis is caused by the more drastic price drop. Similarly, Schelkle (2015) provides evidence from his dynamic simulation to show the importance of the aggregate house price during the recent mortgage market meltdown. Besides house prices, the longer recession period in the late 2000s seems also influence the homeowner foreclosure behavior.

From the perspective of bankruptcy, we study the path of aggregate bankruptcy results in the simulation after 2005. Data before 2005 are not comparable to the later data because reforms made to U.S. Bankruptcy Code in 2005 made a bankruptcy filing more difficult and costly for homeowners (Bernstein, 2008; Li et al., 2011; Morgan et al., 2009). The top panel of Figure 1.7 shows that the path of bankruptcy filing numbers from this simulation follows the same trend of non-business bankruptcy filing data. The highest bankruptcy number occurred in 2010 for both the data and simulation path, while the overall weaker value in the simulation may be caused by the calibration in steady state. As shown in the steady state simulation (Table 1.5), it is noteworthy that bankruptcy filing numbers are 682 and 782 in the normal and in the recession economy. In contrast, the dynamic simulation results in 2005 and 2010 are around 400 and 1,100, respectively, which are closer to the empirical data. It is rather clear that the high bankruptcy filing number in 2010 is caused not only by the high unemployment rate in the recession economy but also by the frustrated mortgage debtor in the sliding housing market. In the bottom panel of Figure 1.7, the charge-off rate data on consumer loans and credit card loans is compared with that of the credit card debt in the simulation. Similar to the bankruptcy filing result, the credit card charge-off rate path follows the same trend of data. Compared to the real data series, the simulation path has a lower peak and a fatter tail after 2010. This could be driven by the slow action by banks for the same reason as with mortgage foreclosure. It is noteworthy that both the foreclosure rate and bankruptcy rate trended positively from 2007 to 2010 simultaneously. The complementary relationship between bankruptcy and default can be explained at the micro level and macro level. Individuals who file for bankruptcy and those who default their mortgage tend to share common properties: unemployment and over-indebtedness, which is shown in the steady state analysis. In aggregate, the decline in house value increases lots of mortgagors' propensity to default or file for bankruptcy in this dynamic simulation and in the data.

In view of the overall performance of this dynamic experiment, there is strong evidence that our model is good at representing and predicting aggregate U.S. mortgage foreclosure and bankruptcy behaviors during periods of recession and declining house prices.

1.8.2 Counter-Factual Policy Experiments

To quantify the role of downpayment ratio and credit exclusionary period in the crisis using our model, we simulate a set of scenarios with the same price path and the same model economy path as in the baseline experiment.

In the first experiment, I set up four scenarios with different downpayment ratios and run independent simulations for each scenario. Figure 1.8 presents paths of the mortgage charge-off rate in these four scenarios. In the 20% downpayment ratio scenario, the major peak in 2010 is reduced from 3% in the base scenario to 1%, and the minor peak in 1993 disappears. On the contrary, in the 5% and 0% downpayment ratio scenarios, the major peaks in 2010 jump to 4% and 5%, respectively. According to those observations, a high downpayment ratio requirement will considerably alleviate the burst of mortgage defaults in the house market bust periods. This result is consistent with the findings from the above steady state study and some findings in the prior literature which studied foreclosure during the crisis. Corbae and Quintin (2015)'s model reveals that by relaxing of the mortgage underwriting standard, the larger fraction of high-leverage loan that emerged prior to the crisis can explain 60% of the inflation of the foreclosure rate. In Hatchondo et al. (2014), a stricter downpayment limit significantly lowers the mortgage default rate and combining recourse mortgages and LTV limits will make the mortgage default rate less sensitive to fluctuations in aggregate house prices.

It has been debated among empirical studies whether the extremely low downpayment led to the mortgage meltdown (Liebowitz, 2009; Solomon, 2011). Pinto (2010) use data of FHA and GSE purchased loans to show that the percentage of high leverage mortgage, meaning higher than 95% LTV, was about 1% in 1990 but rose to almost 40% in 2007. In the view of many scholars, this increasing trending of low home equity mortgages were a major factor in the recent U.S. mortgage crisis.

Figure 1.9 presents the results of the second experiment. In this experiment, I set up five scenarios with five different lengths of the credit exclusionary period and run independent simulations for each scenario. By visual inspection, there is no apparent difference between these five paths from the 5-year penalty scenario to the 15-year penalty scenarios. This result was comparable with the steady state result. It is highly likely that the credit exclusionary period has a very trivial effect on a household's mortgage foreclosure behaviors in either a house price steady state environment or a house bust period.

1.9 CONCLUSION AND POLICY SUGGESTIONS

We present a heterogeneous agent model that can match both key long-run features and crisis characteristics of the U.S. personal bankruptcy and residential housing mortgage foreclosure data. Given the observed path of house prices and other economic variables, the simulation of this model matches the mortgage charge-off rate from 1985 to 2014. This paper provides evidence that the house price decline is the major reason for the explosion of foreclosures and also contributed to the elevated bankruptcy and credit card charge-off rates. For individuals, there is a substitution effect between bankruptcy and mortgage foreclosure; however, from the aggregate point of view, an upward trend in the bankruptcy filing rate and mortgage charge-off ratio simultaneously exists in the recent crisis. As one of the major contributions of this paper, we proved that the credit exclusionary period after default seems to be a useless punishment in preventing foreclosure. In consideration of its high social cost, it is not a cheap and effective tool in foreclosure prevention. On the other hand, a high downpayment ratio is quantitatively proved to be very effective in controlling the mortgage foreclosure in both the crisis and steady-state environments. Unfortunately, in late 2014, Fannie Mae and Freddie Mac reduced the minimum down payments to 3% from 10% for some qualified loans. If we cannot draw enough lessons from the past and keep encouraging homeowners to own a house with very low home equity, it will be very hard to prevent a future mortgage crisis.

Table 1.1 The Monthly Unemployment Rate in the United States.

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1985	7.3	7.2	7.2	7.3	7.2	7.4	7.4	7.1	7.1	7.1	7.0	7.0
1986	6.7	7.2	7.2	7.1	7.2	7.2	7.0	6.9	7.0	7.0	6.9	6.6
1987	6.6	6.6	6.6	6.3	6.3	6.2	6.1	6.0	5.9	6.0	5.8	5.7
1988	5.7	5.7	5.7	5.4	5.6	5.4	5.4	5.6	5.4	5.4	5.3	5.3
1989	5.4	5.2	5.0	5.2	5.2	5.3	5.2	5.2	5.3	5.3	5.4	5.4
1990	5.4	5.3	5.2	5.4	5.4	5.2	5.5	5.7	5.9	5.9	6.2	6.3
1991	6.4	6.6	6.8	6.7	6.9	6.9	6.8	6.9	6.9	7.0	7.0	7.3
1992	7.3	7.4	7.4	7.4	7.6	7.8	7.7	7.6	7.6	7.3	7.4	7.4
1993	7.3	7.1	7.0	7.1	7.1	7.0	6.9	6.8	6.7	6.8	6.6	6.5
1994	6.6	6.6	6.5	6.4	6.1	6.1	6.1	6.0	5.9	5.8	5.6	5.5
1995	5.6	5.4	5.4	5.8	5.6	5.6	5.7	5.7	5.6	5.5	5.6	5.6
1996	5.6	5.5	5.5	5.6	5.6	5.3	5.5	5.1	5.2	5.2	5.4	5.4
1997	5.3	5.2	5.2	5.1	4.9	5.0	4.9	4.8	4.9	4.7	4.6	4.7
1998	4.6	4.6	4.7	4.3	4.4	4.5	4.5	4.5	4.6	4.5	4.4	4.4
1999	4.3	4.4	4.2	4.3	4.2	4.3	4.3	4.2	4.2	4.1	4.1	4.0
2000	4.0	4.1	4.0	3.8	4.0	4.0	4.0	4.1	3.9	3.9	3.9	3.9
2001	4.2	4.2	4.3	4.4	4.3	4.5	4.6	4.9	5.0	5.3	5.5	5.7
2002	5.7	5.7	5.7	5.9	5.8	5.8	5.8	5.7	5.7	5.7	5.9	6.0
2003	5.8	5.9	5.9	6.0	6.1	6.3	6.2	6.1	6.1	6.0	5.8	5.7
2004	5.7	5.6	5.8	5.6	5.6	5.6	5.5	5.4	5.4	5.5	5.4	5.4
2005	5.3	5.4	5.2	5.2	5.1	5.0	5.0	4.9	5.0	5.0	5.0	4.9
2006	4.7	4.8	4.7	4.7	4.6	4.6	4.7	4.7	4.5	4.4	4.5	4.4
2007	4.6	4.5	4.4	4.5	4.4	4.6	4.7	4.6	4.7	4.7	4.7	5.0
2008	5.0	4.9	5.1	5.0	5.4	5.6	5.8	6.1	6.1	6.5	6.8	7.3
2009	7.8	8.3	8.7	9.0	9.4	9.5	9.5	9.6	9.8	10.0	9.9	9.9
2010	9.8	9.8	9.9	9.9	9.6	9.4	9.4	9.5	9.5	9.4	9.8	9.3
2011	9.2	9.0	9.0	9.1	9.0	9.1	9.0	9.0	9.0	8.8	8.6	8.5
2012	8.3	8.3	8.2	8.2	8.2	8.2	8.2	8.0	7.8	7.8	7.7	7.9
2013	8.0	7.7	7.5	7.6	7.5	7.5	7.3	7.2	7.2	7.2	7.0	6.7
2014	6.6	6.7	6.6	6.2	6.3	6.1	6.2	6.1	5.9	5.7	5.8	5.6
2015	5.7	5.5	5.5	5.4	5.5	5.3	5.3	5.1	5.1			

Note: The shading data are all higher than 7.0.
Source: U.S. Bureau of Labor Statistics.

Table 1.2 Unemployed Persons by Duration of Unemployment

[Numbers in thousands]

Duration	1994	1995	1996	1997	1998	1999	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Total number	7996	7404	7236	6739	6210	5880	6801	8378	8774	8149	7591	7001	7078	8924	14265	14825	13747	12506	11460
< 5 weeks	2728	2700	2633	2538	2622	2568	2853	2893	2785	2696	2667	2614	2542	2932	3165	2771	2677	2644	2584
5 to 10 weeks	1651	1631	1576	1474	1375	1283	1525	1732	1734	1594	1569	1460	1529	1888	2408	2082	1906	1832	1780
11 to 14 weeks	757	711	711	664	575	549	671	848	878	787	735	661	703	917	1420	1186	1087	1035	979
15 to 26 weeks	1237	1085	1053	995	763	755	951	1369	1442	1293	1130	1031	1061	1427	2775	2371	2061	1859	1807
27 to 51 weeks	645	561	577	479	379	325	388	821	899	747	599	535	539	812	2175	2117	1709	1472	1339
>52 weeks	978	717	685	589	496	400	413	714	1037	1031	891	700	704	949	2321	4298	4307	3664	2971

Source: Bureau of Labor Statistics

Table 1.3 The Externally Calibrated Base Case Parameters

Parameter	Value	Description	Source
α	3	Coefficient of risk aversion	(Lopes, 2008)
γ_{normal}	5%	Unemployment rate in normal economy	(Wang and Miranda, 2015)
$\gamma_{recession}$	9%	Unemployment rate in recession economy	(Wang and Miranda, 2015)
η	0	Bequest motive	(Low, 2015)
κ	0.035	Maintenance cost proportion	
λ	3×10^7	Hodrick–Prescott filter multiplier	
ξ	0. 833	Rent cost proportion	Zillow Research Data
ρ	0.33	Economy reinstatement rate	
σ	0.15	Debt increase limits during bankruptcy filling	Base case assumption
τ	7	Credit Exclusionary Period	Base case assumption
ϕ	0.28	Foreclosure value discount	(Campbell et al., 2011)
χ	0.04	None-foreclosure value discount	(Campbell et al., 2011)
Ξ	1	homestead exemption	Base case assumption
b	0.36	Credit limit	(Wang and Miranda, 2015)
r_s	3%	Risk-free asset rate of return.	3-month treasury bond
r_m	6%	Mortgage interest rate	Market Quote
r_b	12%	Interest rate on unsecured debt	Market Quote
D	15%	the downpayment ratio	Base case assumption

Table 1.4 The Internally Calibrated Parameters

Description	Parameter	Value	Target	Actual	Model
Independently calibrated:					
Discount factor	β	0.95	Average credit debt	0.05	0.05
Social stigma	Θ	-0.57	Credit card charge-off rate	5%	5%
Death rate of household heads	ω	0.06	Fraction of homeowner with mortgage	0.67	0.66
Joint calibrated:					
Emotional attachment to the house	δ	0.152	Mortgage charge-off rate	0.15%	0.15%
Exponential mean Parameter	μ	1.38	Homeownership rate	0.66	0.66

Table 1.5: Validation of the Calibrated Model

	Model	Actual	Source
<u>In the normal economy:</u>			
Bankruptcy filing number per 100,000 household	682	614	Non-business bankruptcy, ABI (2006,2007)
Annually foreclosure rate (per 1k home)	3.74	2.45	National foreclosure rate, Zillow (2004~2006)
Homeownership rate of bankrupt household	50%	50%	(Zhu, 2011) and BAPCA chapter 7
Home equity of bankrupt household	0.14	0.21	(Miller, 2011)
Fraction of households with credit card debt (%)	48.33	38.1	Credit card balance, SCF 2013
<u>In the recession economy</u>			
Bankruptcy filing number per 100,000 household	783	1130	Non-business bankruptcy, ABI(2008~2013)
Credit card charge-off rate (%)	9.46	9.43	Credit card loans; All commercial banks, FRB 2009~2010

Note:

ABI: American Bankruptcy Institute
BAPCA: Bankruptcy Abuse Prevention and Consumer Protection Act
FRB: Board of Governors of the Federal Reserve System
SCF: Survey of Consumer Finances

Table 1.6 The Steady State Net Carryover Saving Per-capita and the Rate of Bankruptcy, Foreclosure, and Home Purchase

		Saving	Bankruptcy Filing Rate (%)	Saving Given Bankruptcy	Rate of Mortgage Foreclosure (%)	Saving Given Foreclosure	Rate of Home Purchase (%)	Saving Given Home Purchase
Renter	Employed, Worthy	0.104	0.83%	-0.235	N/A	N/A	5.78%	0.292
	Unemployed, Worthy	0.097	3.47%	-0.181	N/A	N/A	3.01%	0.405
	Employed, Unworthy	0.751	N/A	N/A	N/A	N/A	N/A	N/A
	Unemployed, Unworthy	0.744	N/A	N/A	N/A	N/A	N/A	N/A
Homeowner	Employed, Worthy	0.027	0.64%	-0.181	0.48%	-0.122	N/A	N/A
	Unemployed, Worthy	0.021	2.33%	-0.141	1.80%	-0.071	N/A	N/A
	Employed, Unworthy	0.091	N/A	N/A	N/A	N/A	N/A	N/A
	Unemployed, Unworthy	0.088	N/A	N/A	N/A	N/A	N/A	N/A

Note: saving represents the average net carryover saving which is calculated by the last period saving plus one-period interest.

Table 1.7 Sensitivity Analysis: Downpayment Ratio (100,000 Households)

		Downpayment Ratio			
		20%	10%*	5%	0%
Mortgage Charge-off Rate (%)		0.006	0.149	0.462	1.034
Annually Foreclosure Rate (1k Home)		0.19	3.74	13.44	68.61
Charge-off Rate on Credit Card (%)		7.5	5.05	4.1	4.18
Annual Homeowner Foreclosure		6.18	248.37	829.07	2453.2
Annual Homeowner Bankruptcy		229.09	341.2	156.86	37.53
Annual Renter Bankruptcy		390.13	341.32	321.26	250.25
Renter Annual home purchase ratio (%)	Employed	1.14%	5.95%	7.39%	7.15%
	Unemployed	0.54%	1.26%	2.21%	4.29%
Renter Annual Bankruptcy Ratio (%)	Employed	0.47%	0.98%	0.90%	0.45%
	Unemployed	3.15%	4.57%	4.07%	2.44%
Homeowner Annual Bankruptcy Ratio (%)	Employed	1.11%	0.70%	0.32%	0.11%
	Unemployed	2.15%	3.01%	1.67%	0.74%
Homeowner Annual Foreclosure Ratio (%)	Employed	0.03%	0.57%	1.88%	8.90%
	Unemployed	0.05%	1.13%	4.87%	14.48%
Annual Homeowner short sale Ratio (%)	Employed	0.00%	0.00%	0.02%	0.02%
	Unemployed	0.00%	0.01%	0.15%	0.10%
Renter Net Asset Given Home Purchase	Employed	0.686	0.265	0.212	0.166
	Unemployed	1.271	0.955	0.549	0.208
Renter Net Asset Given Bankruptcy	Employed	-0.236	-0.246	-0.249	-0.245
	Unemployed	-0.179	-0.196	-0.197	-0.190
Homeowner Net Asset Given Bankruptcy	Employed	-0.314	-0.200	-0.199	-0.202
	Unemployed	-0.282	-0.164	-0.164	-0.142
Homeowner Net Asset Given Foreclosure	Employed	-0.321	0.017	0.038	0.139
	Unemployed	-0.251	-0.026	0.014	0.130

* The Base Case Scenario

Table 1.8 Sensitivity Analysis: Credit Exclusionary Period (100,000 Households)

		Credit Exclusionary Period				
		15 yrs	10yrs	7 yrs*	5yrs	3yrs
Mortgage Charge-off Rate (%)		0.131	0.140	0.149	0.157	0.168
Annually Foreclosure Rate (Per 1k Home)		3.46	3.58	3.75	3.94	4.24
Charge-off Rate on Credit Card (%)		5.12	5.07	5.05	5.09	5.13
Annual Homeowner Foreclosure		219.96	233.77	248.59	263.44	284.33
Annual Homeowner Bankruptcy		322.60	330.71	339.69	350.12	367.64
Annual Renter Bankruptcy		327.88	338.03	342.78	348.48	347.12
Renter Annual home purchase ratio (%)	Employed	5.92%	5.96%	5.95%	5.93%	5.85%
	Unemployed	1.34%	1.36%	1.34%	1.27%	1.05%
Renter Annual Bankruptcy Ratio (%)	Employed	0.98%	0.99%	0.99%	0.98%	0.95%
	Unemployed	4.59%	4.60%	4.51%	4.56%	4.39%
Homeowner Annual Bankruptcy Ratio (%)	Employed	0.74%	0.71%	0.70%	0.70%	0.72%
	Unemployed	3.19%	3.01%	3.02%	3.09%	3.16%
Homeowner Annual Foreclosure Ratio (%)	Employed	0.56%	0.55%	0.57%	0.59%	0.62%
	Unemployed	1.17%	1.16%	1.18%	1.18%	1.26%
Annual Homeowner short sale Ratio (%)	Employed	0.00%	0.00%	0.00%	0.00%	0.00%
	Unemployed	0.01%	0.01%	0.02%	0.01%	0.01%
Renter Net Asset Given Home Purchase	Employed	0.390	0.327	0.266	0.213	0.141
	Unemployed	1.445	1.193	0.958	0.733	0.470
Renter Net Asset Given Bankruptcy	Employed	-0.246	-0.246	-0.246	-0.247	-0.246
	Unemployed	-0.195	-0.196	-0.196	-0.196	-0.196
Homeowner Net Asset Given Bankruptcy	Employed	-0.199	-0.199	-0.199	-0.199	-0.200
	Unemployed	-0.164	-0.164	-0.163	-0.164	-0.164
Homeowner Net Asset Given Foreclosure	Employed	0.002	0.020	0.021	0.009	-0.017
	Unemployed	-0.023	-0.033	-0.025	-0.033	-0.050

* The Base Case Scenario

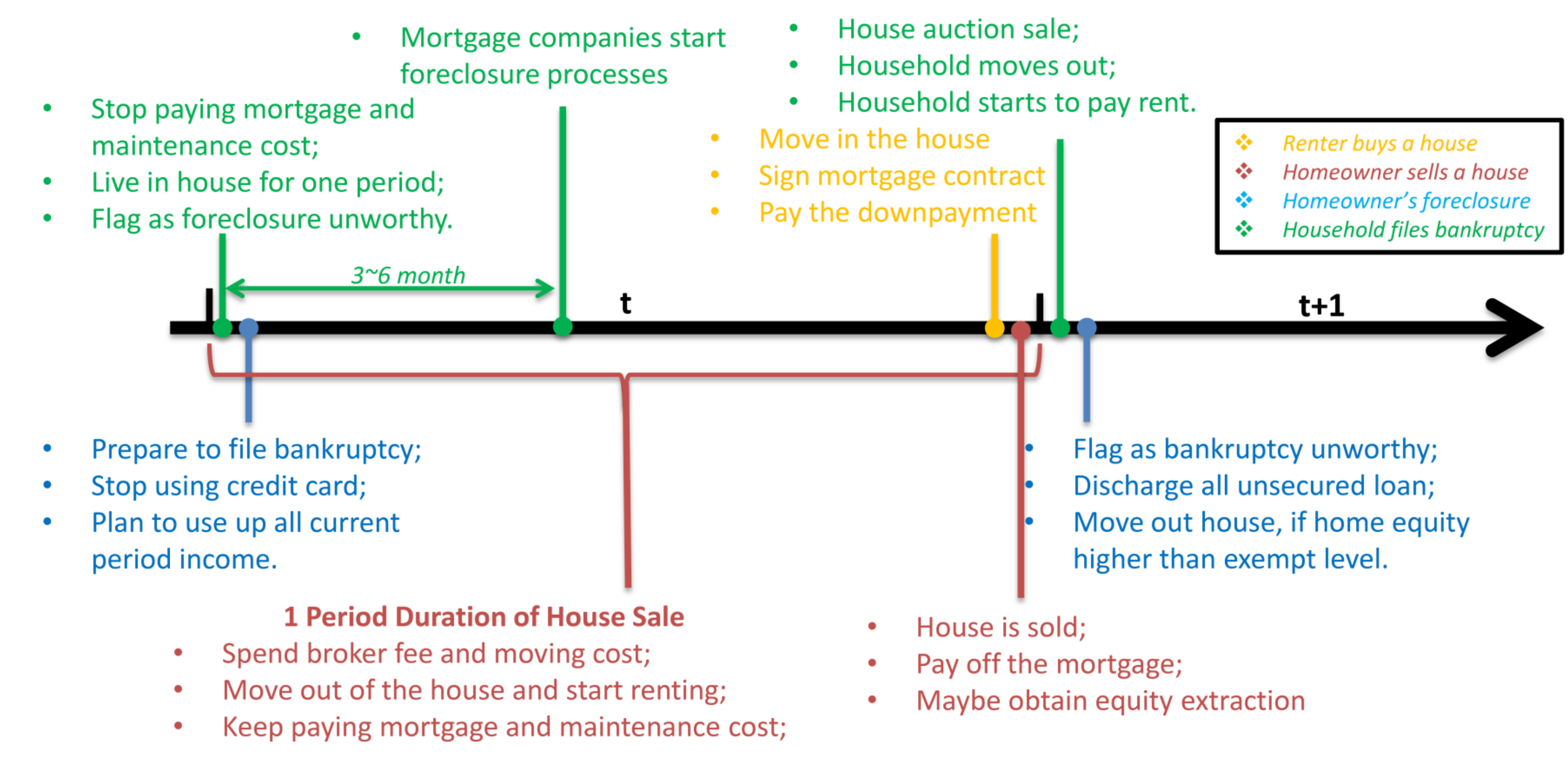
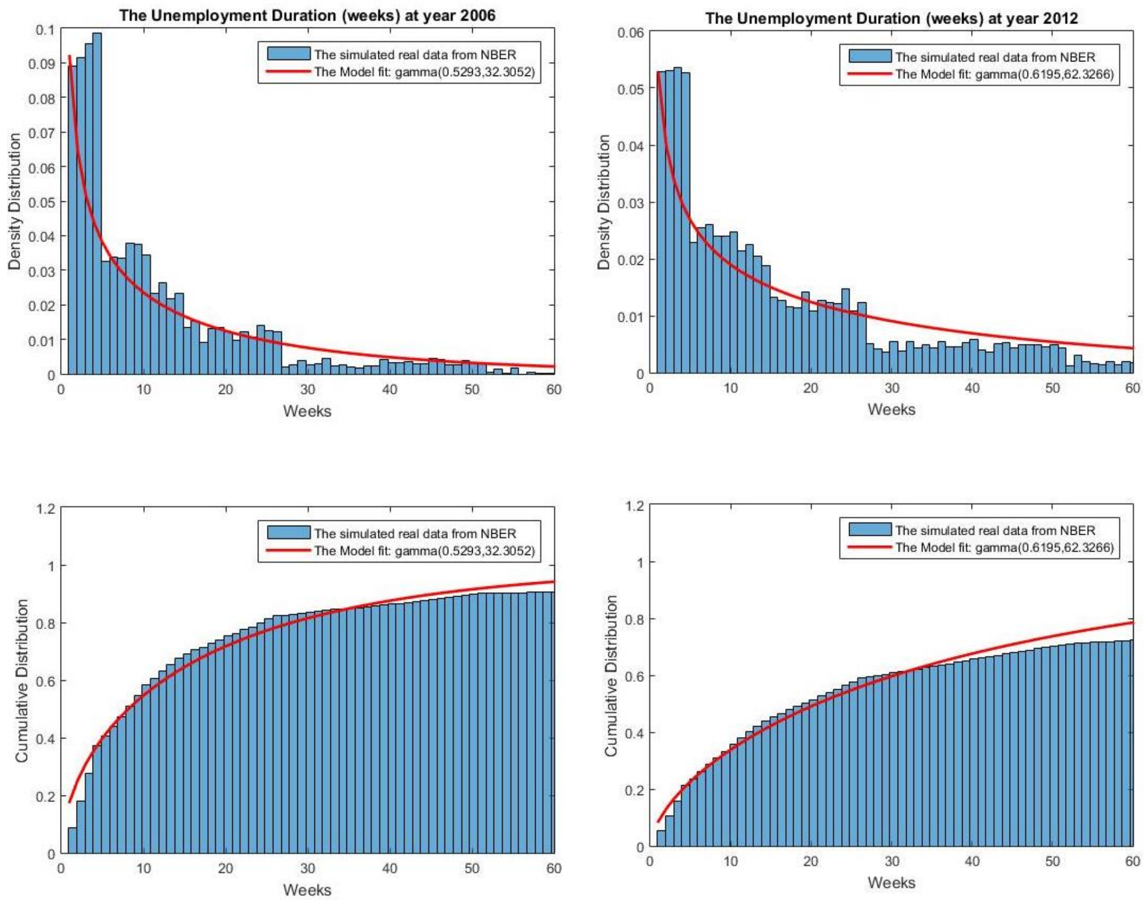


Figure 1.1 The Timeline of Events within a Period



Normal Economy
$gamma(0.5293,\ 32.3052)$
Unemployment Carryover Rate p_{00}=7.89%
Annual Income Expectation of the Unemployed Agents $\underline{y}$ = 0.7317

Recession Economy
$gamma(0.6195,\ 62.3266)$
Unemployment Carryover Rate p_{00}= 25.27%
Annual Income Expectation of the Unemployed Agents $\underline{y}$ =0.5507

Figure 1.2 The Distribution of Unemployment Duration.

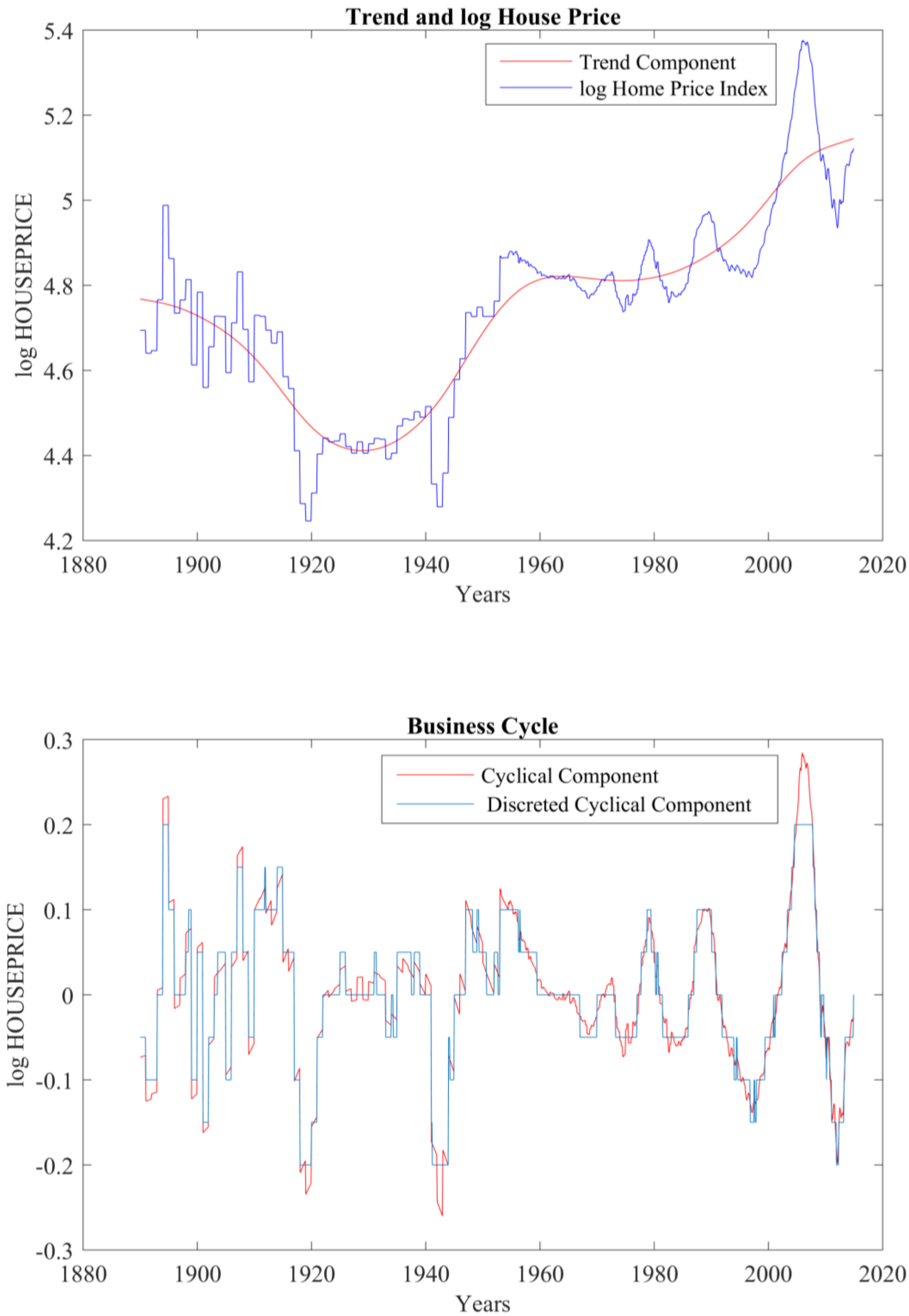


Figure 1.3 The Decomposition of Real US Case-Shiller Home Price index, without Seasonally Adjusted.

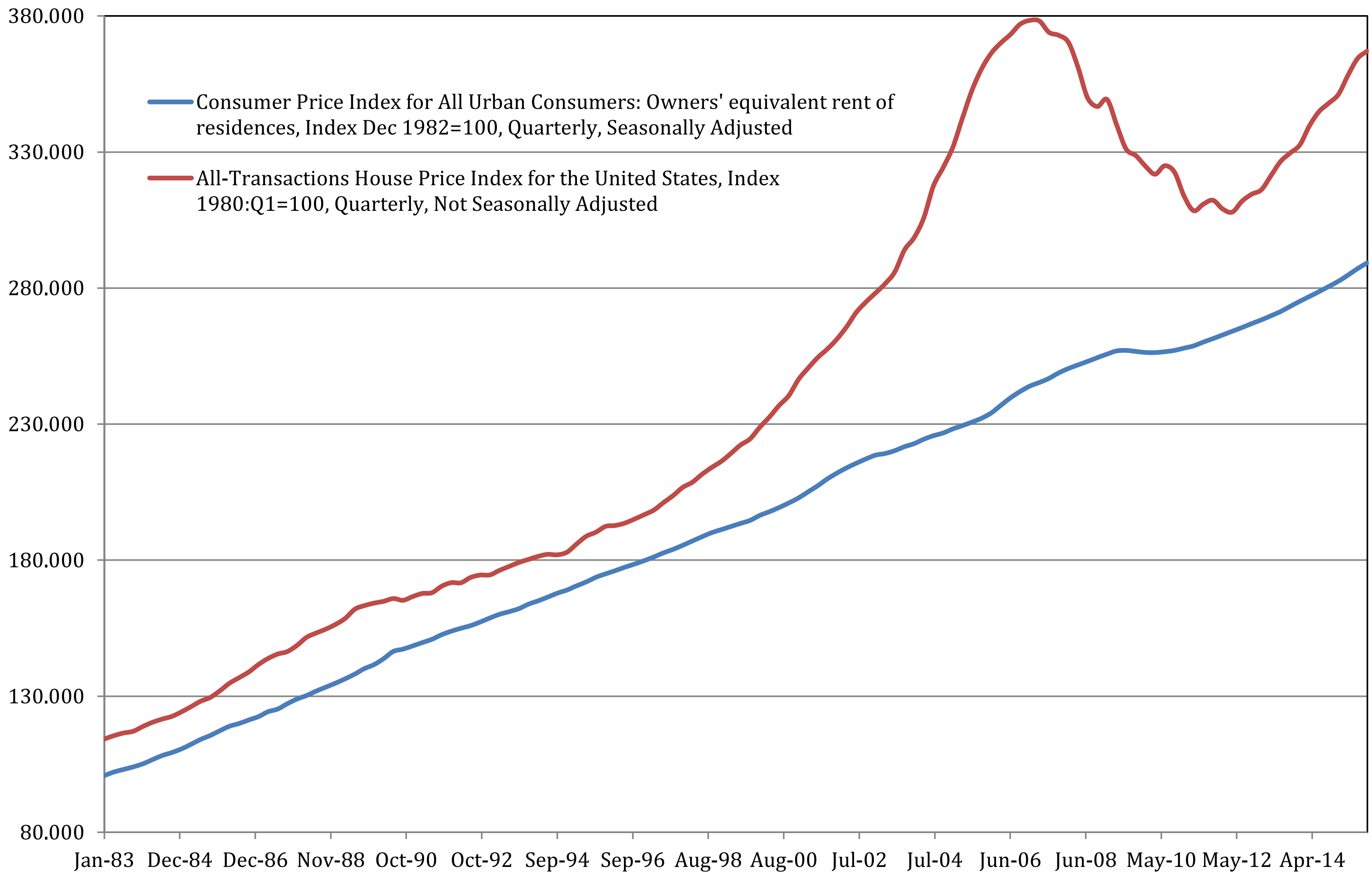
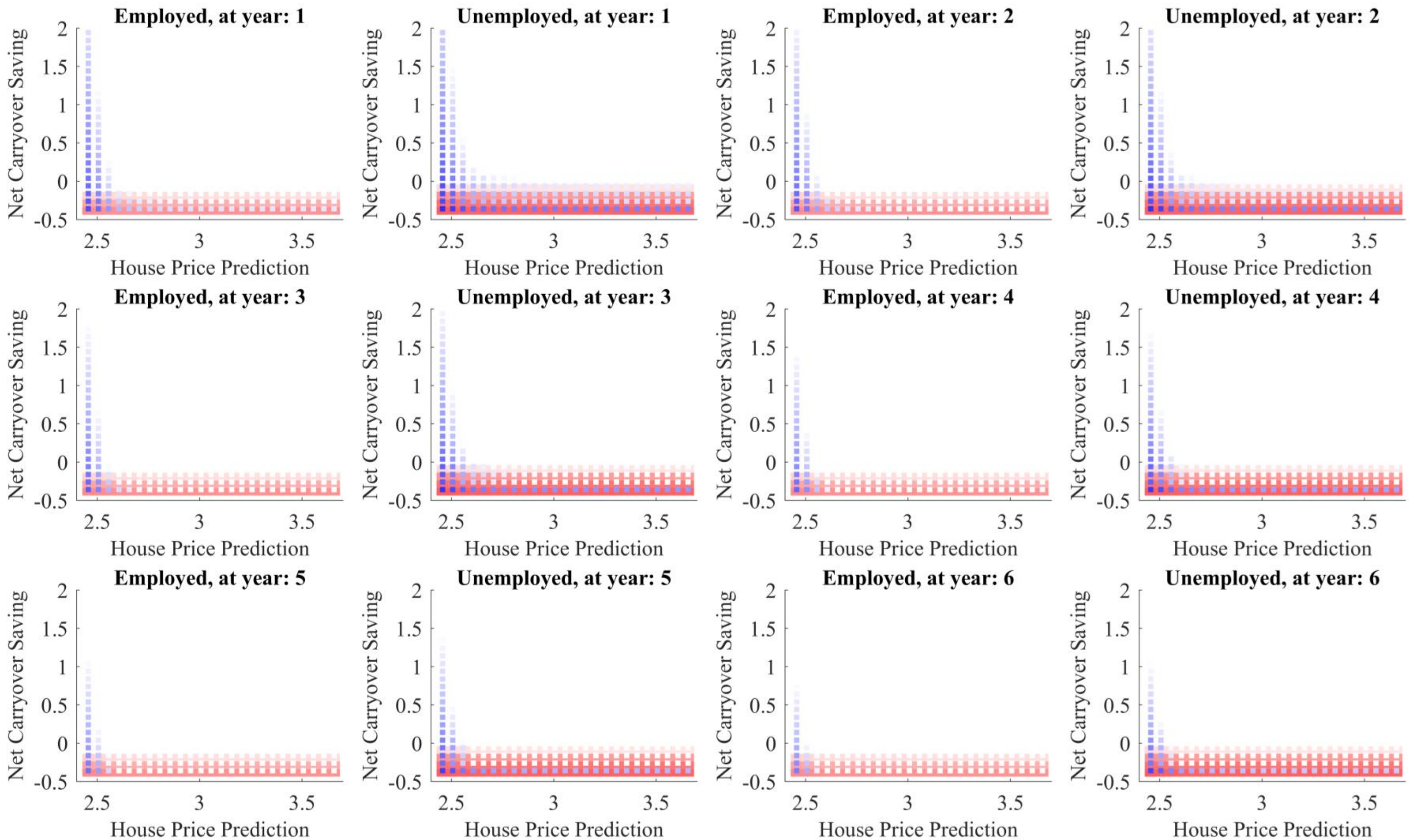


Figure 1.4 The Trend of House Price Index and Rent Price Index (Federal Reserve Bank of St. Louis)



Note: The color saturation represents the probability of household's strategic decisions.

Figure 1.5 Effects of House Price Observation and Asset on Homeowner Repayment Function

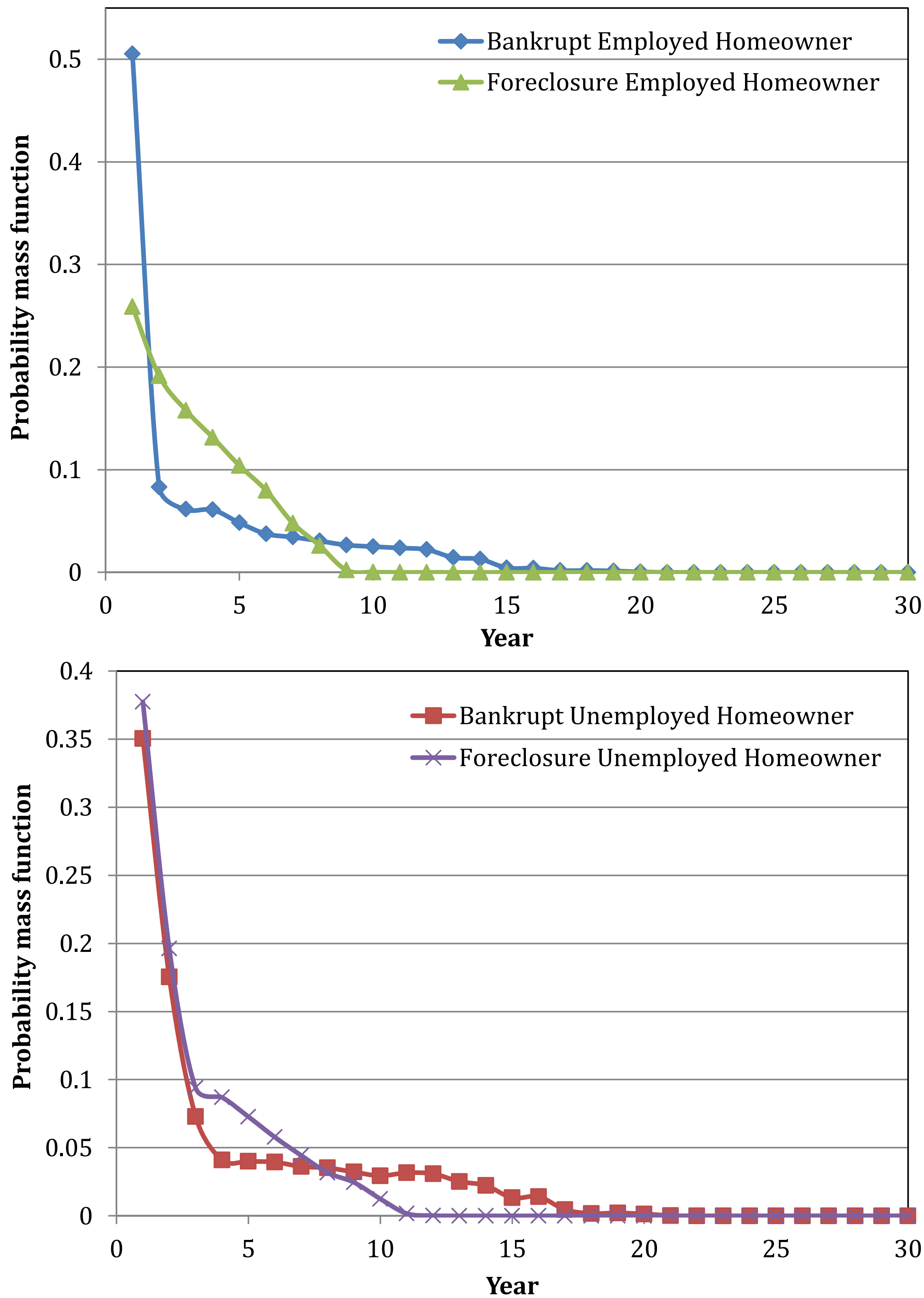


Figure 1.6 The Distribution of Homeownership Years of The Households Who File for Bankruptcy and Mortgage Foreclosure

Figure 1.7 The Simulated Path of Bankruptcy Filing Number and Unsecured Debt Charge-Off Rate Post-2005

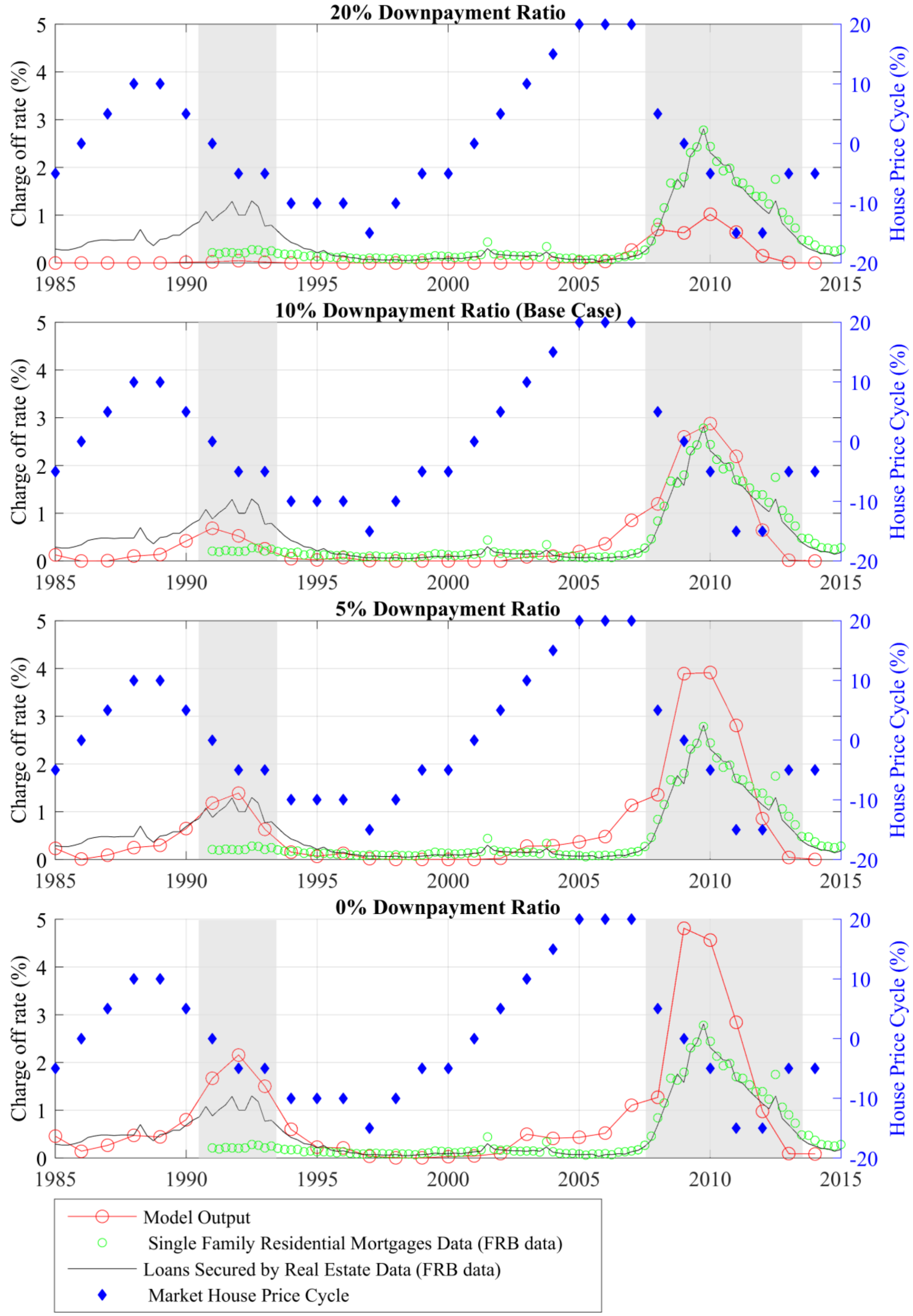


Figure 1.8 The Charge-Off Rate of Mortgages with Different Downpayment Ratios between 1985-2015: Model vs. Data

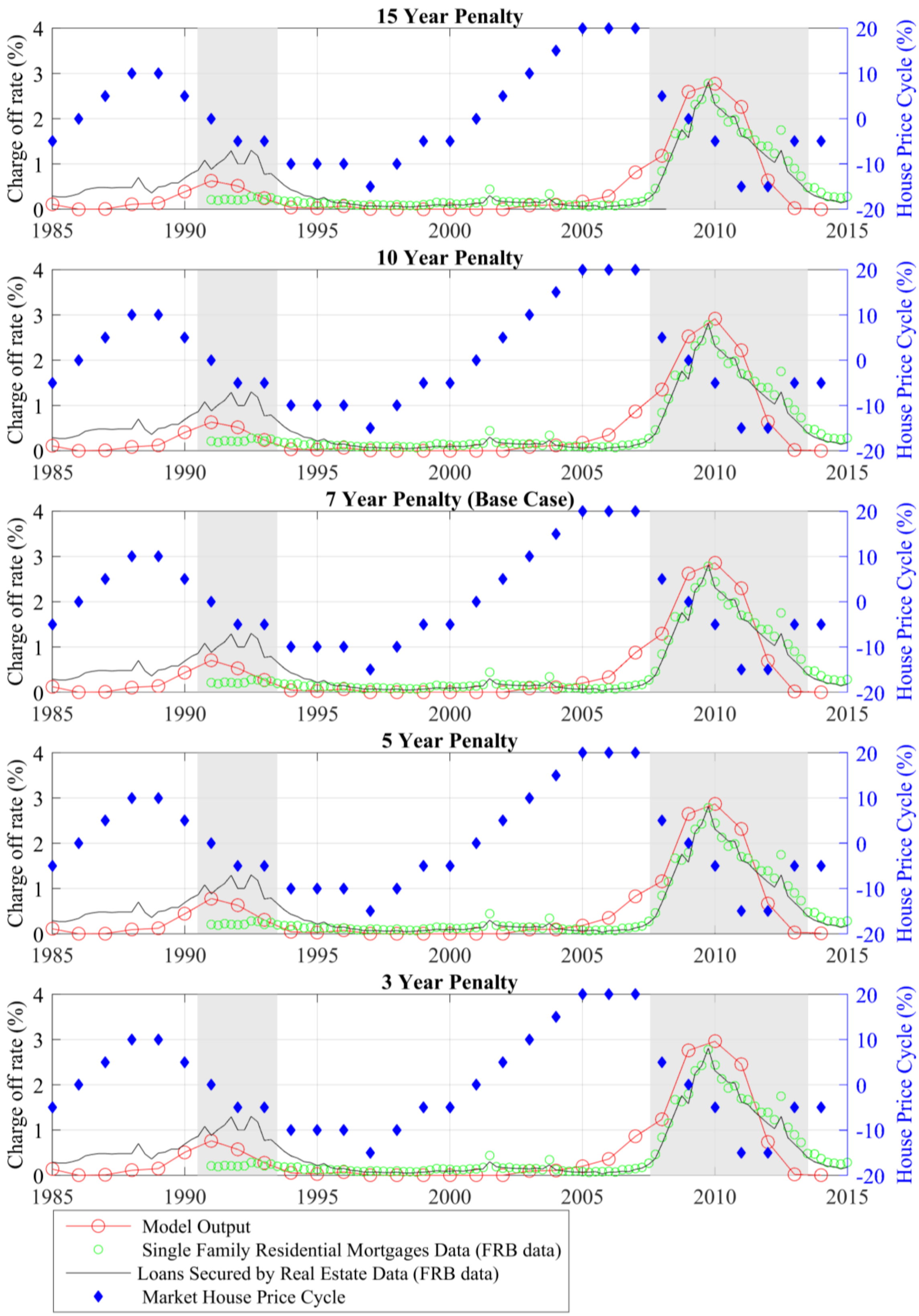


Figure 1.9 The Charge-off Rate of Mortgages with Different Lengths of Credit Exclusionary Period between 1985-2014: Model vs. Data

CHAPTER 2

DYNAMIC HETEROGENEOUS AGENT MODELS OF DEFAULT ON FARM REAL ESTATE LOANS

2.1 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 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 of 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 losses, 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 low commodity prices 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 defaults 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.

2.2 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. 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. Farmland's value may have two channels for affecting the risk of agricultural loans. Firstly, because the land is the collateral for agricultural loans, a fall in farmland 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 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 cropland 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.

2.3 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.

2.3.1 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)[3].

$$E_{t-1}y_t = \max_{n_t\, x_t}\{\tilde{y}(1-n_t), +E_{t-1}(P_tA_t)k_t{}^{\gamma_k}n_t{}^{\gamma_n}x_t{}^{\gamma_x} - M_{t-1}x_t\} \qquad \textbf{(2.1)}$$

When $n_t < 1$, this household 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

[3] When farmers optimize their production, the intermediate input is purchased at the beginning of production, such as fertilizer, seed, animal feed, etc. However, they won't 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.

farm hire wage rate are denoted by $\tilde{y}$, 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.

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

$$y_t(k_t, P_t, M_t) = \max_{n_t\, x_t}\left\{\tilde{y}(1 - n_t), +P_t\left(A_t {k_t}^{\alpha} {n_t}^{\beta} {x_t}^{\gamma}\right) - M_{t-1}x_t\right\} \quad \textbf{(2.2)}$$

2.3.2 Value Function and Budget Constraints

The household 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.

2.3.2.1 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:

$$V^N(s, j = 0) = \max_{c}\{u(c) + \beta V^N(s', j' = 0)\} \quad \textbf{(2.3)}$$

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.

2.3.2.2 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.

$$V^U(s,j) = \max_c\{u(c) + \beta V^U(s', j+1)\} \quad \forall j \in \{1,2,3,4,5,\dots,\tau-1\} \qquad \textbf{(2.4)}$$

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

$$V^U(s, j=\tau) = \max_c\{u(c) + \beta V^N(s', j'=0)\} \qquad \textbf{(2.5)}$$

subject to

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

$$s' \geq 0.$$

2.3.2.3 Farmer

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

$$V_k^F(s, j=0) = \max_c\{u(c,k) + \beta[\omega\eta\Phi + (1-\omega)V_k^F(s', j'=0)\} \qquad \textbf{(2.6)}$$

Subject to

$$c + \frac{s'}{1+r} = s + E_{t-1}y_t$$

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

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

If a farmer owes for a farmland loan ($s' < 0$), he/she 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 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 the value function and save computation time, the total loan note size can only be approximated by $k\Lambda$,

$$\Psi(Loan, r_{secure}, L) = 12 \times \frac{k\Lambda \times {r_{secure}}/{12}}{1 - \left(\frac{1}{1 + {r_{secure}}/{12}}\right)^{\iota \times 12}}. \qquad \textbf{(2.7)}$$

In each period, farmers are forced to sell their farm with probability ω due to 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. Φ is the total equity of the farmer, which depends on farm size (k), farm price (F), and riskless asset level (s).

$$\Phi(F, k, s) = max[0, s + (1-\chi)Fk] \qquad \textbf{(2.8)}$$

2.3.3 Strategic Decision

2.3.3.1 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 origination or refinance, lenders will restrict their total loan-to-asset value (LTV) ratio to lower than Λ. This implies that the lifetime utility of changing farm size from k to $\tilde{k}$ should be as follows:

$$W_k^{\tilde{k}}(s) = V_{\tilde{k}}^F(\tilde{s}) \tag{2.9}$$

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: $Pr[n = 1; P(\tilde{k}_1), P(\tilde{k}_2), P(\tilde{k}_3), \dots, P(\tilde{k}_m)]$. Mathematically, each farmer has m possible mutually exclusive farm size choices, with corresponding probabilities $P(\tilde{k}_i)$ 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.

$$\begin{aligned} &when\ V_k^F(s) \geq W_k^{\tilde{k}_i}(s)\ \forall i, \qquad P(\tilde{k}_i) = \begin{cases} 1, & \tilde{k}_i = k \\ 0, & otherwise \end{cases} \\ &otherwise \qquad\qquad P(\tilde{k}_i) \propto max\left[0, W_k^{\tilde{k}_i}(s) - V_k^F(s)\right] \end{aligned} \tag{2.10}$$

2.3.3.2 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 farmland for a year after they decide to default. The lifetime utility of the farm default is given by

$$W_k^{defaut}(s) = \max_c\{u(c) + \beta V^{\mathrm{U}}(\check{s}, j = 1)\} \tag{2.11}$$

subject to

$$c = s + E_{t-1}y_t$$

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

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

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 $W_k^{defaut}(s) > W_k^{\tilde{k}}(s)$, the farmers will choose to default on their farms.

2.4 SOLVING THE MODEL

Because these value functions (2.3) and (2.6) in the Bellman Equations do not have closed-form solutions, they are solved numerically using dynamic programming on the MATLAB 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 was divided into 513 equally spaced grid points; then, a linear interpolation[4] 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[5]. 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}

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

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

[5] $fminbnd$ 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

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

2.5 CALIBRATION

2.5.1 Farm Land

The national average of farm real estate values from 2006 to 2015 is presented in Figure 2.2. Since 2010, the real estate value has been trending from \$2000 to \$3000 per acre. As a base case, the farmland value in the model is set at \$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 ${}^{46700}/_{2200} = 21.23$ acres.

The farm size distribution in the United States is given in Figure 2.1. It is rather clear that there is a large number of farms smaller than 100 acres. Owners of these small farms are 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.

$$21.23 \times k \sim lnN(3.1567, 2.229), \quad given\ 21.23 \times k \in [100, +\infty) \qquad \textbf{(2.12)}$$

2.5.2 Production Function

To simplify this problem, I assumed that the farming production function is a constant return to scale. 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:

$$A_{l,t} = \widetilde{A_{l,t}} \times A$$
$$ln\, \widetilde{A_{l,t}} = \lambda\, ln\, \widetilde{A_{l,t-1}} + \epsilon_t \quad where\ \epsilon_t \sim N(0, \sigma) \qquad \textbf{(2.13)}$$

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:

$$E_{t-1}(A_{l,t}) = E_{t-1}(\widetilde{A_{l,t}}) \times A = exp(\lambda\, ln\, \widetilde{A_{l,t-1}}) \times A \qquad \textbf{(2.14)}$$

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 2.3, when A is calibrated to 0.83, the model output matches that census data in every farm size level. Ideally, this idiosyncratic productivity stochastic process of $\widetilde{A_{l,t}}$ should be estimated using farm level yield data. Because we lack the farm level production, 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:

$$\tilde{A}_{county,t} \equiv \frac{\overline{yield}_{county,t}}{\overline{yield}_{state,t}} \quad \textbf{(2.15)}$$

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

2.5.3 Preference

Weber and Key (2014) provided strong evidence to show that the wealth gain from 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 the land acquisition. However, farmers make their production and land use decisions independent of the price of land. Therefore, it is rather clear that the farmer's land purchase behavior is not only from increased net income but also from wealth accumulation. Actually, 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:

$$\mathrm{u(c,k,F)} = \frac{\mathrm{c}^{1-\alpha} - 1}{1 - \alpha} + \delta \frac{(\mathrm{Fk})^{1-\ddot{\alpha}} - 1}{1 - \ddot{\alpha}}\ \mathrm{I(own)} \quad \textbf{(2.16)}$$

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 coefficient 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. By necessity, 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 (2.17).

$$\delta \sim \mathrm{N}(0, \theta) \text{ given } \delta \in [0, +\infty) \tag{2.17}$$

2.5.4 Financial Intermedia

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 publishes three types of agricultural interest rate quarterly in their agricultural credit survey. The 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 2.4, 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 Fed has kept their benchmark interest 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 practice, the average length of farmland loan (ι) was set as 30 years, 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 to 0 for simplicity.

2.5.5 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 parameters: the discount factor (β), standard deviation of the truncated normal distribution of farm wealth desirability (θ), and constant relative risk aversion for land wealth ($\ddot{\alpha}$) by minimizing the distance between the empirical farm size distribution and model output. The farm size domain was divided into 24 non-equally spaced levels. As shown in Figure 2.5, the calibrated log-normal empirical farm distribution was discretized into these 24 levels. Then, the farm size distribution in the model simulation was used to calibrate the above three parameters internally. A 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 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 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 2.5) matches the empirical data in the regions of both big farms (upper figure) and small farm (lower figure).

Another parameter, the 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 constant prices of farmland, agricultural commodities, and the 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%. In order to match this base case default rate target, the one-period social stigma utility loss is estimated to be -0.2.

2.6 BASE CASE MODEL RESULTS

In order 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 afterward. The average of 1,000,000 Monte Carlo experiments resulted in economic paths and an aggregate distribution of outcomes.

The average characteristics of farmers in different farm sizes are shown in Figure 2.6. 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 the 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 2.6. The default rate of the smallest farm size is high because all beginning farms are in this farm size category. In this model, all non-farmers are only allowed to purchase land and to be farmers with the smallest farm size. Besides this, the default rate tends to 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 2.2). The farmers with the 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 2.7. 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 1,317 acres weakly monotonically increase with the farm size. It is noteworthy that a farm with 10,000 acres is an outlier because a farmer with 10,000 acres cannot purchase more land but rather accumulate equity. As 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 2.3. 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 farm their land 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.

2.7 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. Compared to default rate data in a real crisis, the absolute value given by the simulation is likely to be higher due to the constant interest rate assumption. One explanation is that the procyclical decline of interest rate will attract some farmers to refinance instead of defaulting their debt. Estimating a model with constant interest rates means we overpredict defaults somewhat, but adding dynamic interest rates to the model makes it so complex as to be essentially computationally impossible.

2.7.1 Agricultural Commodity Price

The food price index increased from 80 at 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 index 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 2.8. For all experiments, the prices increases 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 2.8, 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 at 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[6]. 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. This observation shows that it is very critical to keep the agricultural commodity price stable during this price

[6] 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).

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 2.8, 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 farmers' incomes, and this negative income impact will accumulate across periods. The longer the economy stays at 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 further understand the effect of commodity price on different farmers, the decomposed default rates of different farmers are presented in Table 2.4. In the first period of low commodity price, the default rate of the whole population is still lower than that in a normal state. The default rate of the whole population peaked one year after the end of low commodity price periods. At the peak, the big farmers and the young farmer have 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 are the most sensitive to the commodity price shock. That is because that the smallest and youngest farmers' usually have a large proportion of off-farm income. As described earlier, this off-farm income can help farm household make ends meet during the period of weak farm earnings. On the other side, the older farmer is wealthier and bigger farmer might pay off the loan by selling their land.

2.7.2 Farmland Price

From 2011 to 2015, the farmland price increased from $2,178 per acre to $3,020. Recently, farmland prices have started to slide. It is interesting to understand whether the farmland price is a major factor of the farm default. An experiment of three different farmland price shocks is found in Figure 2.9. All of the farmland prices increased from base level (1) up to a high price level (1.6), then dropped to three different price levels (1.2, 1 and 0.8). According to the model simulations, the severity of the defaults not only depends on commodity prices but also depends on the farmland price. In the period of high farmland price, there are very few beginning farmers, because they can't 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 successful farmers. Farmers who bought land in late 1960 have accumulated wealth during the farmland booming period. The farmers who "miss the train" will never be able to afford farmland. During this good time, 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 2.5. The older and median farmers have close to 0% default rate. The default rate of big farmers reduced about 18 times from that in the normal state. On the contrary, the default rate of young and small farmer only decreased by half. In short, owning more land before the farmland price boom brings capital gains and discourages loan default. This finding aligned with facts in the agricultural expansion in the 1970s.

However, when the farmland price starts to adjust to a lower level after the boom, there are more and more beginning farmers because of this affordable price. After farmland price drop to 1.2, the default rate adjusts to a higher level gradually without significant peaks. If the farmland price drops back to 1 (the base case) or 0.8, the peak of default rises up to 3% and 5.69% respectively. During the farmland price boom period, all landowners have more and more credit, due to increasing land property value. Instead of choosing default, the farmers with poor performance can survive by borrowing more. When the farmland boom stopped, the decreasing land price drives their loans underwater and leads to more strategic defaults. In Table 2.5, the decomposed default rates of farmers with different size and age 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 rate is as high as 18.78% at peak. The young farmers react to the farmland price drop quicker than other farmers, and their default rate is as high as 13.27% at peak.

According to the observation in the second panel of Figure 2.9, the long run aggregate default rate is lower under the lower farmland price. It is contrary to the short run observation, but it tells an intuitive story. If the farmland price is low in the long run, all farmers pay a lower cost of capital and are more likely to survive. As shown in the third panel of Figure 2.9, there are fewer new farmers under the price 1.2 in the long run compared with that in the base case.

2.7.3 Joint Shock

In the real world, a decrease in land value is usually correlated with a tumble in commodity prices. Under the influence of weak commodity prices, the demand for farmland will be weakened by farmers' exit. The farmland price will feel the pressure from the demand side. If both commodity price and farmland price fell substantially, even efficient farmers will be hit by a double blow, income shock, and credit shock. That is what occurred in the early 1980s at a time when both borrower and lenders were in serious financial troubles.

An interesting question is whether we can see the interaction effect of farmland price shock and agricultural commodity price shock in this simulation economy. In this dynamic simulation scenario, both farmland and agricultural commodity prices increase from 1 to 1.6, which represent the booming agricultural period in the last decade. Then, farmland price drops back to baseline (1) and simultaneously agricultural commodities drop to a low price level (0.8) for one period, then come back to baseline. The default rate under this scenario was compared with the single shock scenarios previously reported.

As revealed by Figure 2.10, the default rate increases 1.48% and 2.23% under the independent shock of farmland price and agricultural commodity price respectively. Neither of the price declines causes a severe outcome. In contrast, under the double blow, the default rate of farmland loan rises 4.65% from baseline, from 1.37% to 6.02%. This incremental default is significantly higher than the sum of those in the two single shock scenarios. As expected, the concurrence of two price shocks is very critical for indebted farmers' survival in the crisis.

2.8 CONCLUSIONS

This paper provides a structural study on the impacts of agricultural commodity prices and farmland price on farmland loan default in the U.S. The result of a dynamic experiment on agricultural commodity price shocks suggests that the lower commodity price drops and the longer the low price period lasts, the larger the increase in aggregate farmland loan defaults. The impact of farmland price on default is more complex than the impact of an agricultural commodity. In the short run, high farmland price will hold back beginning farmers but make existing farmers richer, and then the default rate will be low. In the long run, the higher farmland price means more capital cost and thinner profit margins, which can lead the default rate to be higher. After serval periods of elevated farmland price, a plummeting price will be followed by an aggregate default peak. Given future expectations of lower commodity price and lower farmland price, agricultural banks should expect an increase in default rate.

Table 2.1 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	the 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 2.2 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 2.3 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 a baseline.

Table 2.4 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 2.5 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%

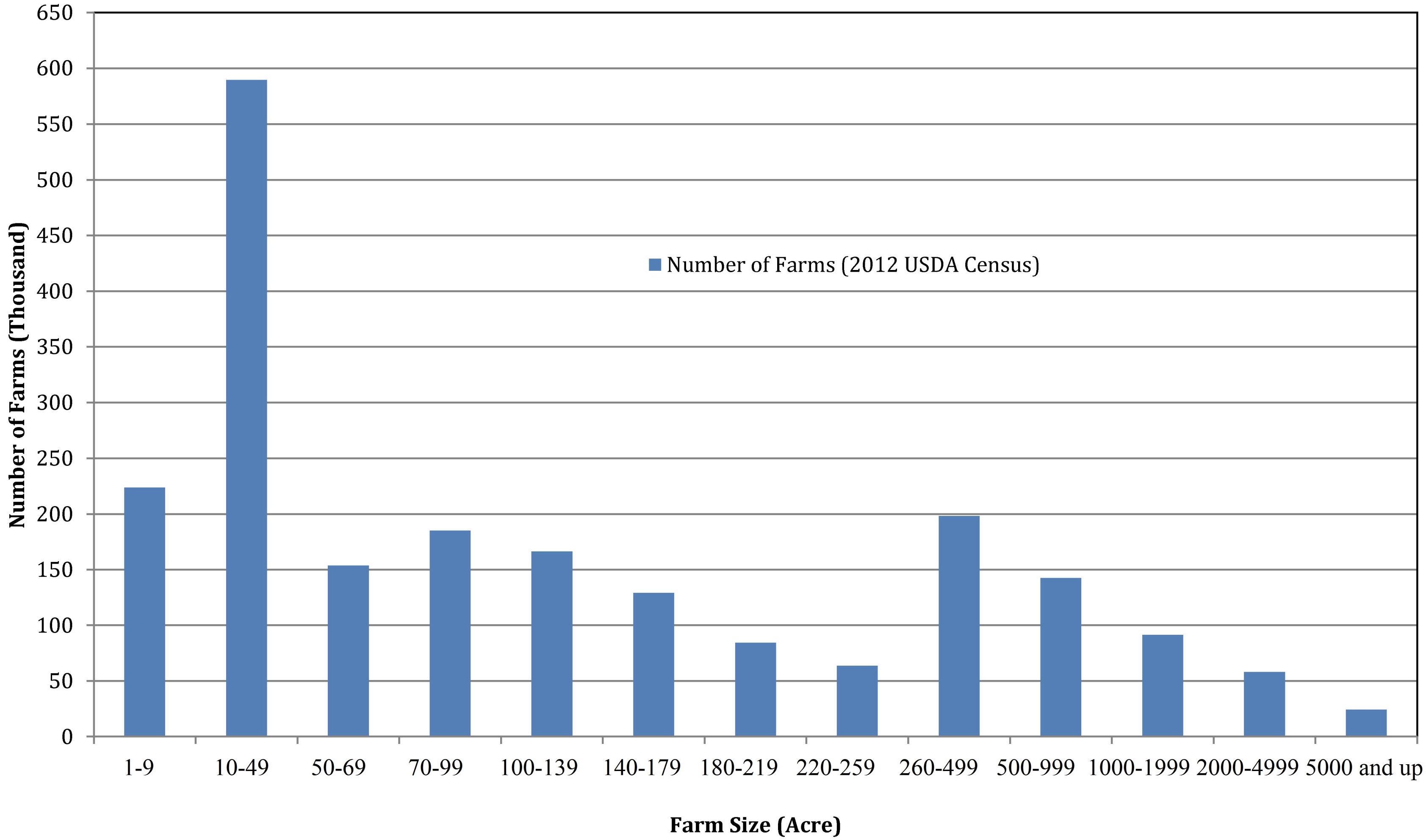


Figure 2.1 The size distribution of U.S. farms, 2012 USDA census

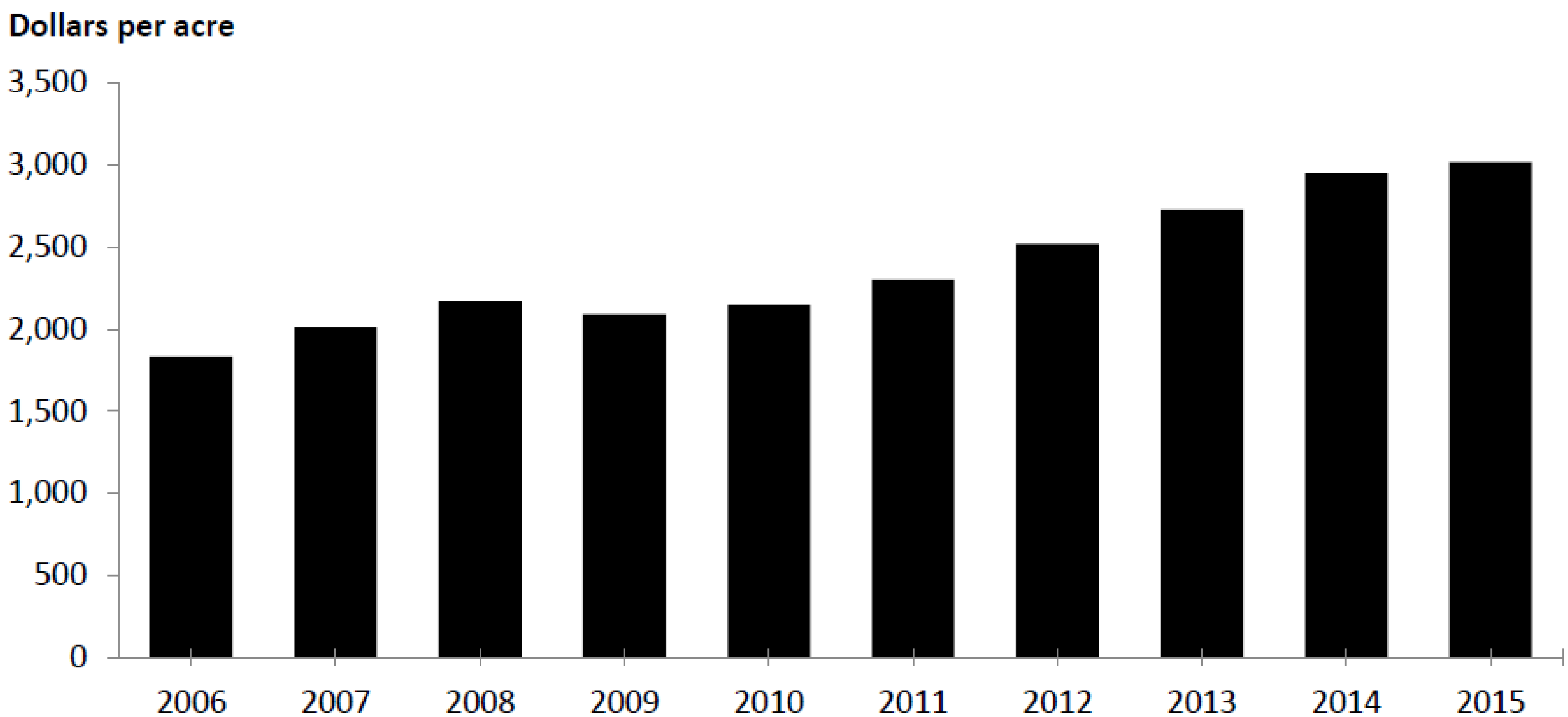


Figure 2.2 Average Farm Real Estate Value in the United States (USDA NASS 2015)

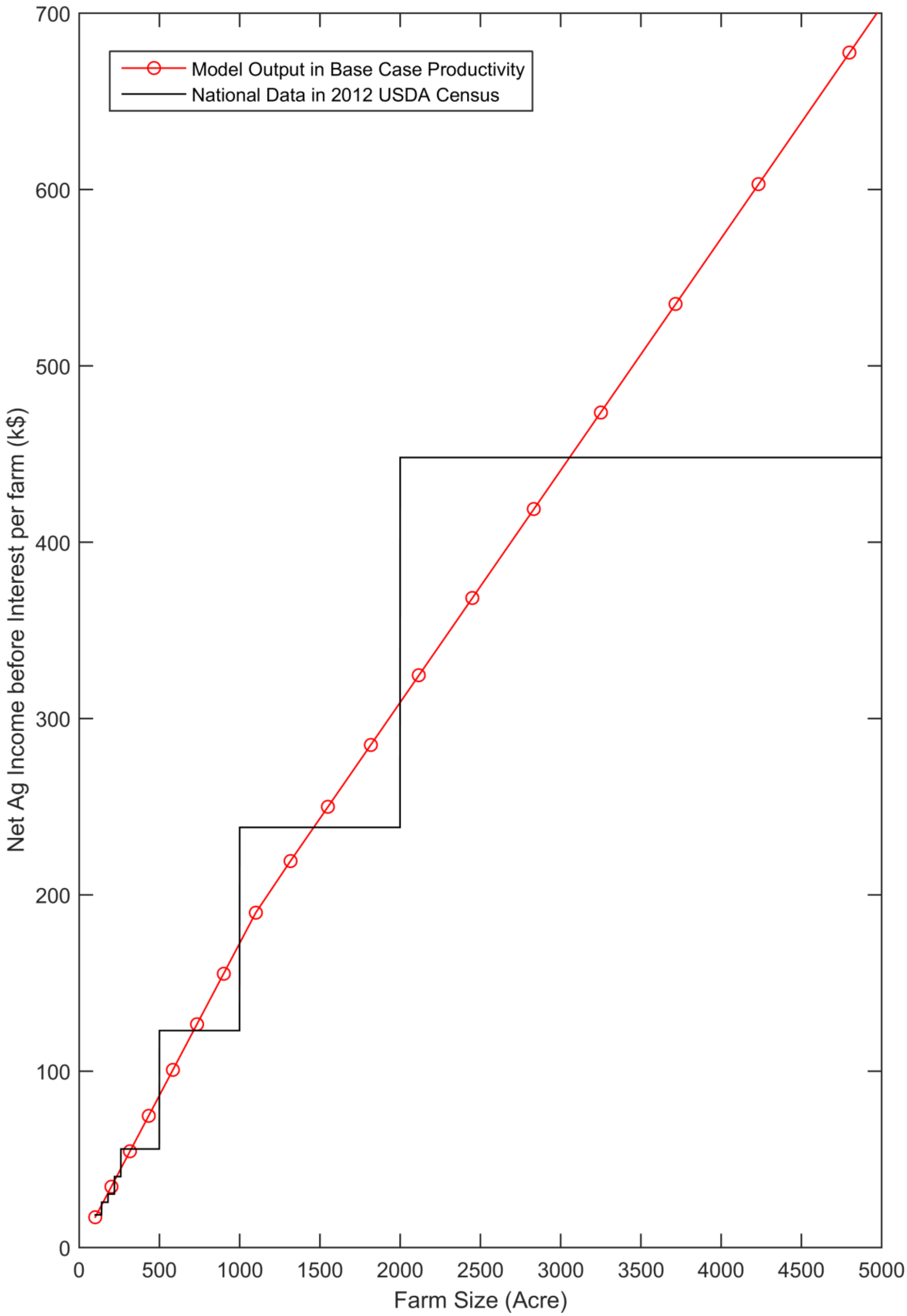
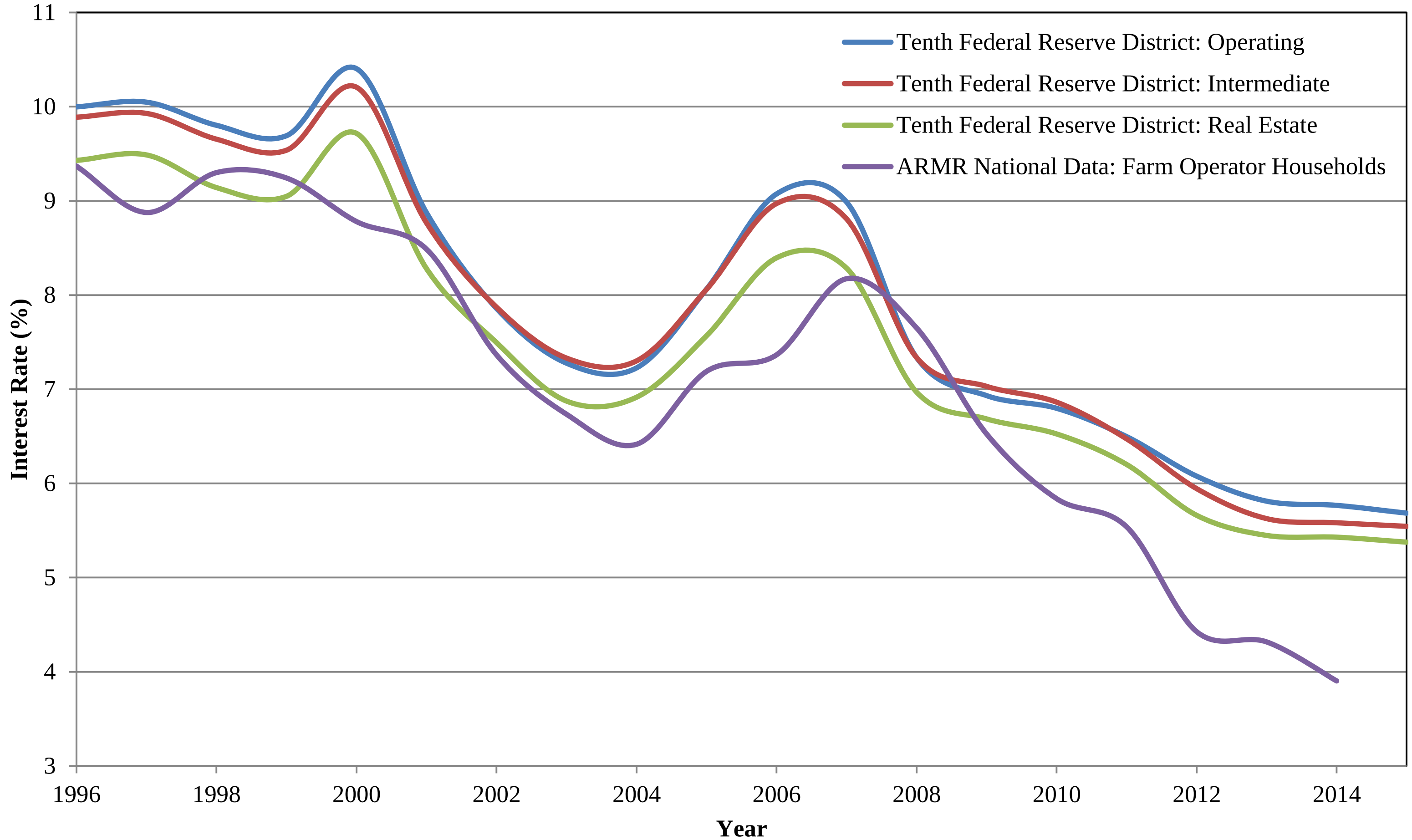


Figure 2.3 The Calibration of Productivity Based on Net Ag Income per Farm



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 paymentfarm operator households

Figure 2.4The agricultural loan interest rates

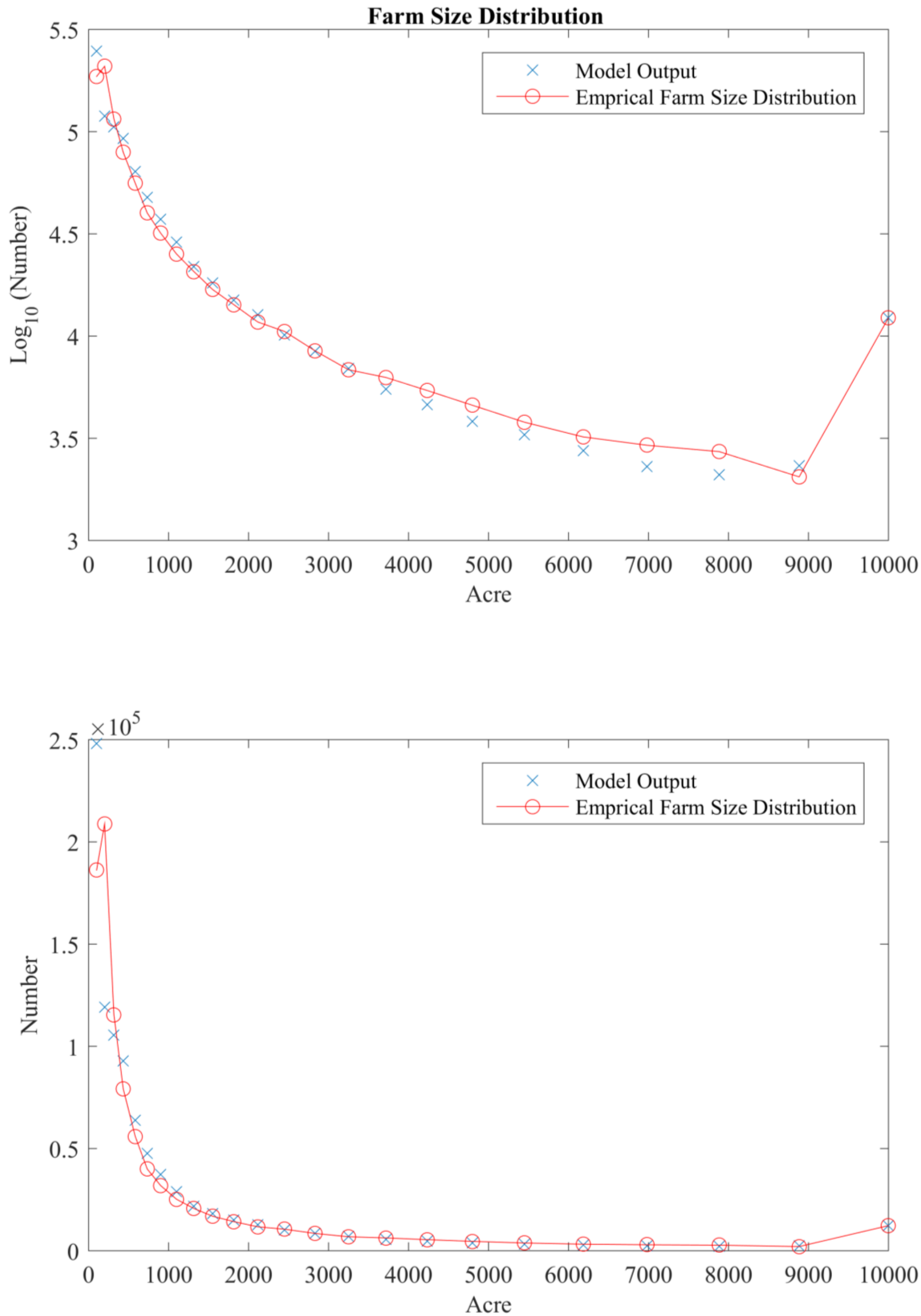


Figure 2.5 The Farm Size Distribution Calibration

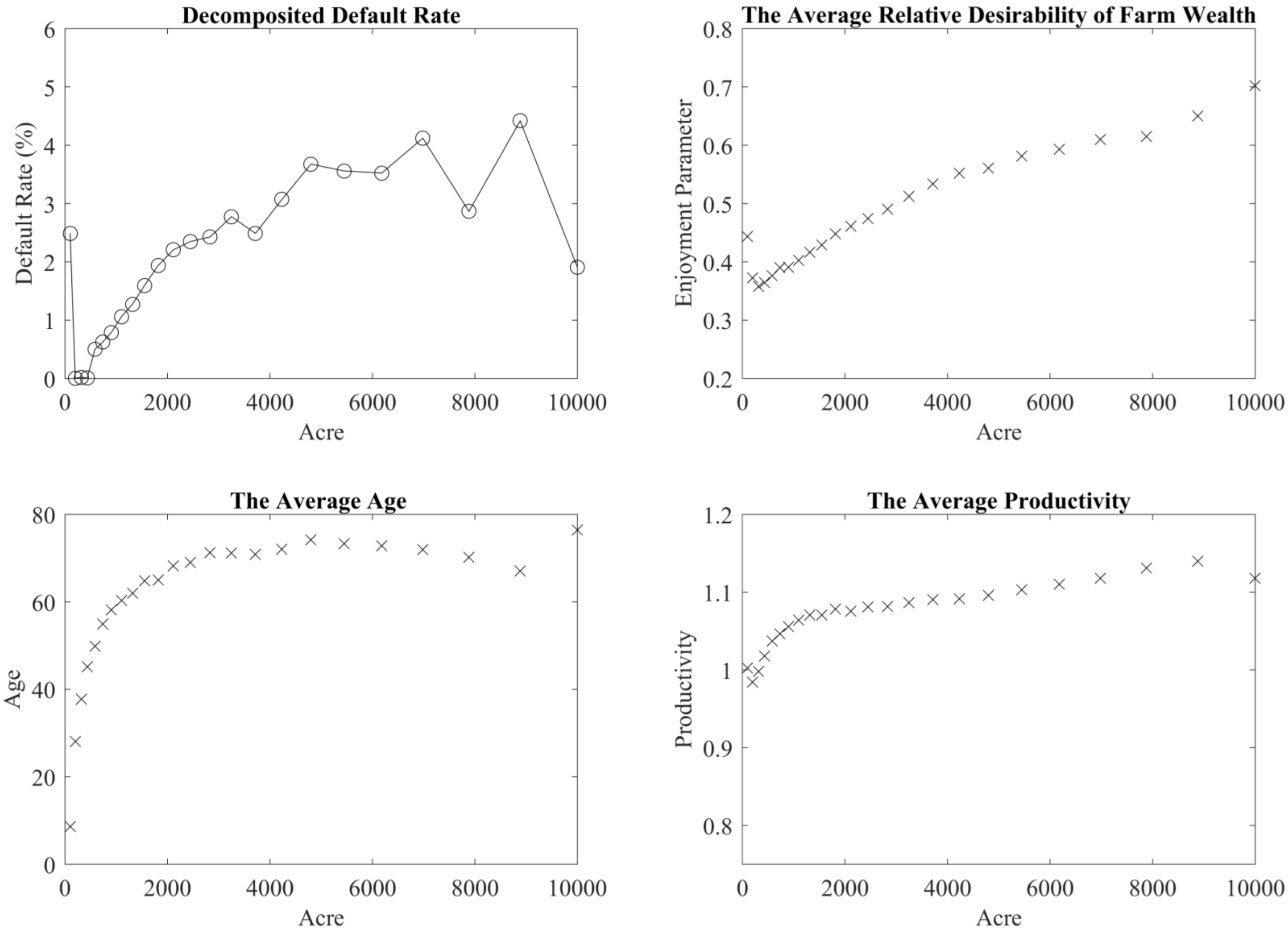


Figure 2.6 The Average Characteristics of Farms in Different Size Level

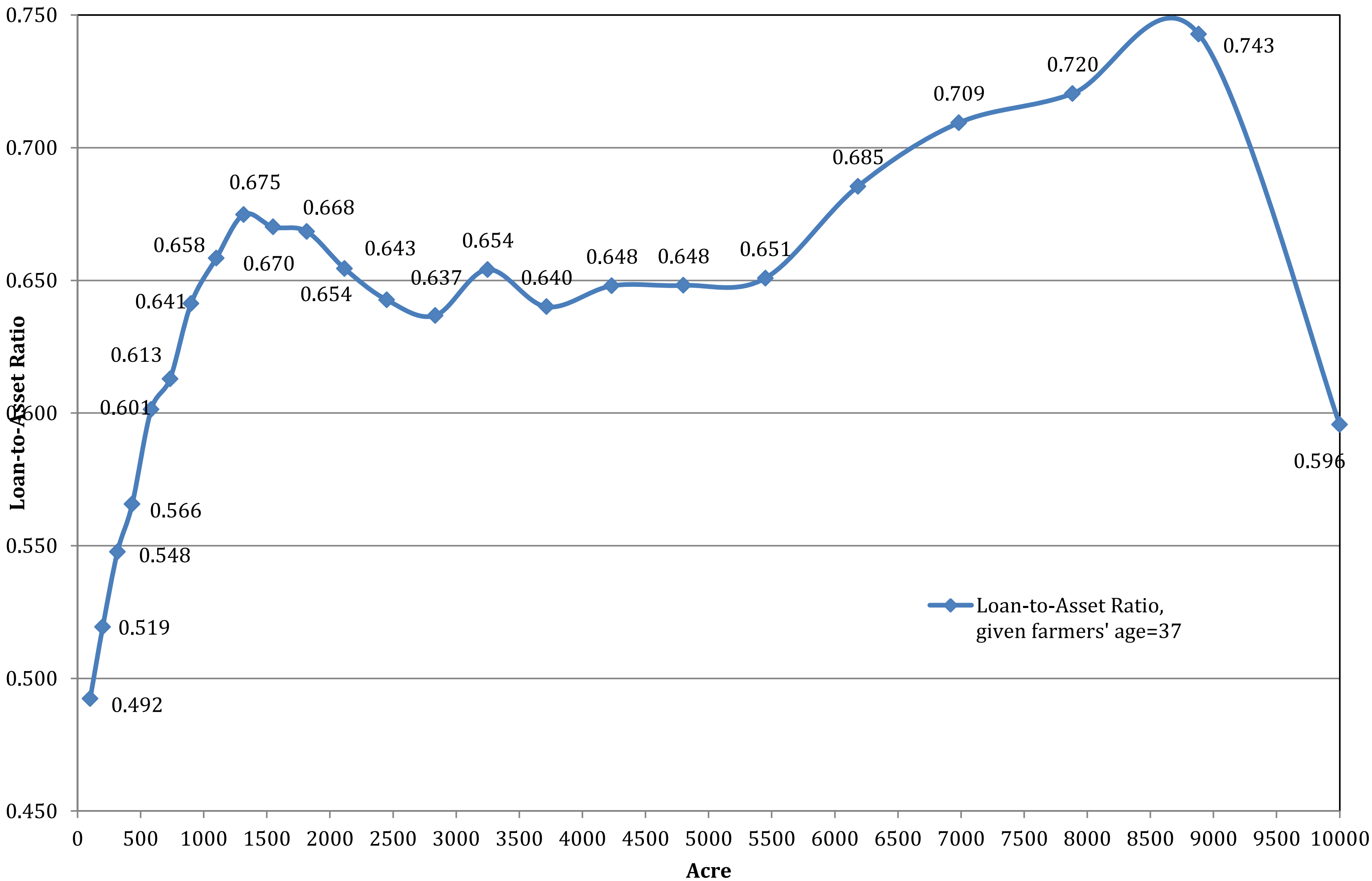


Figure 2.7 The Conditional Average Loan-to-Asset ratio, given Farmer's Age is 37 (The average age in this economy).

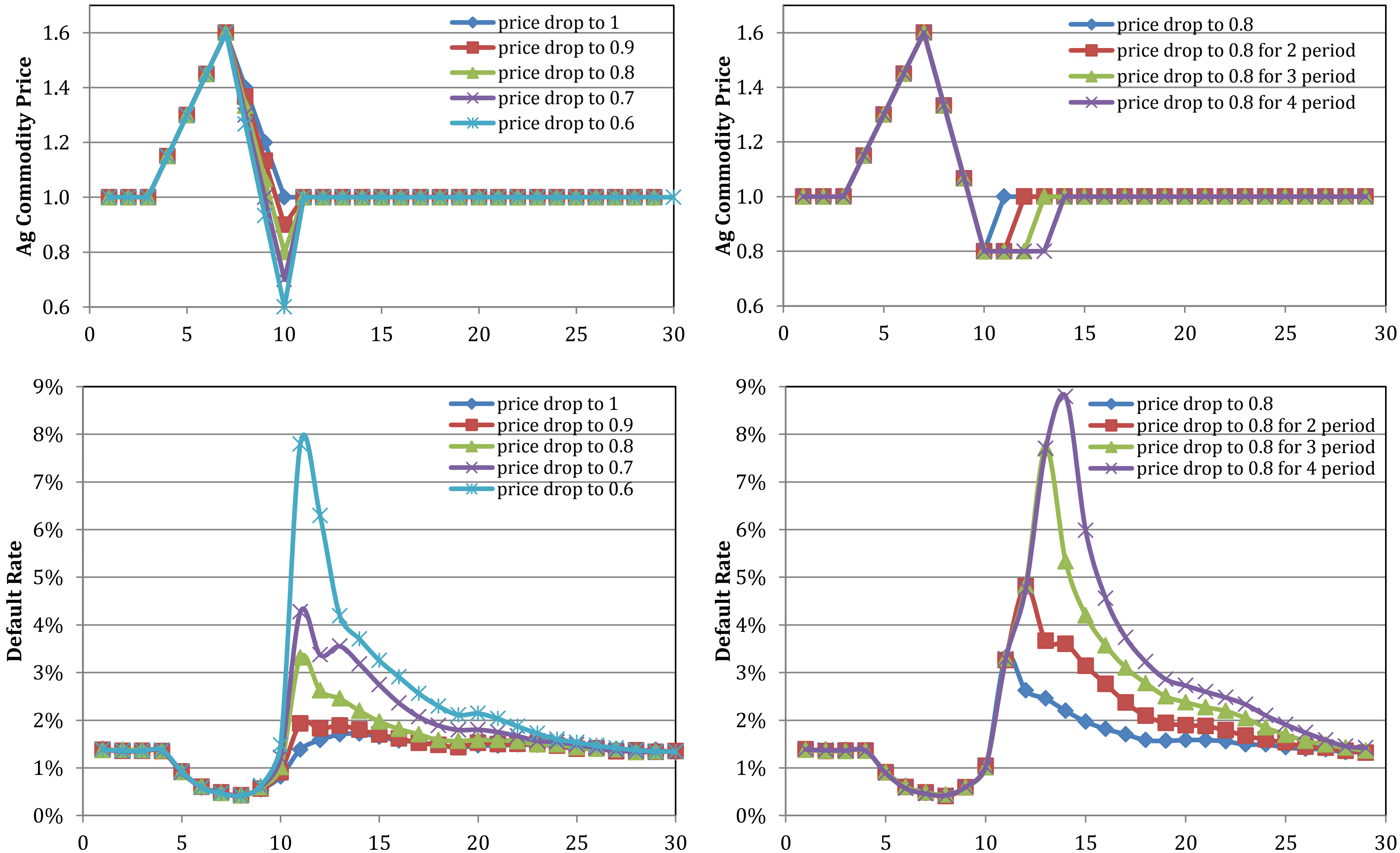


Figure 2.8 Dynamic Default Rate of Farmland Loan with Different Ag Commodity Price Shock

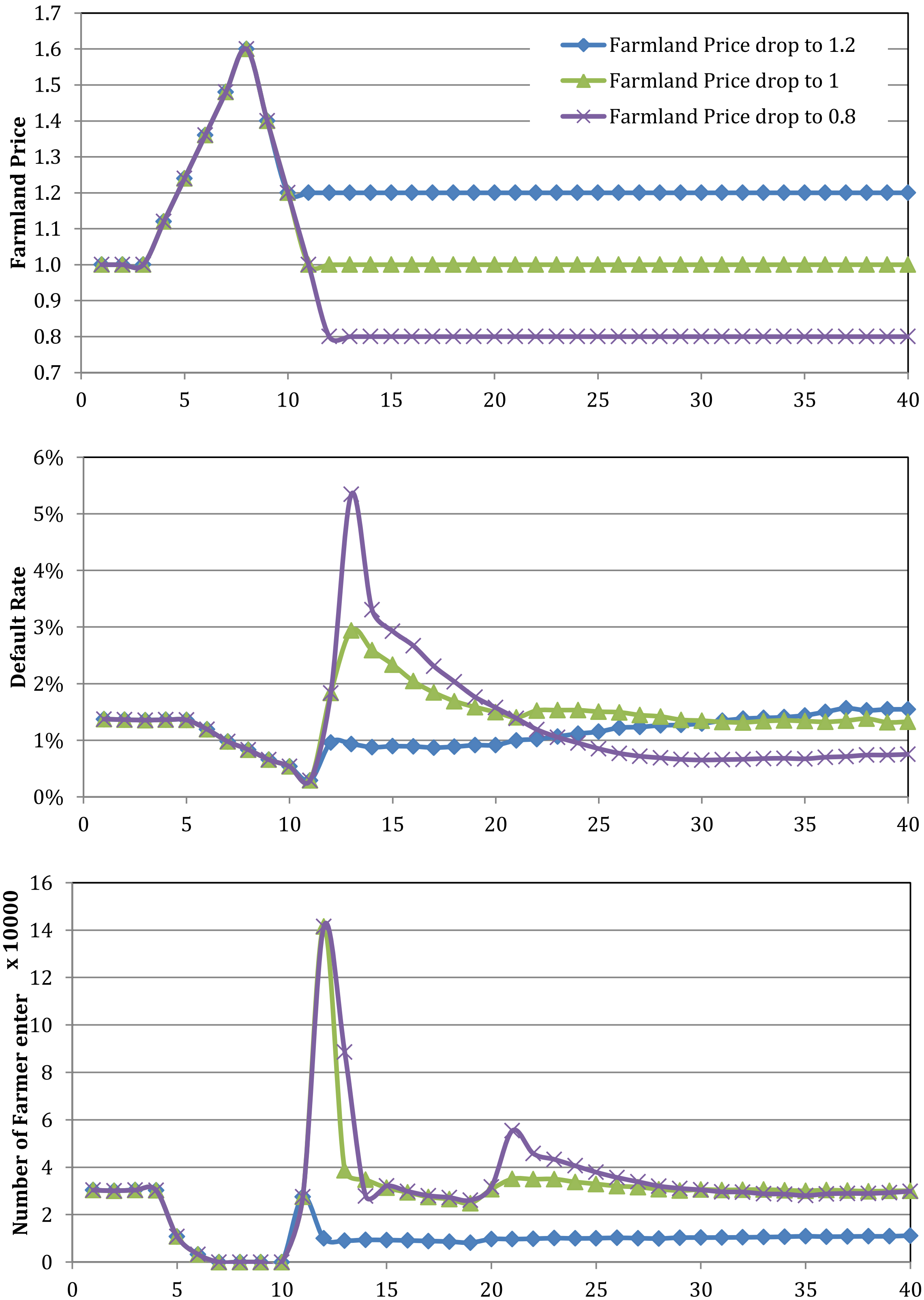


Figure 2.9 Dynamic Default Rate of Farmland Loan with Different Farmland Price Shock

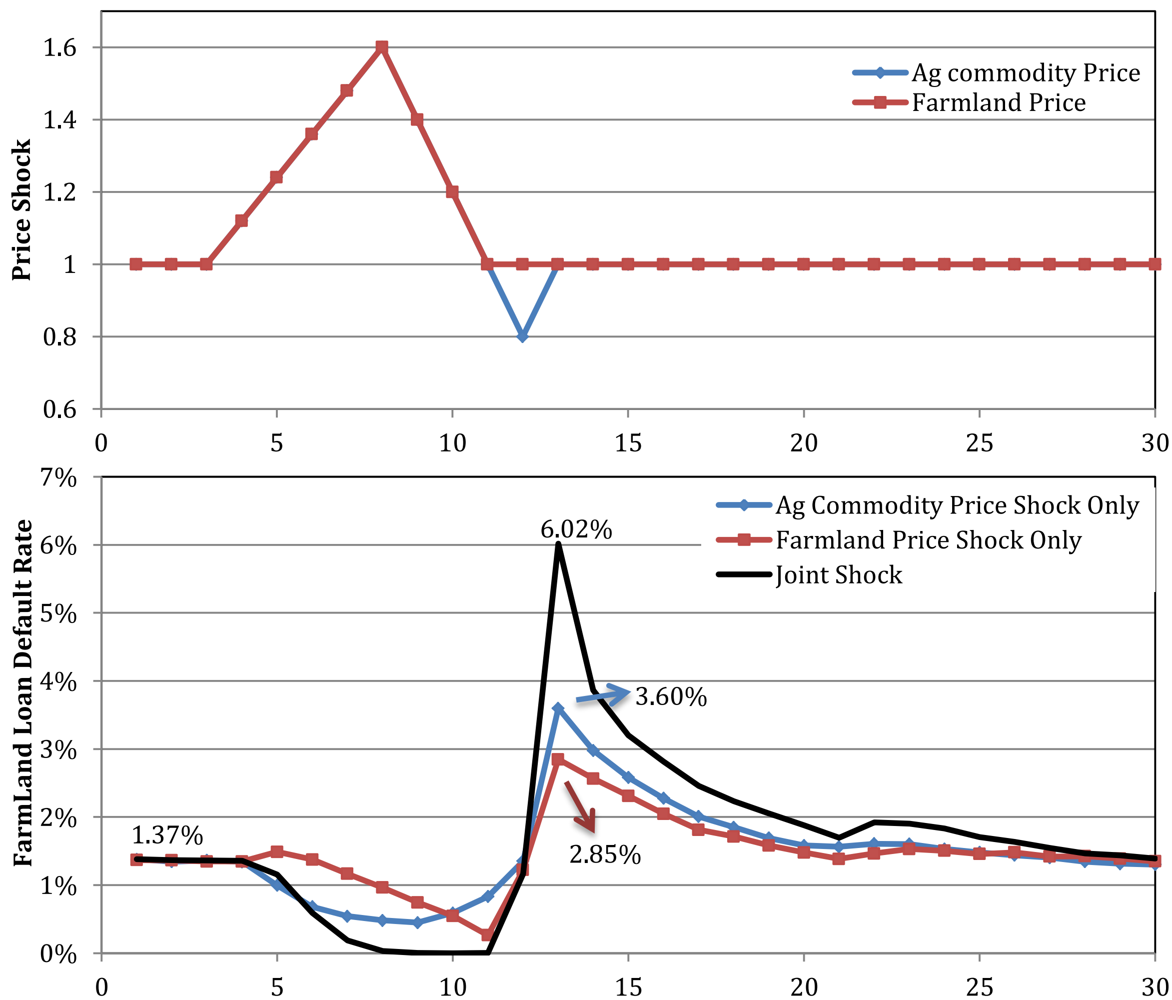


Figure 2.10 Dynamic Default Rate of Farmland Loan with Joint Shock from Farmland Price and Agricultural Commodity Price.

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