KUO, HENG HUNG. The Determinants of Exit Behavior under a Structurally Changing Industry: Evidence from the U.S. Swine Industry. (Under the direction of Kelly Zering)

This study estimates the determinants of the exit behavior in a concentrating industry that encounters industrial restructuring. The swine industry has experienced the dramatic change in many perspectives, especially farm size and operation numbers, in the United States in past decades and the process still continues. Characterized by industrialized hog production, hog industry provides available data and a significant case study for exploring the issue related to structural change and exit behaviors. This study uses U.S. swine industry data to explore the factors that affect small producers’ quitting decision. Balanced panel data for 14 major hog production states from 1988-2003 was collected. Fixed effects models and random effects models, either one-factor or two-factor are all considered in this study. By observing the aggregate leaving pattern: exit rates, we can evaluate how exogenous shocks, macroeconomic conditions, technological improvement and scale of production, drive small-farm operators’ decision-making. Moreover, this study evaluates two driving forces of leaving behavior, voluntarily or non-voluntarily. It is implied that timing of leaving is important. In addition, this paper evaluates the existence of a crowding-out effect among large-scale modernized entrants and small traditional family producers’ exit.

Comparing the models by R-square, F-test and Hausman test, this study chooses one-factor random-effects model as the major results and two-factor fixed-effects model as auxiliary results.
Whether the exiting behaviors of producers, especially for smaller producers, are volunteering or forcing to leave, that is related to the fairness of competition within the industry. In this study we find out new large-scale entrants do not displace the incumbents. It means that the crowding-out force does not happen between large-scale producers and small-scale producers. Alternatively, we find out that the expanding larger producers’ hog operation sizes pressure the small producers to leave swine industry. As for this expanding is benign or hurtful, this study does not provide the evidences to judge.

As for technology improvement, it affects the survival space for smallest hog producers. It implies that smallest category of producers have difficulty to access the improvement technology. Furthermore, technology improvement plays a buffer role for producers with scale of 100-499 head of hogs. It implies that for producers in this category need to change its efficient capacity, match the necessity of improved technology and/or raise the management skills to survive in this business. Also the unemployment rate plays a guiding role for smallest and second-smallest producers’ decision-making of quitting hog business.

Illustrate the exiting behaviors might increase the forecasting precision of supply for the whole industry, especially established the relationship between exit behaviors and supply, that might help clarifying further hog cycles. In this study we conclude that hog price is the factor to affect the incentives of producers with scale of 100-499 head. In addition, from this study, we do not observe that state-specific factors affect the exit behaviors of small producers strongly enough. It implies that state-level public programs or policies, such as environmental regulation, do not have crucial influence on small producers’ exodus.
THE DETERMINANTS OF EXIT BEHAVIOR UNDER A STRUCTURALLY CHANGING INDUSTRY: EVIDENCE FROM THE U.S. SWINE INDUSTRY

by
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A dissertation submitted to the Graduate Faculty of North Carolina State University In partial fulfillment of the requirements for the Degree of Doctor of Philosophy

ECONOMICS

Raleigh
2005

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Chapter 1 INTRODUCTION

1-1 Background

The U.S. swine industry has exhibited dramatic change in many characteristics in past decades and the process still continues. From technological improvement in production to modernized vertical linkage marketing channels and skills, change has upgraded the swine industry into a new stage: industrialized production. Rhodes (1998) defined industrialized hog production as production in specialized facilities, under standard procedures and specialized labors and the sizes of hog producers varying with the size and number of facilities instead of the acres of associated corn land.

Improvements in technology are responsible for the production efficiency in swine industry. For example, the annual average pigs-per-litter has increased 30% from an average of 7.18 pigs per litter in 1980 to 8.75 in 1998 and attained 8.85 in the first quarter of 2004. The number of pigs sold per sow per year has increased an average of 1.7% per year since 1935 (Plain, 1997). These facts show that average hog producers have become more efficient in production in the U.S. The improvement of production technology is also reflected in increasing slaughter weights. In the past 40 years, the average slaughter weight for all hogs (258 pounds in 1995) has increased by an average of 0.8 pounds per year (Plain, 1997). Cromwell and Hays (1999) in “The Swine Industry – Significant Events of the Past Century” mentioned significant changes in breeding, reproduction, nutrition and feeding programs, and health and disease control fields. All these factors upgrade hog production efficiency and affect the entire industry structure. Moreover, the technological disparity between different producers due to large capital investment makes the cost
structures of hog producers highly disparate. For example, the current trend among most large hog producers is to raise pigs in facilities that are in sophisticated, state-of-the-art buildings with computer-controlled environments (Cromwell and Hays, 1999). One indicator of technological differences between large producers and small producers is the numbers of pig per litter. According to Statistical data from *Quarterly Hogs and Pigs* (NASS, 2004), the average pigs per litter in the smallest size of operation (with 1-99 head) is 7.60, while the number in the largest size of operation (with over 5000 head) is 9.00 in the same period. The number of pigs per litter increases with the sizes of operations. Various cost structures, capital-dominated or labor-dominated, among producers, result in producer competitiveness and profitability being heterogeneous. Hence, this characteristic could be a significant reason for the changing structure of swine industry.

One of the significant observations related to structural change, in the swine industry, is that the number of hog producers is dramatically decreasing. In 1965, the number of operations is 1,057,570 in the United States. Between 1980 and 2003, the number of operations in the U.S. has drastically dropped almost by 89%, from 666,550 to 73,720. As for state level data, take the largest hog production, Iowa, for example, the number of operations is from 53,000 down to 9,200 between 1983 and 2004. It is over 80%. This kind of economics of capital flowing to its best and most productive application is not observed in other livestock sectors in the United States (Goldsmith, 2000). Growing production scale, mass production in one situ combined with industrialized production methods, is one of the most significant results from the revolutionary change in swine industry. As evidence of this dramatic change, note that the statistical data collected by the USDA has changed format twice since 1993 to better view the whole industry more
precisely. The USDA used “above 2000 head” as their biggest category per producer before 1993. After 1994, the biggest category was adjusted to “over 5000 head per producer” which reflects the need to oversee the entire picture of the entire swine industry. Since this new category, the operation size of over 5000 head has reached 53% of total inventory in the U.S. in 2004, indicating industrialized hog production has become the mainstream production method.

1-2 Statement of Topic

Producers’ exit behaviors can be affected by several factors, such as industrial surroundings and firm-specific factors, etc. This issue seems to have been given less attention in recent decades, perhaps due to relatively stable industrial features and production structure in agricultural industries. U.S. agricultural economists have paid only limited attention to economic determinants of producer exits (Goetz and Debertin 2001), especially under the changing structure of agribusiness. With the emergence of industrialized hog production, the swine industry provides data and a significant case study for exploring structural change and exit behaviors.

By observing the aggregate leaving pattern, can we recognize which exogenous shocks drive hog producers’ exit decisions? The driving forces of leaving industries, voluntary or non-voluntary, can be observed by the timing of leaving. Will producers leave the industry based on expectation of price fluctuation? Inefficient hog producers might tend to leave the industry when the hog prices are high and/or profits are maximized over the exit period. Another possibility is that they might be forced to leave when pig prices are low and/or profits are minimized. Asymmetric hog price reactions imply that the hog price
is one of the important factors that might affect producers’ willingness to leave the industry. It is hypothesized that timing for leaving is important by examining that the exit decisions happen significantly in some specific years. In addition, it is hypothesized that there is a crowding-out effect when the competition of large modernized producers enter forcing small traditional family producers to exit.

Technological improvement is considered to be the major driving force for concentrating the industry, thereby improving the productivity of the producers that use new technology. Due to the difficulty of measuring technological improvement or innovation, understanding of the consequences and influences of technological improvement on exit behavior and industry structure is relatively underdeveloped (Geroski, 1994). This study tests the effect of technological change on exit behavior by observing the exiting producers’ pattern and the entry of new producers that use newly developed skills or equipment in the swine industry. The interaction between incumbents who consider leaving industry and new entrants might exhibit some kind of relationship.

Macroeconomic influences on exit have received little attention (Ilmakunnas and Topi, 1999). Moreover, how macroeconomic conditions affect producers’ exit behaviors are unclear in previous research. The swine industry, with its rapid structural change, provides a case for potentially supportive evidence on this issue.

1-3 Motivations and Objectives

The recent dramatic change of the U.S swine industry provides a good empirical case example for the concentrating industrial features discussed by previous researches. The dynamics of exit patterns in industry and services are complex and still poorly understood.
(van Kranenburg, 2002). Furthermore, past studies (Ilmakunnas and Topi, 1999) focused on diverse industries, combined with short time series or discrete census data that is collected every fifth year (Dunne, Roberts, and Samuelson, 1988). In this study, using the significant feature of large-scale and long-term annual exodus in a single industry, we can study patterns of exit behavior and estimate the relationship between producers’ (hog producers) exit behavior and determining factors under structural change.

Therefore, the objectives of this research are:

1. Determine the factors, macroeconomic and microeconomic conditions affecting the exit pattern of the swine industry in the U.S.
2. Illustrate the relationship of hog producers’ exit behavior and affecting factors under a structural change stage, especially the larger producers’ entry and/or extension of production scale.
3. Examine whether the different size categories of producers that are affected by variable exogenous factors.

The exit rate of producer numbers (calculated by difference between previous and current periods then divided by previous period’s producer numbers) can provide meaningful information for interpreting the structural change of an industry, especially through observing small producers’ decision-making about leaving the industry. Moreover, the superior data set from NASS (National Agricultural Statistics Service), reporting both number of operations by size and percentage of inventory, can detect the more detail results of different size categories of producers since they have different production structures, attributes and demographics.
The U.S. swine industry provides a good empirical case for observing a concentrating industry. Basically, this study focuses on observing what affects the small producers’ decision to about leaving the industry.

The analysis proceeds according to the following outline: In chapter 2, the U.S swine industry is overviewed, including industrial features, such as producer size and operations numbers; in Chapter 3, literature is reviewed from two dimensions – the research related to industrial exit and entry and the swine industry structure; next, a conceptual model is developed and described in Chapter 4; Chapter 5 contains the process of choosing the proper variables and building up the adequate econometric model for estimation relationships between exit rate and the factors that affect it; the results of the econometric model are discussed in Chapter 6; finally, in the Chapter 7, the conclusions of the study, relative policy issues and the limitations in this study are presented.
2-1 The Current Situation of Hog Production in U.S.

2.1.1 Heterogeneous Cost Structures of Hog Producers

The structures of hog production costs are diverse among individual producers. Feed, labor and capital are the three major inputs in hog production (McBride and Key, 2003). According to the McBride and Key’s report (2003, page 14), production costs of per cwt gain, including feed costs, operating costs and ownership costs, can be more than double among different costs group of hog producers. Take feed costs for example, feed costs for some producers can be as low as 15.83 (dollars per cwt gain); for other producers, it is 35.98 (dollars per cwt gain). This differential cost structures form the basic different competitive powers among producers.

Hog production costs do not only vary among individual producers but also by regions. Traditionally, hog production has been located in or near the major grain growing areas to take advantage of low feed transportation costs. The Corn Belt, Great Lake States and Northern Plains accounted for 78 percent of total U.S hog production in 1950 and in 1980. In the last decades, the Southern states and isolated areas of the West have become increasingly important areas for hog production. The Corn Belt, Great Lake States, and Northern Plains share of U.S. hog production has fallen to 68 percent in 1999. While Iowa remains the largest hog-producing state in terms of hog inventory, North Carolina has gained the lead in terms of farrowing sows. Technological change has been an important factor in the growth of hog production in these nontraditional areas. Producers in the southeast have been able to take advantage of the efficiencies that accompany larger
operations and newer production methods, despite less locally available feed supplies. Continued growth in these nontraditional areas is likely to hinge on the improved feeding efficiency. This fact also reflects that each state/area has its own niches and problems of hog production.

According to the report, *Economic and Structural Relationships in U.S. Hog Production* (McBride and Key, 2003) from the USDA, nearly all indicators (feed, labor and capital) of physical and economic performance improved as the size of operation increased. Industrial-scale farrow-to-finish and hog finishing operations, defined by the largest number of hogs and pigs (5,000 head or more) on the farm at anytime during the whole year (1998), were nearly 40 percent more feed efficient on average than small-scale operations (with 1-499 head), while industrial-scale feeder pig producers were about 65 percent more feed efficient than small feeder pig operations (McBride and Key, page 16, 2003). Likewise, the labor requirement on the largest operations was only a fraction of that used by the smallest operations for all producer types. Differences in capital efficiency by size as indicated by pigs weaned per sow and by production per unit of facility capacity were significant (McBride and Key, 2003).

One of the most obvious trends in the swine industry has been the rapid shift to fewer and larger operations, associated with technological change and evolving economic relationships between producer, packers and consumers. However, the advantages of large-scale producers do not mean that small-scale producers have no chance to survive and be successful. Ikerd (2001) pointed out that management is more important than the size of the operation in determining the economic efficiency of a hog operation. Actually farm records collected by various state universities have consistently indicated that 20-40 percent of
family hog producers, using conventional methods of production and marketing, are as cost efficient as are the large-scale hog operations (Ikerd, 2001). Therefore, small-scale producers can still co-exist and compete with the large-scale corporate hog operations. This fact shows that the small-scale producers must upgrade/improve their production skills to systems that require high levels of technical skills in animal husbandry and all aspects of production management (Ikerd, 2001), or they can choose to leave voluntarily or be forced to quit.

2.1.2 The Role of Technology Improvement

The improvement of production technology plays a crucial role in the restructuring of the swine industry. Production efficiency has allowed large-scale operations to gradually develop. However, the driving forces do not come from market growth and consumption, because market growth changes incrementally, due to population growth, and the growth in consumption due to income or economic growth. Hence, the swine industry’s competitive framework historically focused on cost competitiveness, rather than developing new markets (Buhr, 1999).

A fundamental indicator of efficiency is the amount of pork produced per sow (breeding female) per year. Also, while cost values can be skewed greatly by definitions and types of operations which vary across regions, pork produced per sow is a relatively consistent measure. This figure concisely includes litter sizes, conception rates, and yield of live animals (carcass weight). Industrial-scale operations farrow about five to seven more pigs per litter, and obtain about three times more litters per sow capacity and twice the
market hogs per unit of finishing capacity than the small-scale operations (McBride and Key, 2003, page 16).

The influence of technology improvements on small-scale producers seems to be ambiguous. Small-scale operations can take advantage of new technology when it is accessible. By contracting, allying with other producers or spillover effect of new technology, small-scale producers still have the chance to access the new technology. Nevertheless, most hog producers still prefer autonomy (Gillespie, Davis and Rahelizatovo, 2004). Alternatively, such newer skill or technology in hog-raising might involve a lot of capital or investment. It might also discourage small-scale producers’ incentives to stay in the business. Therefore, this study will estimate the relationship between the exit behaviors of small-scale producers and the improvements in technology. Small-scale producers may exhibit willingness to stay in hog production and accept the technology improvements or alternatively, decide to leave because they are unable to compete or being crowded-out by the producers accepting new technology.

2-2 Characteristics of Swine Industry

Farm size and numbers of operations are important concepts and observing points for the industrial structure. Especially, in agricultural economic research, farm size and number of operations have been the major observations and the focuses of structural change (Goddard, Weersink, Chen and Turvey, 1993). The decreasing numbers of operations and the ever increasing average farm size illustrate the structural change within the industry.

This study uses the term “hog operation” instead of “hog farm”. Since the primary data used here are the number of operations provided by USDA NASS. Operation is
defined as the establishments primarily in engaged in keeping, grazing or feeding or livestock or poultry for animal products, for animal increase and value increase. Also number of operations used in this study means that “an operation is any place having one or more hog or pigs on hand at any time during the year” according to the Agricultural Statistics Board, NASS, USDA.

2.2.1 Farm Size

In 1965 the average U.S. hog farm size was only 48 head per operation. Between 1980 and 1989 the average hog farm size in United States still remained below 200 head. In 1992 hog farm size started to grow rapidly. Between 1992 and 1999 the average hog farm size grew 206% to average 596 head per operation. This trend was due largely to industrialized operations entering the swine industry in 90s combined with the rapid exit of operations with fewer than 1000 head. In 2002 the average hog operation size reached almost 800 head. By 2003, the average hog operation size (in all categories) attained 821 head per operation according to the calculation from NASS data. The trend of U.S. average hog farm size is shown in figure 2-1.

The inventory shares of different categories can show the relative importance of different farm sizes. In 2004, 53% of United States’ hog inventory was located on operations with over 5000 head – up from 18% in 1993. The inventory share of the second-largest category (operations with 2000-4999 head of hogs) also continues growing from 15.5% (1993) to 26% (2004). During the same period, operations in the 100 to 499 head category have lost 17.5% of the total hog inventory share in the U.S. Furthermore, the
inventory share of operations with 100 to 499 head in 2004 is only 4%. Also, operations with 1 to 99 head have remained 1% of total hog inventory after 2002.

According to data from the USDA, the inventory of total pigs and hogs has not significantly changed in past decades. Therefore, the decrease of the operation/farm numbers seems to come from the concentration of the industry into larger operations, more than the expansion of the industry.

![Figure 2-1 U.S Annual Average Farm Size (1965-2003:All categories)](image)

(Data Source: calculated with data from NASS, USDA)
2.2.2 Farm Numbers

The decrease of hog operation numbers is one of the most significant characteristics of structural change of swine industry. In 1965 the United States had 1,057,570 operations/farms, with a total inventory of 50,519,000 head (Dec. 1). By 1981 the number of operations/farms fell to less than one half of the 1965’s level, 575,310. The dwindling trend continues in 80s and 90s. From 1982 to 1999, the number of operation fell 80%. In 2002 the number of operations was 75,350 with a total inventory of 59,513,000 head. In 2004, the total number of operations dropped below 70,000 to 69,420 with a total inventory of 60,645,000 head. According to the Rhode’s forecast (1995), probably 80 percent of the current producers will exit the industry before 2015.

The total number of operations is declining. However, investigating component of the total different sizes of operations has opposite trends. Operations with 1 to 99 head are decreasing rapidly. In 1993, there are 131,160 operations with 1-99 head. The number
drops to only 44,490 in 2003, and drops further in 2004 to 42,015 operations. Similarly, the number of operations with 100 to 499 head and the number of operations with 500 to 999 head have decreased from 56,295 in 1993 to 11,530 in 2003 and from 18,270 in 1993 to 5,687 in 2003, respectively. In 2004, there are 10,368 operations with 100 to 499 head and 5,155 operations with 500 to 999 head. Meanwhile, the number of operations with 1000 to 1999 head has also decreased.

Alternatively, the number of operations with 2000 to 2999 head and operations with over 5000 head are increasing. For example, the number of operations with over 5000 head rose from 990 in 1993 to 2,265 in 2003 and to 2,291 in 2004.

2-3 The Phenomenon and Trend of Exit / Entry in the U.S. Swine Industry

The structure of the U.S. swine industry is changing from the perspective of farm size and farm numbers as discussed in 2-2. Based on the facts and characteristics of the swine industry, this study uses one kind of useful information derived from the data of farm numbers – exit rate.

Exit rate, defined here as the difference in farm numbers between concessive periods (usually years), is the dependent variable that we use for this study. The exit rate can record the industry structure’s transition, which reflects the willingness of producers, producers’ decision-making behaviors and the change of total related industrial environment.

The exit rate provides an useful index for observing the aggregate hog producers’ decision-making behaviors. Roughly speaking, it seems to have the specific pattern/trend in hog producers’ exiting behaviors. From the data collected since 1966, the annual exit rates
range between 0.15% (1966) and 16.96% (1982), except 1979 and 1980 which show a net increase of hog operation numbers. The number of hog operations decreases consecutively over the 23 years since 1981. The annual exit rate was 5.83% in 2004, up from 3.32% in 2003. The trend of exit rate on the national-level since 1966 is shown in Figure 2-5. According to the USDA report from McBride and Key (2003), more than 60 percent of small producers surveyed have intentions of exiting hog production within the next 5 years. By observing the exit rate of previous years, there are several apparent characteristics:

- First, the aggregate annual exit rate is not stable. Some years are quite high; some years are relatively low. Not only the national-level numbers show this phenomenon, but state-level annual exit rates present even more drastic fluctuation.

- Second, the exit rates vary significantly from state to state. For example, in 2003 the exit rate of smallest producers is 6.25% in Iowa; while in the same year the smallest producers’ exit rate was 13.14% in North Carolina – more than double. However, the U.S. average exit rate in 2003 was only 3.32%. These facts indicate that the national-level numbers cannot fully reflect the real situation of each individual state. This feature suggests that there are some regional or localized reasons/events that might affect producers’ exit decision-making behaviors. This fact supports the idea that state-level data can provide valuable insights.

- Finally, the gross exit rates among different categories, smallest (1 ~ 99 head) and second smallest (100 ~ 499 head), are different. From the Figure 2-3, it can be seen that the exit rate in the second smallest size category has shifted and is larger than that of the smallest category in some years.
Even though, the total number of operations is decreasing, the number of large-operations is still increasing. This phenomenon is shown in Figure 2-4. The fact provides strong evidence that swine industry in the U.S. is in a stage of restructure. Aggregate producer numbers from past decades provide useful data for recording the transition of the U.S. swine industry.

The survey data from McBride and Key (2003) also suggests that many more small and medium-size operations will cease production in the next few years. One impressive illustration of the trend is in feeder pig production, where about 75 % of small producers plan to leave the industry by 2003 while 98 % of industrial-scale operations plan to remain in business (McBride and Key, 2003, page 16).

Meanwhile, improvements in performance from the small to the industrial-scale operations were not linear, but rather incrementally less with each size group. The largest
efficiency gains on farrow-to-finish and feeder pig operations were made between the small and medium groups. Average costs on medium-sized farrow-to-finish operations were 20 percent less than on small operations, while the average costs of feeder pig production fell 37% between the small and medium farms (McBride and Key, 2003).

McBride and Key (2003) reported that production costs are reduced significantly as the size of operation increases from the relatively small sizes, and that there are further cost-reducing incentives for operations to continue growth toward the industrial-scale size.

In addition, while average costs by size of operation reveal information about the relative competitiveness of various sized operations, they mask the underlying variation in costs within size categories. The variation in cost was greatest among the small hog operations, and least among the large and industrial-scale operations. This result coincides with the greater diversity among small producers relative to other size categories of producers. The cost distributions also show that among small- and medium-sized groups, many operations produce at a cost that is competitive with large operations (McBride and Key, 2003).

Small-scale producers, especially using conventional methods of production, part-time or full-time, producers are facing the crucial decision: should they leave the business? However, Ikerd (2001) pointed out that family-style hog producers can still survive by lowering hog production cost by taking advantage of their unique assets – their willingness to work, their commitment to farming, and their skills in animal husbandry and business management. McBride and Key (2003) concluded the same in their report.
In summary, the small-scale producers are forced to change regardless of whether they intend to stay in swine industry or decide to leave. Therefore the determinants of exit behaviors of small-scale producers, especially under such structurally changing industry, are worth discussing. By understanding the decision-making criteria of small-scale hog producers, we might collect useful information for understanding other industries that are in a restructuring phase.

Figure 2-4 U.S. Hog Operation Numbers by Farm Size (1993-2002)

(Data Source: calculated by data from NASS, USDA)
Figure 2-5 The Exit Rates of Hog Operations in U.S. (1966-2004)

(Data Source: calculated by data from NASS, USDA)
Chapter 3  LITERATURE REVIEW

3-1 Previous Research on Industrial Exit and Entry

The structure change of industry interests economists. The structure of an industry or a sector is typically dimensioned in terms of its size, its financial characteristics, the resource ownership, technology, and similar criteria (Boehlje, 1999).

*Divergent entry and exit prices and size correlated efficiency in competitive models*

Dixit (1989) explained the exit and entry decision of a firm by using a model with a pair of trigger prices for exit and entry. The entry trigger exceeds the variable cost plus the interest on entry cost, and the exit trigger is less than the variable cost minus the interest on the exit cost. Dixit’s model illustrates the importance of cost, profit and timing in decision-making of exit and entry.

Eckard (1990) examined that the role of relative efficiency of large firms and small firms. Eckard’s hypothesis was that concentration changes should be correlated with changes in relative large-firm – small-firm efficiency for which that relative labor productivity growth is a proxy. The argument that superior large-firm efficiency causes industrial concentration has thus been supported by evidence from U.S. manufacturing industries data.

*Divergent exit and entry behavior in declining versus growing industries*

Studies of declining industries revealed that the motive or priority of exiting firms among large firms and small firms is still in dispute. Small producers might be expected to
close first, given the lack of scale economies, predicted by so-called “shakeout” model that indicates that lager plants were less likely to close – implies “shakeout” of smaller plants (Lieberman, 1990). However, the related theories, such as the “stakeout” model, (Ghemawat and Nalebuff, 1990) suggest that large producers may have greater incentives to exit or cut capacity. Both predictions receive some empirical support.

Lieberman (1990) concluded that the exit behaviors in declining industries appear to have been influenced by two frequently offsetting factors: (1) scale economies favoring the survival of large firms and (2) the strategic liability of firm size. Lieberman’s findings (1990) imply that inter firm differences in both cost and marginal revenue can influence the order of divestment. Other findings support the “stakeout” models of Ghemawat and Nalebuff (1990) and Reynolds (1988). Controlling for operation size, the probability of operation closure increased with the firm’s capacity share, assuming that the firm operated multiple operations. Thus the “shakeout” and “stakeout” theories provide complementary explanations of exit behavior. Lieberman (1990) also concludes that the declining industries (products) data sample showed a strong trend toward size convergence, resulting from the exit of small firms and the shrinkage of large firms. In the growing industries (products) data sample, using 30 growing chemical products for comparison, there was no significant trend toward either convergence or divergence. Changes in the coefficient of variation in firm sizes were almost evenly split between increases and decreases. For a typical product in the growing industries (products) sample, small exiting firms were replaced by new entrants, large producers continued to expand, and the mean firm size gradually increased over time.

*The role of technology improvement and correlation with business cycles*
Audretsch (1995) mentioned the relationship between technology improvement and exit. Audretsch suggested that the likelihood of survival for small size entrants is less than large size ones. Only in technologically intensive industries and/or under mature stages of the product life cycle, does the likelihood of lower survival rates for small size entrants not apply. Audretsch described the revolving-door phenomenon: new small sized producer enters followed by exit from the market, with high probability. The revolving door phenomenon is observed in low-tech and infant-stages-of-the-product-cycle industries. This relationship between industry technology intensity and exit behavior implies that technology affects exiting behavior and industry dynamics.

Another analysis related to exit, entry, technology and the business cycle is reported in Campbell’s (1998) paper. It provides support for the hypothesis that shocks to the pace of embodied technological progress are significant sources of business cycles. His model depicts that technological progress embodied in entering operations and the pace of such progress has a similar locus with the cyclical behavior of entry and exit in the U.S. economy.

One recent empirical study (Fotopoulos and Spence, 1998) examined the interaction between firm entry and exit and found that entry and exit are very much related in Greek manufacturing industries between 1992 and 1998. Entry and exit have similar symmetric motions: both entry and exit rates move in the same direction, they increase and decrease as affected by price and cost margin.

Ilmakunnas and Topi (1999) examine the entry and exit process in Finnish manufacturing industries using a six-year panel of three-digit industries and covered 6 years
of time that included business cycles (expansion and recession). The results show that industry growth has a negative influence on exit, but also variables describing the general economic climate have an influence on the exit-entry process. In addition, the influence of macroeconomic variables describing the monetary transmission mechanism on exit is inconclusive. However, exit barriers (scale economies), concentration, industry growth (size), and current profitability were found to influence on exit rate (Ilmakunnas and Topi, 1999).

A recent empirical study of exit behavior is by Van Kranenburg et al. (2002). They analyzed factors that affect the survival rate in a concentrating industry by using the Netherlands’ newspaper industry as an example. Their research found that circulation size, ownership and number of incumbents are reasons for the exit hazard rates of the newspaper industry, but they did not find any significant effect of macroeconomic factors.

3-2 Previous Research Related to Hog Industrial Structure

Previous studies of hog industry structural change mostly focused on the transition of farm size (Wilson and Eidman, 1985; Disney, 1988; Von Massow et al., 1992). Many previous studies identify the hog-corn price ratio as a major factor that drives the dynamic adjustment of hog farm size.

The individual producer’s perceptions also affect his farm size. Wilson and Eidman (1985) detected that the producers’ attitudes toward risk, risk-averse or risk-loving, will affect their farm sizes. The hog producers with better abilities to manage risks prefer larger swine operations (Wilson and Eidman, 1985).
Using Canadian data, Von Massow et al. (1992) examined the effect of exogenous variables on the movement from one size class to another rather than just how these variables affect the average size. They used estimated stationary and non-stationary transition probability models to predict that there would be approximately 60% fewer hog producers in Ontario by the turn of the century than at the beginning of 1990.

In addition, Von Massow et al.’s study (1992) found that the hog-corn price ratio, interest rate and labor-capital price ratio all have some effect on the transition dynamics of Canadian swine industry. The mechanism of this change includes in a combination of technological advances and improvements in labor capital. Their study also illustrates that poor prices tend to draw producers out of business, especially smaller ones.

In an overview of the changing swine industry in U.S, Rhodes (1995) provides a historical summary. He described hog-raising as profitable in the late 60s and most of the 70s. The trend of the industry in that period was that “Profitable hog price combined with investment tax credits for building new facilities, encouraged a general substitution of capital for labor – on a per hog basis – through the building of specialized hog facilities, and encouraged the general surge toward large units.” Later, the farm crisis of the early 1980’s squeezed out numerous operations and expedited entry and/or expansion into that gap by those who continued to invest in the facilities, equipment and new technological production. During the late 80s, profits were still available to all except the least efficient producers, so that entry and expansion of efficient operations generated more profits than in the past. Rhodes wrote, “Late 1994 was the first period in which expansion of production led to prices so low that virtually every producer was temporarily experiencing losses.”
According to a recent study (Gillespie and Fulton, 2001), hog-corn price ratio still has an important effect on producer’s expansion and contraction decision; especially affecting the entry and exit of small hog operations. They illustrate that the hog-corn price ratio has influenced the movement of hog farms among size categories by using Markov chain analysis. Other factors, such as interest rate, processing capacity, and agglomeration economies, also have influences on new entry of hog operations in the United States (Gillespie and Fulton, 2001).

Lawrence and Wang (1998) probe the motivation for exiting hog production in the 1990s by using survey data of nearly 1,000 Iowa hog producers who quit raising hogs between 1991 and 1997. They quantified demographic characteristics of the enterprises and operators, motivations for leaving, and the prospects for re-entering hog production. They found that economic reasons are why Iowa hog producers quit raising hogs during the research period. They found that the exiting hog producers are not likely to return to production. The general profiles for exiting hog producers are older, small-size operation owners (they define small as 500 head of hogs or less marketed per year). Although economic forces were cited for quitting hog production, amazingly, over 80% of the hog producers did not know exactly their cost of production. Higher operating margins and restrictions on competition were needed before these producers would produce hogs again (Lawrence and Wang, 1998).

Anderson et al. (1998) analyze the determinants of operation exit from the cattle-slaughter industry using a probit model to estimate effects of firm-level (e.g., age, scale, and scope) and market-level (e.g., market share, concentration, and competitive fringe) factors. Market variables are shown to be less important determinants of exit than firm-level
factors. A significant tendency for very small operations to exit an already highly concentrated market is apparent. The general findings in their analysis (Anderson et al., 1998) are that, as groups, both firm-level and market—structure variables influence the decision to exit from the beef packing industry. Firm-level variables are the most important determinants of exit. Economically, the (negative) effects on exit probability of operation capacity, horizontal integration, and vertical integration are robust, significant, and unambiguous. Another operation variable, operation age, is equally robust. Conditional upon surviving the first year, the probability of exit, declines each year for about the first twenty years and then the probability of exit increases, thereafter, each year. This result suggests that there are offsetting technology and experience effects co-varying with operation’s age.

Regarding the much debated issue of concentration’s role in exit, Anderson et al. (1998) found that concentration, by itself, as measured by the Herfindahl index (for the cattle procurement area in which each plant is located), is not a significant determinant of exit. However, concentration does play an interactive role with capacity share, as shown by the statistical significance of the competitive fringe index (Herfindahl index divided by each plant’s capacity share). Producers are somewhat more likely to exit already-concentrated markets if they are relatively small producers in that market. It is not necessarily that the small competitive fringe operations are being strategically “forced out” by larger efficient producers. They argue that it is unclear whether noncompetitive practices by larger operations or normal pro-competitive market forces (exit of inefficient operations), explain the faster exit rate of competitive fringe operations.
Whatever the causes of competitive fringe exits, Anderson et al.’s (1998) empirical findings suggest that even if anticompetitive factors are at work, the corresponding welfare losses from industry consolidation are likely to be offset by efficiency gains. Anderson et al.’s (1998) results show that scale effects are significant, and the smaller operations are exiting at higher rates than larger operations, controlling for other factors. Their evidence suggests that technical inefficiencies are stronger determinants of exit behaviors than market structure factors.

Hog production is affected by different issues/factors in various states. Roe, Irwin and Sharp (2002) examine the hypothesis that hog production does not benefit from a robust local economy that attracts a substantial workforce and a varied pool of other industrial specialties in traditional hog production states. They also conclude that hog-raising counties in the western states, favorable property taxes, and lax environmental regulations, attract hog production – even in the presence of larger human population and higher building activity. These differences imply advantages and disadvantages for each hog-raising state. Furthermore these niches may lead to different degrees of reliance on increasing feedstuffs, lack of labor forces, and land supply limitation.

Roe, Irwin and Sharp’s research (2002) examines differences cross states in regulatory stringency, policy and production surroundings that their effects on location, movement, and intensity of hog production by using spatially explicit, county-level data within 15 main hog production states. Their analyses suggests that the western states in the sample may shape hog production levels by wielding traditional business recruitment and retention tools (e.g. tax rates, environment stringency). Meanwhile, the Corn Belt states may shape hog production via nontraditional tools (e.g. land use control).
Chapter 4  ECONOMIC MODEL

4-1 The Characteristics of Production/Cost Functions of Hog Producers

In this chapter, the conceptual framework and economic models are set up. Basically, hog production cost can be divided into three parts: 1) feed cost \( (m) \), 2) labor cost \( (l) \), and 3) other costs \( (F) \). Most portions other than feed and labor costs are the capital investment on the equipment and facilities that are fixed costs.

Feed cost, treated as the variable cost the increases directly by period of raising hogs and the highly related to production scale, is traditionally the major cost of raising hogs. However, empirically the importance and the component ratio in total cost have been marginally declining by production scale (Ridgeon, 1993). It implies that the importance of cost structure of feed cost in large-scale production is decreasing.

The production function of single producer \( (i) \) in one period set up in this study as follows:

\[
q_i^t = f(l_i, m_i, F_i) \quad (1)
\]

Here, the \( F_i \) can be considered as the capital cost for the simplicity.

As described in chapter 2, the production cost structures are heterogeneous among U.S hog producers. In this section, for interpreting the small producers’ quitting trend, or exit behaviors, we assume that there are only two kinds of producer production cost structures. One is labor-dominated style production that usually is operated by the small production scale producers, also representing the traditional technology of raising hogs; the
other is the capital-dominated style production that is operated by the large production scale producers, also representing the modern technology of raising hogs.

Due to the two different kinds of production technologies used in the same homogeneous products, heterogeneous production functions are described as below:

Traditional technology of raising hogs is related to the variable cost. The traditional technology, subscribed by $T$, is a backstop technology that exhibits constant returns to scale and is reliant on effort:

$$q_i^T = \min[\theta_T l_i, e_i, \theta_T f_i]$$ (2)

where $l_i$ is the amount of labor devoted to this production process, $\theta_T$ is the marginal productivity of labor using the traditional technology, $q_i$ is the output of operation $i$, and $e_i$ is the level of effort supplied by the producers.

The other is related to the fixed cost. The modern technology, subscribed by $M$, does not use traditional effort as an input. Instead, it is an increasing return to scale technology using only labor:

$$y_i^M = \theta_M (l_i - F)$$ (3)

where $F$ represents a fixed input requirement. For simplicity, as in many models in industrial organization we assume that this takes the form of pure labor overhead. The cost function $C_i = f(l_i, F_i, c_i)$ for each producer in one period can be described as follows: total cost for operation $i$ using the traditional technology:
\[ C_r(q_i) = \min_{\omega} \{w_r q_i / \theta_r + g_r(e_i)\} \quad (4) \]

Here, \( w_r \) is the wage paid by such operations. Total cost for modern technology operation is given by:

\[ C_M(q_i) = w_M(F + q_i / \theta_M) \quad (5) \]

With a constant wage, average costs for managerial operations are decreasing everywhere. However, marginal labor costs, \( w_M(q) \) and \( w_T(q) \), both potentially depend on the level of output. The reason for this could be span of control issues, coordination issues, influences costs or monitoring costs. These could constrain the size of managerial firms if their rate of increase was faster than technological gains from scale economies. However, both the ability to adopt holding company models and the possibility of substituting incentive of efficiency wage contracts for monitoring mean that unit labor costs are potentially bounded from above (Gans and Quiggin, 2003).

Here, \( q_k^i \) is output of producer type \( k, k \in [T, M] \). M represents large-scale producer, which is capital-dominant and using modern technology for raising hogs; T represents small-scale producer, which is labor-dominant and using traditional technology for raising hogs. Therefore, \( q_M^T > q_T^T \) and \( TFC_M > TFC_T \) because the capital-dominant cost structure producers invest large amount fixed cost than small-scale producers. Past study (Massow et al, 1992) shows that a combination of technological advancements and improvements in human capital, which are highly related to the fixed costs, are the major reasons to affect the producer size transition. The relationship between two kinds of cost structures can be described as below:
Starting from the static analysis, we assume that each producer’s objective, for both small-scale producer and large-scale producer, is to maximize his profit:

\[ \pi_K = P^*q_K - TC_K; \pi_K = P^*q_K - TC_K \]  \hspace{1cm} (6)

\[ \frac{\partial \pi_T}{q} = P - MC_T = 0; \frac{\partial \pi_M}{q} = P - MC_M = 0 \]  \hspace{1cm} (7)

\( MC_T > MC_M \) represents that the production of large producers are more efficient than production in small producers. Empirically, this relationship does exist (Rhode, 1995). Rhodes (1995) points out that successful efficient producers must: (1) have access to and quickly adopt new technology; (2) have access to and use market information; (3) have increased specialization so the first two points are feasible; (4) have equal or superior access to all inputs including capital, etc. These success factors are less available to smaller producers. Also, Fulton and Gillespie (1995) point out that the introduction of new technologies in the swine industry has decreased per unit cost of production. However, these technologies require substantial investment and thus can be feasibly used only for sufficiently large operations.

**The Trend: Small producers out, large producer in**

Here we expend the cost structures of the whole producers as continuing and differential. Then the marginal cost for producer \( i \); \( i \in \{1, ..., N\} \) \( j \); \( j \in \{1, ..., N\} \), \( i \neq j \) in period \( m \) is arrayed:

\[ MC_i^m \geq MC_j^m \]  \hspace{1cm} (8)
Hog price is known as to exhibit fluctuation for a long historical period. Obviously, when $P$ is smaller than $MC_T$, small producers will be under loss condition. However, if $P$ is still larger than $AC_T$, small-scale producers will still stay in the industry in the short run, but in the long run, the small-scale producers will be out-of-business due to the loss. In some cases, the relationship between

$$AC_T^i > P^i > AC_M^i$$  \hspace{1cm} (9)$$

Empirically, during the late 1980’s, profits were available to all but the most inefficient producers, so that entry and expansion of efficient large operations were facilitated by larger than normal competitive profits (Rhodes, 1995).

There are some other additional factors that might force the small producers decide to leave the industry: not wanting to take larger risks or to supervise non-family labor, or because further expansion seems irrational given the operator’s age or poor health and lack of family successor (Rhodes, 1995). Therefore, the question for the small-scale and the higher costs producer becomes that, the timing to leave the business.

Average variable cost plays an important role on raising hogs. Empirically, about two thirds of the cost of producing a market hog (farrow-to-finish) is feed. About 80% of finishing operation costs comes from feed (Grannis and Seidl, 1998). Feed is the most important variable cost for a producer. Besides, the advantages of highly capitalized investment of large, specialized facilities, the employment of full-time and high-skill labors need to be recovered by increasing the production size and scale that minimize capital cost per unit produced (Zering, 1998).
Now if we assume that all hog producers’ cost functions are continuously heterogeneous and array from highest to lowest, we could observe the number of producers that are forced to quit the business. All the producers whose short-term average variable costs ($SAVC$) are higher than price ($P$) are forced to exit.

\[ iSAVC_T'(q_i) \geq \ldots \geq_{i-k} SAVC_T'(q_{i-k}) > P \geq_{i} SAVC_T'(q_i) \geq_{i} SAVC_M'(q_i) \geq \ldots \geq_{i} SAVC_M'(q_j) \quad (10) \]

Therefore, in the long run, small producers are facing the choice of increase the production scale and efficiency or choose the timing to quit the industry. Gans and Quiggin’s study (2003) illustrates that the operations in the medium-size output range, lying between the largest optimal for an entrepreneurial firm and the minimum efficient scale for a managerial firm will display highly variable and highly skewed growth rates, pursuing in effect a strategy “get big or get out”. Furthermore, Gans and Quiggin (2003) describe that up to some minimum output, $q^*$ the average cost is lower for the traditional technology, but cost-minimization beyond this point requires adoption of the new-modern technology. In this figure, the traditional technology actually has higher minimum average costs than the new modern technology for higher output levels. This needs not to be the case. If the opportunity costs of traditional effort are low, then average costs for a traditional producer might be lower than that of a new modern firm operating at a high output level. Alternatively, this could be the case if the traditional technology is more efficient at the margin.

Also, according to the empirical observation, the various production cost structures create incentives for the expansion of profitable producers and liquidation of unprofitable producers (Zering, 1998).
Intertemporal decision-making – trigger price and timing for quitting the industry

From the description above, we conclude that when the small producer decided to leave business, the final decision is timing for doing so. For examples, when an aging small producer decides to retire from raising hogs and stop investing in new facilities, he will look for the period when hog prices are high so that his last hog sale will be profitable. Therefore, ready-to-leave producers will tend to close their business under the stage of upward price, at least they expect that it is the best price for them.

Dixit (1989) examined that a producer’s entry and exit decisions when the output price follows a random walk. He solves a pair of trigger prices for entry and exit, $P_H, P_L$ and interprets the relationship among the variables:

$$P_H > \omega + \rho \kappa \equiv W_H ; P_L < \omega - \rho \ell \equiv W_L$$ (11)

Here, $\omega$ represents variable cost of output, $\rho$ is discount rate, $\kappa$ is sunk investment cost and $\ell$ means that a lump-sum exit cost (the Marshallian trigger prices for investment and abandonment are $W_H$ and $W_L$, respectively). In words, two equations can be described that the entry trigger exceeds the variable cost plus the interest on the entry cost, and the exit trigger is less than the variable cost minus the interest on the exit cost.

Now we discuss swine industry’s situation. The uncertainty for hog price is less than Dixit’s (1989) original assumption, random walk price locus. Instead, hog price is more like cyclical change. This characteristic, less price uncertainty, will shrink the gap of $(P_L, P_H)$, $(P_L, W_L)$ and $(P_H, W_H)$. Meanwhile, the lump-sum investment cost will increase in swine industry due to the increase in capital investment and exit cost will decrease due to
inefficient operation. Therefore, that range of \((P_L, W_L)\) will be less than \((P_H, W_H)\) because of both increase in \(P_L, P_H\). It can explain why small hog producers, who tend to leave business, will not come back. It also can explain indirectly that input cost, variable cost, has less impact on hog producers’ decision to remain in hog production than it had in the past. Producers express items such as labor, environmental regulation, and market access as more important influences now, or at least in Nebraska’s case (Prosch, 2002).

When producers decided to leave the business at time \(t\), they will sell out all their inventories \(q^d_t\). This quantity is either larger than usual quantity or is treated as a shock on supply. Under this situation, the real market price \(P_t^R\) will reflect \(\sum q_t + q^d_t\). Therefore, \(P_t^R\) will be smaller than expected price \(E(P_t) = P_t\), which reflects the predicted hog cycle price.

According to the econometrical analysis from Bessler (1984), he identifies that the shocks to slaughter, which comes from an increase in supply, leads to lower hog prices in the short run. In the accelerating change of swine industry structure amplifies this effect due to the exodus from small producers. The discussion above, it implies the relationship between exit behaviors of small producers and hog prices.

4-2 Small Producer’s Inter-temporal Decisions – Exit or Investment

From the model derived and discussion so far, we realize that the decreasing producer numbers come largely from the exit of small producers due to relatively higher cost. Hence, from now on, we will focus on the small producers’ exit behaviors. Following
the production function and cost function used in this chapter, we will discuss more of the
details and expand this model:

Here, we start to look into the mechanism of decision-making process for small
producers. We will create the model for exit decision for each producer in industry. This
research takes the framework of Van Ewijk’s model (1997) into consideration and expands
it.

In this section, the production function is expended as below:

\[ q_{ij} = f(\pi, h_j, F_j, x_j) \] (12)

Here, we reconsider and adjust the production structures to get closer to the target
we want to achieve and interpret. The assumptions are set up as follows:

The whole swine industry consists of a fixed number of infinitely active producers
in the beginning period. All producers are risk-neutral and price-takers in this model. Each
producer is assigned a fixed amount of capital (normalized to unity), which it can spend on
production or non-production research activities. Production uses capital only; the capital
represents the technology and knowledge of raising hogs. Total net output \( q_{ij} \) of producer \( i \)
is give by with production style \( j, j \in [T, M] \).

\[ q'_{ij} = [\pi'(m_i)h_j(t) - F_j(t)]x_j(t) \] (13)

where \( \pi'(m_i) \in \{\pi^1(m_i), \pi^2(m_i), ..., \pi^n(m_i)\} \) represents the fluctuation of the economy that
are related to inside industrial environment, such as feed cost, \( h_j(t) \in [0, 1] \) denotes the time
spent on hog production; \( F_j(t) \) denotes the fixed cost of the producers. Also the scale factor \( x_j(t) \) represents accumulated technology of the operation, including improved marketing skill from better information. Here, the technology is a spectrum, continual improvement that includes all the operations.

Here we assumed that knowledge and technology used for each producer is firm specific, i.e. among small producers there is no technology transfer. However, spillover effect of skill/technology is allowable among large-scale and small-scale producers. \( \pi_i \) represents shocks in productivity that will drive the fluctuation of the whole swine industry, such as grain prices for inside industry and job opportunities related to macroeconomic situations. We assume that is i.i.d. over time; each state \( \pi_i \) has a given probability \( P_i \). The fixed costs \( F_j \) are essential to explain if producers will shut down hog production facilities. They can be interpreted as the costs of staying in business (advertisement, overhead, etc). This study assumes that once producers decide to exit, they will not reenter into the industry. One of these situations means that contract with the large-scale producers that significantly improve production costs and efficiency.

The producer allocates it’s investment into two parts: 1) direct investment \( (h_y) \) that is related to production. It is proportional to hog quantities, such as feed cost and weaned pigs. Furthermore, this investment can refer to production scale; 2) indirect investment \( (1-h_y) \) that is related to either enhance production efficiency or required activities by regulations. Growth of productivity and/or efficiency improvement depend on these latter activities i.e., R&D; as well as on learning –by-doing. Since knowledge is subject to decay
these operations therefore face a decline in productivity. That is, instead of benefiting from learning-by-doing inactive operations suffer from forget-by-not-doing. This means that after a period of inactivity producers enter at a size smaller than the size they had previously at the moment of exit. This assumption describes one empirical situation that if a producer is under idle situation, he is probably ready to leave sooner than later. Defining the growth rate by one plus that rate of change, thus \( g_{ij}(t) = x_j(t+1)/x_j(t) \), we can write

\[
g_{ij}(t) = \psi(1 - h_{ij}(t)) \quad (\geq 1) \text{ when active}
\]

\[
g_{ij}(t) = g_0 \quad (<1) \text{ when inactive}
\]

The learning function \( \psi \) is concave \((\psi' > 0 \text{ and } \psi'' < 0)\) and greater than unity for any feasible \( h_{ij} \). Due to learning-by-doing growth is positive even if all time is devoted to direct production activities, therefore \( \psi(0) > 1 \). Inactive firms face a decline due to the decay of knowledge and depreciation of production facilities that refers to production efficiency, \( g_0 < 1 \). Inactive producers will not consider further investment for renewing or upgrading equipment. It implies that this type of inactive producer is waiting the optimum time to leave business. The economic meaning of \( g_{ij}(t) \) can be considered as scale economy. i.e. a producer at least has to maintain production scale by investing the depreciation amount of production equipment. Otherwise, a producer is facing the decline of competitive power with other producers.

**Decision-making criteria**

A producer has to make two decisions in each period. The first is whether to be active or not; the second is how to allocate investment between direct production and
indirect production activities. First, consider the optimal allocation of investment when the producer is active. To take the various possibilities into consideration we can treat this as a dynamic programming problem. Following the Van Ewijk’s (1997) method we use \( V^A(t+1) \) as the net present value per unit of capacity of an active small producer, at the beginning of period \( t+1 \). Similarly we define \( V^N(t+1) \) for non-active producer. These values are derived under optimal conditions, and taken before the next period’s shocks \([\pi_i^{t+1}(m_{t+1}), F_i(t+1)]\) are revealed. Then, the optimal allocation of labor follows form

\[
\text{Max}_{h_j(t)} \pi_j'(m) h_j(t) - F_j(t) + \rho g_j(t) V^A(t+1) 
\]

subject to the growth function. The discount factor \( \rho(\leq 1) \) is assumed to be constant. The present value \( V^A(t+1) \) is, as shown below, independent of the producer’s variables in this period. An important feature of this model is that the optimum for \( h_j(t) \) is independent of the fixed cost \( F_j(t) \). This is convenient, as it implies that all small (active) producers choose the same allocation of capital, and therefore grow at the same rate, which depends on the state of the economy. The size of the fixed costs only affects the entry and exit decisions, not the optimal rate of growth. We can therefore drop the second index \((j)\) for growth and labor. By taking the derivative of (14) with respect to \( h_j \) we obtain the following first-order condition for optimal learning.

\[
\pi_j = \psi'(1-h_j) \rho V^A 
\]

The condition equates the opportunity cost of learning, i.e. the direct profitability of capital in current production to the marginal return of learning. The latter depends on the
marginal efficiency of learning, $\psi'(1 - h_i)$, and the present value of an extra unit of capacity,

$\rho V^d$. Since $\psi''(\cdot) < 0$ the impacts of $\pi_i$ and $V$ on growth are

$$\frac{dg_i}{d\pi_i} = -\frac{1}{\rho \eta_i V^d} (< 0); \quad \frac{dg_i}{dV^d} = \frac{\pi_i}{\rho \eta_i (V^d)} (> 0)$$

where $\eta_i = -\psi''(\cdot) / \psi'(\cdot) (> 0)$ is a measure of the concavity of the $\psi$ function. Current productivity $\pi_i (m)$ represents the opportunity costs of new technology, and therefore has a negative effect on staying in hog industry or incentive to invest.

The present value per unit pf capacity $V^d$ determines the return on R&D, and therefore has a positive effect on staying in the industry or keeping investment at least maintaining the hog production scale or extension.

**Intertemporal factors: price expectation**

Next we consider the exit decision. If profits become low, the producer may stop hog-raising. However, when deciding on this, they must take into account the fact that it will have to incur a sunk cost if the producer wants to enter again in the future. Investment in marketing distribution and reputation are typical prerequisites for entry. Their (re-entry) costs are proportional to the size of the producer. A producer will go out of business if the value of continuing the active state is less than the producer’s value in the inactive state. Similarly for entry: an idle firm becomes active if the value of being active net of entry costs exceeds the value of remaining idle. Thus (per unit of $x_i$)

Exit if $\pi_i h_i - F_i + \rho g_i V^d < \rho g_0 \rho V^N$
Entry if \( \pi_{i}h_{i} - F_{i} - c + \rho_{g}V^{A} > \rho_{g_{0}}V^{N} \)

Where \( c \) is the cost of entry per unit of capacity. This is a sunk cost. The left hand side of these inequalities gives the value of the operation if it is active. This is equal to current earnings plus the discounted value of the (greater) future capacity of the producer. The right hand gives the value of the producer if it would be inactive; since there are no returns (nor losses) from production, the value is simply the discounted value of the operation’s capacity (inactive state) at the beginning of the next period. The exit decision depends on the state of the economy \( (\pi_{i}) \) and the operation’s fixed cost \( (F_{i}) \). Which operations enter and exit can be established as follows: Consider the critical values of \( F_{j} \) that trigger exit and entry, denoted by \( \overline{F}_{i} \) and \( \underline{F}_{i} \) respectively, thus from (16)

\[
\overline{F}_{i} = \pi_{i}h_{i} + \rho_{g}V^{A} - \rho_{g_{0}}V^{N} \tag{16}
\]

\[
\underline{F}_{i} = \pi_{i}h_{i} - c + \rho_{g}V^{A} \rho_{g_{0}}V^{N} \tag{17}
\]

The trigger point for exit, \( \overline{F}_{i} \) is the maximum of fixed costs at which producers stay in hog industry. All operations with \( F_{j} > \overline{F}_{i} \) will exit. Similarly, for the critical value for entry, all producers with fixed cost smaller than \( \underline{F}_{i} \) will enter.

With positive entry cost \( (c > 0) \) it is obvious from equation (17) that the critical value for exit is higher than that for entry, i.e. \( \overline{F}_{i} \geq \underline{F}_{i} \). So, there is a zone between where producers neither exit nor enter.
Note that the critical point for exit is at negative net returns. From (16) we can see that the net returns are given by \( \pi_i h_i - \bar{F}_i = \rho g_o V^N - \rho g_i V^A \), which is evidently negative since \( g_o < g_i \) and \( V^N < V^A \). The producers continue to produce even at negative profits. Apparently, the expected losses associated with exit are more important than the current losses on production. The reason is twofold: first, the operation benefits from positive growth in the active state. Secondly, by remaining active the firm avoids the cost of reentry that it would encounter in the inactive state. So, losses have to go beyond some threshold before a producer will decide to go out of business. Therefore, the timing to exit becomes the important issue. Similarly, it can be shown that entry occurs already when current returns (including entry cost) are still negative. Net returns at the critical value are \( \pi_i h_i - \bar{\epsilon} - c = \rho g_o V^N - \rho g_i V^A \) which is again strictly negative.

How many producers exit in a particular state of the economy depends on the distribution of fixed costs vis-à-vis the critical value for enter and exit. It is obvious that there are less exiting decisions in high states (high \( \pi_i \)) than low states. How many producers fall into this status depend on the distribution of the figure also shows the density \( f(F_j) \).

Let \( F(F_j) \) represent the distribution of the fixed costs \( F_j \) of the operations with density \( f(F_j) \).

4-3 Economic Model Specification

Now we observe the aggregate level, then we can define the exit probability of active producers as \( \beta_i = 1 - F(\bar{\epsilon}_i) \), where \( F(\bar{\epsilon}_i) = \int_{-\infty}^{\bar{\epsilon}_i} f(\epsilon_i) d\epsilon_i \). Since this probability is the
same for all small producers, we can also interpret $\beta_i$ as the fraction of active producers that goes out of business in a particular state of the economy ($\pi_i$).

Now we can write for the value per unit of $x_j$ for the active state (A) and the inactive state (N) (using ( )).

$$V^A = \sum_{i=1}^{n} \beta_i [ (1-\beta_i)(\pi_i h_i - \epsilon_i + \rho g_i V^A) + \beta_i \rho g_i V^N + Z(\epsilon_i) ]$$  \hspace{1cm} (18) $$\quad \quad \quad \quad$$

$$V^N = \sum_{i=1}^{n} \beta_i [ \alpha_i (\pi_i h_i - \epsilon_i + c + \rho g_i V^A) + (1-\alpha_i) \rho g_i V^N + Z(\epsilon_i) ]$$  \hspace{1cm} (19) $$\quad \quad \quad \quad$$

Here the value is written as the sum of the unconditional expected values in the active and the inactive state, plus an additional term $Z(\epsilon_i)$, which is defined by

$$Z(\epsilon_i) = F(\epsilon_i) \epsilon_i - \int_{-\infty}^{\epsilon_i} f(x) \epsilon d\epsilon \quad (\geq 0)$$  \hspace{1cm} (20) $$\quad \quad \quad \quad$$

This variable represents the real option value of the possible to switch between active and inactive states. The option value $Z(\epsilon_i)$ is always positive. It is zero in the extremes where $\epsilon_i \rightarrow -\infty$ and $\epsilon_i \rightarrow \infty$, and it is strictly positive for finite values of $\epsilon_i$. That the option value is zero in the extremes for $\epsilon_i$ is not surprising since there are no opportunities for arbitrage then; whatever the costs of the operation, it will in that case always make the same choice, namely to be active (if $\epsilon_i \rightarrow \infty$) or to be inactive (if $\epsilon_i \rightarrow -\infty$). The values $V^A$ and $V^N$ are taken at the beginning of period, that is, before the state of the economy in this period is revealed.
The item $P_i$ plays a crucial index for producers’ decision-making. As we mentioned earlier, the almost regularly fluctuation of prices, so-called hog price cycle, makes the expectation adjustment production significant. Hence, it is reasonable to consider that the decisions of exit are influenced by hog price factor. Therefore $\pi_i$ and $\varepsilon_i$ are i.i.d. over time the valuations are constant, however $P_i$ is basically not following i.i.d locus. Therefore,

Either $V^A(t + 1) \leq V^A(t)$ or $V^A(t + 1) \geq V^A(t)$ also,

Either $V^N(t + 1) \leq V^N(t)$ or $V^N(t + 1) \geq V^N(t)$

For those producers that predict that the next period’s price will go up, $V^A(t + 1) \geq V^A(t)$, they may delay their exit until the next period. Alternatively, for those producers that forecast that current period’s price is higher than next period, $V^A(t + 1) \leq V^A(t)$, they will consider leave the business end of the current period.

Comparing (18) and (19) we can see that the difference in value between active and idle states is solely due to the entry costs. If $c > 0$, from (16) and (18), we observe that the value for the active state exceeds the value for the inactive state, hence $V^A > V^N$. As a necessity the sum of the transition probabilities is less than unity, hence $\alpha_i < 1 - \beta_i$. In case of zero entry costs ($c = 0$) there is no difference in value between active and inactive states, therefore $V^A = V^N$ if $c = 0$. Then the critical values for entry and exit are the same as well, thus $\alpha_i = 1 - \beta_i$. 

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In conclusion, probability of exit, \( P_t(\text{exit}) = \beta_t \), is affected by number of existing producers, price and cost expectation, economy situation (including macroeconomic conditions and industry surroundings) and so on.

In each period the producer must decide whether to continue in the industry \( (b_t = 0) \) or to exit \( (b_t = 1) \) if the producer continues in the industry, then a decision must be made as to how hard to work, \( L_t \); with \( L_t \) selected from \([0, L]\).

Next, we add the element of outside-job opportunity that Frank (1988) used in his intertemporal model of industrial exit into consideration and combine with the intertemporal we are using. If the producer cannot compete with other producers, the producer can search the new job that pays \( U_t \) (in utility terms) each period. There is a nonrefundable entry fee of \( C \geq 0 \) dollars needed to start the new producer. One may think of these sunk costs as incorporation expenses for example. To write down the producer’s problem in terms of a value function, some notation is required. Let \( \Pi_t \) be the present discounted value of the producer’s expected utility as period \( t \) given that he chose to enter initially and henceforth will select \( \{b_s, L_s\}_{s=t}^{T} \) optimally. Let \( E_t \) be the expectation operator conditioned on the information available as period \( t \), and \( 0 < \beta \leq 1 \) is the discount factor:

\[
\Pi_1 = \max_{b_t, h_t} \left\{ U_t b_t + [E_t R_t - V(h_t)](1 - b_t) + \beta E_{t+1} \Pi_{t+1} \right\} \quad (21)
\]

\[
\Pi_t = \max_{b_t, h_t} \left\{ U_t b_t + [E_t R_t - V(h_t)](1 - b_t) + \beta E_{t+1} \Pi_{t+1} \right\} \quad (22)
\]

\[t = 2, 3, \ldots, T.\]
Since $T$ is the final time period, $\Pi_{t=T} \equiv 0$. A choice of $b_1 = 1$ would mean that expected profits were not sufficiently attractive to induce initial entry. To make the problem of interest, it must be the case that $b_0 = 0$. The function $V(L_t)$ gives the disutility of effort; it is assumed that both the first and the second derivatives exit and are positive. Further, $\lim_{L \to \infty} V'(L) = \infty$, and $\lim_{L \to 0} V'(L) = 0$, where $V'(\cdot)$ denotes the derivative of $V'(\cdot)$.

Here we consider producer’s revenue $R_t$ in any given time period as depending upon three things, effort ($L_t$), expectation ($\varepsilon_t$) and technology improvement ($\alpha$). This may be expressed as $R_t = f(L_t, \alpha, \varepsilon_t)$ with positive effect each on the producer’s revenue. The producer can decide how hard to work, but by definition luck is uncontrollable. In Frank’s model (1988), he assumed that a producer does not truly know his own talent for running the operation. Theoretically, the true value of $\alpha$ is unknown to the producer. This assumption fits in the situation of small hog producers. Usually small hog producers have no information about their status of hog-raising skills and they can not receive newer hog-raising skill, at least not in the beginning period. Hence, small producers might evaluate by observing the numbers of new entry or compare with production scale of other larger scale producer for their decision-makings of operations.

In each period the producer either decides to exit and receives $U_t$ or else selects continuation and must decide how hard to work, $L_t$. Nature then determines the value of $\varepsilon_t$, and the producer receives $R_t$ according to (2). The knowledge of $\{R_t, L_t\}$ allows the operator to use Bayes’ theorem to update the estimate value of $\alpha$. If exit is selected in some period, then in that period no new information is received, and so the next period
estimate of own talent will remain unchanged. If this producer leaves the industry, there will be no reentrance.

According to the model set up above, the gradual dissipation of uncertainty has been suggested as a basis on which a number of features of traditional performance may be understood. Exit comes about in reaction to low revenue. The low revenue causes an increased likelihood of exit because it implies poor future performance.

Also newer operations will tend to exhibit more variable performance from one period to the next for competition. Declining operations will have increasingly idle time or spend time/effort on outside jobs. This idleness is a reaction to, rather than the cause of, the decline. Past good performance never guarantees continued good performance. It all depends on the relative competition power among producers. It is always possible that a sufficiently bad course of action can occur. Near- retirement producers will tend to work less hard than younger potential producers. The older producers will have a “nothing left to prove” attitude.

In conclusion of the theoretical model, we can set up the exit behavior of small producer that is determined by the hog prices, production costs, and technology (personal talents), outside economy and industrial competition from the discussion above. Therefore, we create the parsimonious economic model for this study:

\[ \text{Exit} = (\pi, P, C, g, \alpha, \text{entry}) \]

4-4 The Criteria Affecting the Small Producer’s Decision-Making
From the theoretical economic model above, this study sets up and interprets the factors (macroeconomic conditions, hog price and the related production costs, technological improvements, and the interaction between entry and exit) that affect exit behaviors of small hog producers. In order to detect the relationships, some hypotheses that can be tested and discussed are below:

**Job Opportunity**

Job opportunities from outside of swine industry affect decision making of exiting behavior. Marginal value productivity of labor in swine production and the best alternative employment opportunity are trade-off for a producer who tends to switch to other jobs than hog production. When macroeconomic conditions are relatively weak, the exit behavior also tends to stay in the business. This conservative attitude is due to the opportunity costs which are high for those who are leaving the hog business. Alternatively, when the economy is in good condition, the opportunity costs for small producers are relatively low. Hence, smaller producers tend to leave the swine industry during economic boom periods. So, if this phenomenon sustains, it shows that the voluntary exit behavior dominates. If this phenomenon is not clear or even exists as a negative relationship, it might imply that the involuntary exit behavior would even be more significant in swine industry. The unemployment rate not only reflects macroeconomic conditions but also presents the exiting producers, with difficulties concerning potential job opportunities. This study chooses the unemployment as the proxy for the economy situations.
Price of hog and production cost

The hog price affecting the scale of raising hogs has been tested by previous studies. However, the exiting decisions of small producer haven’t been estimated yet. By observing the price fluctuation, we might make these conclusions: When the hog price is in the increasing stage and the producers are less willing to leave. It shows that the voluntary exit; if the price is in the low stage and the producers are willing to leave, it shows that the involuntary exit.

The exit of small producers can be divided into volunteer and non-volunteer exit. For voluntarily quitting producers, such as aging, timing seems to be an important factor. This kind of producer tends to leave raising hogs when hog price is higher: they will try to predict the prices between this period and next period. If they consider that hog price is going to increase next period, they will tend to leave until next period. Meanwhile, for non-voluntarily quitting producers, such as those facing financial difficulties, they might tend to leave before the hog profit starts to drop.

High cost operations are vulnerable to declining hog prices, and are among the first to exit the industry when faced with a prolonged period of low hog prices. On the other hand, low-cost operations are in a better position to survive periods of low prices and then thrive when prices improve (McBride and Key, 2003).

The interaction among the large producers and the small producers

From the economic model, we found out there exists a relationship between the entry and exit behaviors. It implies that displacement effect happens on exiting hog producers,
i.e. more efficient new entrants aggressively displace the incumbents. (Exit might be positively correlated with entry, i.e. the more new producers enter the industry, the more incumbent leave the business)

Industrial concentration, observed by the large-scale operation’s scale economies that reflect the production efficiency, is related to the exit rate. Exiting behaviors of small producers, instead of observing market shares of large producers, provide alternative and more direct facet for market concentration, linked by scale economies. If this result is sustained, it supports the traditional idea that scale economies are one important source for large-operation efficiency, and therefore of industrial concentration.

*The role of new technology*

Technological improvements and industrial exit patterns are related. The more hog producers practice new improved technology, the less hog producers consider exiting the business. Meanwhile, if the new technology requires large capital investment, small producers, unable to make the investment, may not face competition with operators who use the new modern technology. Hence, small producers with traditional technology will leave the industry. Therefore the technology factor brings the ambiguous sign of exiting behaviors of small producers.

In addition, market timing effect can interpret the exit behavior, i.e. exiting behavior is not driven by exogenous shocks, instead, driven by cost-related variables. If the hypothesis, marketing timing effect affects exit behavior is sustained, the result indirectly supposes that the asymmetry of the supply response, by observing the whole hog producers’ specific exiting pattern, which can proxy the last inventories of willing-to-exit producers,
that is related to hog price.

From the described above, we depict the factors that might affect exit behaviors of small producers and their directions. It can be set up the equation as below:

\[
Exit = (\pi, P, C, g, \alpha, entry)
\]

In next chapter, this study sets up the econometrical model for estimating these relationships among exit rates and the factors that might affect exit behaviors of small producers.
5-1 Empirical Model Specification

The theoretical model developed in the last chapter suggests some potential factors that might affect small producers’ decision-making of exit behaviors. Here, this study divides that exiting behaviors into two stages: 1) decide to leave or stay; 2) the timing to leave. For first level, if producers do not have intentions or incentives to increase investment or at least maintain current fixed capital, i.e. discount expenditure etc, then they may choose to shut down their hog operations. For the second level of decision, the voluntary exiting producers, who choose to leave the business when either inside or outside the industry the conditions are good; involuntarily exiting producers may be forced to leave under bad economic conditions. Therefore we observe the annual state-level exit rates \( (y_{it}) \) and set up the basic econometric structure described as:

\[
y_{it} = \alpha + X_{it}' \beta + u_{it} \quad i = 1, ..., N; \quad t = 1, ..., T
\]

The data structure is panel data that includes time-series and cross-section parts. In this study, different states represent the cross-section; the unit of time-series is one year. \( i \) denotes 14 major hog-raising states and \( t \) denoting years 1989 through 2003. Hence, the total sample includes 210 observations.

Based on different assumptions on error term \( u_{it} \), there are several econometric models considered. For analyzing panel data, two popular models systems, random effects model and fixed effects model, are introduced. The panel data application utilizes a one-factor error component model for the disturbances, with
\[ u_{it} = \mu_i + v_{it} \]

where \( \mu_i \) denotes the unobservable individual specific effect and \( v_{it} \) denotes the true error terms.

**One-factor Error Component Regression Model**

The fixed effects model assumes that \( \mu_i \) is the set of fixed parameters to be estimated and the remainder disturbance stochastic with \( v_{it} \) independent and identically distributed i.i.d. \((0, \sigma_v^2)\). The \( X_{it} \) are assumed independent of the \( v_{it} \) for all \( i \) and \( t \). There are a large number of parameters in the fixed effects model and the loss of degrees of freedom can be avoided if the \( \mu_i \) can be assumed random. In this case \( \mu_i \sim i.i.d(0, \sigma_{\mu}^2) \), \( v_i \sim i.i.d(0, \sigma_v^2) \) and the \( \mu_i \) are independent of the \( v_{it} \). In addition, the \( X_{it} \) are independent of the \( \mu_i \) and \( v_{it} \) for all \( i \) and \( t \). The model is the random effects model.

**Two-factors Error Component Regression Model**

Furthermore, if time-specific is included, the two-factor error components disturbances:

\[ u_{it} = \mu_i + \lambda_i + v_{it} \quad i = 1, \ldots, N \quad t = 1, \ldots, T \]

where \( \mu_i \) denotes the unobservable individual effect discussed above, \( \lambda_i \) denotes the unobservable time effect and \( v_{it} \) is the remainder stochastic disturbance term. Note that \( \lambda_i \) is individual-invariant and it accounts for any time-specific effect that is not included in the regression. For example,
If the $\mu_i$ and $\lambda_t$ are assumed to be fixed parameters to be estimated and the remainder disturbances stochastic with $v_{it} \sim iid(0, \sigma_v^2)$, $u_{it} = \mu_i + \lambda_t + v_{it}$ represents a two way fixed effect error component model. The $X_{it}$ are assumed independent of the $v_{it}$ for all $i$ and $t$. Inference in this case is conditional on the particular N individuals and over the specific time periods observed. Thus, the model is called a two-factor fixed-effects model.

Alternatively, if $\mu_{it} \sim iid(0, \sigma_{\mu}^2)$, $\lambda_{it} \sim iid(0, \sigma_{\lambda}^2)$ and $v_{it} \sim iid(0, \sigma_v^2)$ independent of each other, then this is the two-factors random-effects model. In addition, $X_{it}$ is independent of $\mu_i, \lambda_t$ and $v_{it}$ for all $i$ and $t$. Inference in this case pertains to the large population from which this sample was randomly drawn. Hence, the model is called the two-factor random-effects model.

Each model for panel data analysis has its own advantages. One advantage of the fixed effects model is that the error terms may be correlated with the individual effects. If group effects are uncorrelated with the group means of the regressors, it would probably be better to employ a more parsimonious parameterization of the panel model (Yaffee, 2003).

Among one-factor fixed-effects, one-factor random-effects, two-factor fixed-effects and two-factor random-effects models, which model is more suitable for this study? Baltagi (1995) compared situations and appropriate conditions for using the fixed-effects and the random-effects models. The fixed-effects models are suitable to a specific set of individuals, such as firms, states or countries. Hence, the inference is restricted to the behavior of these sets of states. Alternatively, the random-effect models are appropriate
specifications if a number of individuals are randomly selected from a large population for representing of the population, for example, the case for household panel studies.

The data for this study has the characteristics for both models’ assumptions. According to the data from National Agricultural Statistical Services (NASS), the total number of operations in the U.S in the studying periods (1988-2003) is down from 332,600 to 73,720, furthermore, to 69,460 in 2004. It means that almost 80% of producers quit the swine industry. This large scale’s exit behavior of producers might randomly happen due to individual factors or changing trend of industrial structure and competition, not related to location and/or time effects. In this viewpoint, the random effects model might explain well for the exit behaviors of the producers.

Since \( \mu_i \) represents the unobservable individual-specific effects of the models, there are some states’ characteristics that might have influences on \( \mu_i \) in this study. Therefore the question we want to ask is, “is the “state-factor” important?”

First, each state’s production characteristics are quite diverse. Traditional Corn Belt production areas have a natural competitive advantage from feed costs (an abundant supply of corn provided a relatively cheap source of hog feed), but that advantage has been overcome in non-traditional hog production areas through investment in new technologies and from economies of size (Onal, Unnevehr, and Bekric, 2000). This characteristic explains why the growth and concentration of hog production was the most dramatic in nontraditional areas, such as North Carolina. Also this characteristic shows that each state has its own production niches. For example, North Carolina, the region with the most mature version of supply-chain hog production, is compared with other important hog
raising states with respect to the importance of agglomeration economies in swine sector. (Roe, Irwin and Sharp, 2002). In addition, each state has its own production issue: the Corn Belt’s heavy reliance on land-intensive feedstuffs and the direct conflict with increasing local populations revealed by the analysis (Roe, Irwin and Sharp, 2002) suggest that hog production in these states is undergoing an atomistic devolution in which only counties with large, highly productive farms and lower local populations and building activity retain or increase production.

Roe, Irwin and Sharp’s research (2002), from the viewpoint of transition of space/location, estimate how numerous firm-specific, locality-specific and spatial agglomeration factor affect the location, movement, and intensity of hog production within 15 key hog production states. Spatial agglomeration, urban encroachment, input availability, firm productivity, local economy, slaughter access, and regulatory stringency variables affect the sample region’s spatial organization. Their analysis (Roe, Irwin and Sharp, 2002) suggest that western states may shape hog production levels by wielding traditional business recruitment and retention tools (e.g. tax rates, environment stringency) while Corn Belt states may shape hog production via nontraditional tools (e.g. land use control). Therefore, the unobservable items are significantly different. This strengthens reasonability of the random effects model.

Besides, Firm-external/industry-internal scale economies (localization economies), firm-external/industry external scale economies (urbanization economies), transportation costs and regulatory stringency (especially the stringency of state-level environmental
regulation) are often cited as basic factors affecting firm location. These unobservable factors that reflect on the variables $\mu_i$ might affect on producers’ exit decisions.

Second, the different attitudes toward to swine industry, environmental regulations, and competition of other livestock industries among different states are all the reasons that make state level’s swine industry data meaningful due to the differentiation among different states. Each state’s own swine policies and regulations might reflect on $\mu_i$ due to policies and regulations that reflect the state’s attitude toward to its swine industry. Environmental policy and regulations are various among different states. Thus they do affect the swine industry, especially small producers. For examples, the requirements for the treatment of manure might affect the willingness of small producers due to the investment on the facility for manure treatment that increases the cost. Alternatively, economies of scale with respect to irrigation cause manure value to increase herd size (Roka and Hoag, 1996).

Not only each state has its own regulatory stringency that affect individual exit rate differentially, each state-level’s regulatory stringency has different degree influence on various sizes of hog producers. According to Metcalfe’s paper (2001), that found out that state water quality regulatory stringency as it applies to hog production has different impact on different size producers. For small hog feeding operations, environmental compliance costs are significant. Meanwhile the level of state environmental regulatory stringency does not affect production on large operations.

Since each model has its own econometrical advantages and characteristics, by comparing these differences, we might explain some practical results of this industry. Roughly speaking, two issues have been raised in the literature regarding whether the
effects $\mu_i$ and $\lambda_i$, should be treated as random or as fixed for a linear static model, namely, the efficiency of the estimates and the independence between the effects and the regressors i.e., the validity of the strict exogeneity assumption of the regressors (Hsiao, 2003). When all the explanatory variables are exogenous, the covariance estimator is the best linear unbiased estimator under the fixed-effects assumption and a consistent and unbiased estimator under the random-effects assumption, even though it is not efficient when observation numbers are fixed (Hsiao, 2003).

However, when there exists omitted individual attributes that are correlated with the included exogenous variables, the covariance estimator does not suffer from bias due to omission of these relevant individual attributes, because their effects has been differenced out.

The reason that we consider the both fixed-effects and random-effects models is for comparisons of both models. Due to data constraints, we cannot get the individual characteristics for each producer such as their willingness and other personal factors that might affect the decisions for quitting the swine industry. By comparison, in both models we can get the results that if the individual characteristics are significantly important or not, because the assumptions of models for error term as description above. Also, whether the state reason, recognized as the location factor, is the important issue or not, observation from differences of both models can be also determined primarily.

Since $\lambda_i$ denotes the unobservable time effect in two-factors fixed-effect model, it implies the each period has its own characteristics and/or special events that are related to exit rate. This study examines this effect due to the phenomenon of hog cycle that describe
the relationship between supply and price of hog that might also exist in the exit behaviors of small producers, i.e. the timing has influence on small producers’ decision for leaving swine industry.

From the discussion above, this study will estimate the results of different panel data models: the one-factor fixed-effects, one-factor random-effects, two-factor random-effects and two-factor fixed-effects models.

The dependent variable in this study is the annual exit rate \( (y_{it}) \). Due to the availability of data structure, this study considers two kinds of exit rates by calculating the number difference of previous and current periods in the smallest (operations with 1-99 head) and the second-smallest (operations with 100-499 head) categories.

The reason to calculate the exit rates of the smallest and second-smallest categories of producers separately is that they are inconsistent in different years and in different states. For example, the exit rate of smallest producers is 13% in 2003 in North Carolina; in the same period and same state, the second-smallest producers’ exit rate is only 5%. It implies that the smallest and the second-smallest producers have different decision-making behaviors when facing the different scenarios. It means that the quitting behaviors might be affected by the different factors between smallest and second smallest producers due to different producers’ characteristics. For example, the ratio of income account for hog-raising and if there is other off-farm employment/job. According to McBride and Key’s report (2003), farm specification in hog production increased with size across all producer types, with the value from hog ranging from around 10 percent of total farm value of production on small operations to around 90 percent on industrial-scale operations. Bigger
diversity among small operations is also apparent in symbol classes that show significantly more producers generating the majority of household income from off-farm income sources, operations of small farm enterprises were also generally older and carried less debt than larger operations (McBride and Key, 2003). Therefore, this study uses two groups of dependent variables: smallest and second-smallest categories.

5-2 The Explanatory Variables for Models

*Unemployment rate*

This study uses unemployment rate as the proxy of macroeconomic condition. The unemployment rate is state level. Unemployment rate $\delta_i$ represents the opportunity cost of seeking other jobs and implies the general economic condition in each time period. Past research shows that off-farm employment has no statistical effect on the number of producers quitting. However, macroeconomic factors did not affect firm survival in a concentrating industry in the study of Van Kranenburg et al. (2002). Besides, Goetz and Debertin’s research (2001) reveal subtle and less clean-cut effect of off-farm employment on farm exit by using counties level’s data. The $un_e_rate$ represents unemployment rate in this study.

*New entrance of large-scale operations and change of Average farm size*

There are several candidate variables that can represent for industrial structure features, such as percentage change of inventory, market share of each operation category…etc. This study uses the percent change of number of large-scale operations entering industry each year ($ch_num_large$) and the change of average farm size each year...
(average hog numbers of per farm) that excludes the hog number that smaller scale operations own. The `ch_size_s` is the symbol for the change of average farm size each year. The calculation formula of `ch_size_s` is:

\[
ch\_size\_s = \left( \frac{I_t - I_t^{\text{small}}}{N_t - N_t^{\text{small}}} - \frac{I_{t-1} - I_{t-1}^{\text{small}}}{N_{t-1} - N_{t-1}^{\text{small}}} \right) \left/ \left( \frac{I_{t-1} - I_{t-1}^{\text{small}}}{N_{t-1} - N_{t-1}^{\text{small}}} \right) \right)
\]

Here, \( I_t \) denotes the total inventory hold by entire industry; \( I_t^{\text{small}} \) denotes the inventory hold be small category; \( N_t \) denotes the total number of operations; \( N_t^{\text{small}} \) denotes numbers of producers of the small category. The inventory data is quarterly. In this study, inventory on December first is chosen to represent the annual data. The calculating way of average farm size is to separate the more accurate large operations’ expansion path and erase the interaction of small and large operations by total average farm size. Therefore, when we calculate of `ch_size_s500`, the average farm size of farms that are with hogs larger than 500 head, it is defined as:

\[
ch\_size\_s500 = \left( \frac{I_t - I_t^{\text{small}} - I_t^{\text{sec\_s}}}{N_t - N_t^{\text{small}} - N_t^{\text{sec\_s}}} - \frac{I_{t-1} - I_{t-1}^{\text{small}} - I_{t-1}^{\text{sec\_s}}}{N_{t-1} - N_{t-1}^{\text{small}} - N_{t-1}^{\text{sec\_s}}} \right) \left/ \left( \frac{I_{t-1} - I_{t-1}^{\text{small}} - I_{t-1}^{\text{sec\_s}}}{N_{t-1} - N_{t-1}^{\text{small}} - N_{t-1}^{\text{sec\_s}}} \right) \right)
\]

Increasing average farm size can come from either or both increasing inventory or decreasing number of operations. However, most scenarios are increasing the inventory in this study due to the observations of the significantly growing inventory ratio in the larger categories. The growing rate of large-scale operations can also illustrate the interaction with
small-scale leaving producers. As shown in Table 5-1, each state has its own growth path of average farm size. Even in the same period, the farm size of each state is distinctive. For example, in 2002, the average farm sizes of Ohio, Iowa, and North Carolina are 320, 1560, and 3031, respectively. This characteristic might affect the exit rate of each state differentially.

Price and Corn Price

Hog price per head ($p_{\text{per}\_\text{head}}$) and corn price ($corn\_\text{price}$) are production cost related variables chosen in this study. The variable, corn price implies that the cost part of hog-raising. Hog price per head and corn price are the factors that might affect the individual producer’s decision making about a production plan. In previous studies, hog prices or corn prices or hog-corn price ratios all have an influence on the changes of inventories, furthermore, the changes of farm sizes by using Markov chain analysis that records the change of farm sizes (Bessler, 1984; von Massow et al., 1992; Gillespie and Fulton, 2001). Also, Hamilton and Kastens (2001) linked the relationship between cattle prices and inventory changes by simulating and comparing the profitability within different inventory strategies. Hence, if the exit behavior is considered as the last decision of inventory, these variables, hog prices etc., might provide useful information on producers’ decisions on quitting.

Change of Average slaughter weight

There are also several proxies for technology improvement used in different studies. In swine industry, to rank all the technology improvement, such as nutrition and feeding program and using antibiotics, in order of importance is very difficult (Cromwell and Hays,
1999). Some of them are even not quantitative. Hog, as a product, represents the result of technology improvement. The slaughter weight in past decades has increased because of improvement technology. Therefore the average slaughter weight properly reflects the result of technological improvement. This study considers the average slaughter weights ($ch_{avg\_slaught}$) as the proxy of technology improvement, because the average slaughter weight reflects the facts that either more producers applies that the new efficient methods for raising pigs or the technology continuously improving. Average live weights of hogs are included slaughter in federally inspected and other slaughter plants and exclude hogs slaughtered on farms. Therefore the data quality is reliable. As shown in Figure 5-1, the trend of average slaughter weights is increasing in the long term. The percentage change is not large. However, increase of each pound implies that many more producers, large-scale and/or small-scale, improve or adopt new or improved hog-raising skills in hog production processes, even these skills are incalculable and not quantitative, such as vaccine or nutrition improvement. The technology index is calculated from the formula:

$$ch_{avg\_slaught} = \frac{W_t - W_{t-1}}{W_{t-1}}$$
The descriptive statistics of explanatory variables are shown in Table 5-2.

**TABLE 5-1**  the Average Farm Size in U.S by State, by Period

<table>
<thead>
<tr>
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<th></th>
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<td>1560</td>
<td>NC</td>
<td>280</td>
<td>1367</td>
<td>3031</td>
</tr>
<tr>
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<td>500</td>
<td>902</td>
<td>NE</td>
<td>344</td>
<td>405</td>
<td>763</td>
</tr>
<tr>
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<td>941</td>
<td>OH</td>
<td>147</td>
<td>212</td>
<td>320</td>
</tr>
<tr>
<td>KS</td>
<td>250</td>
<td>342</td>
<td>1020</td>
<td>OK</td>
<td>41</td>
<td>294</td>
<td>900</td>
</tr>
<tr>
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<td>PA</td>
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<td>372</td>
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<td>418</td>
<td>1054</td>
<td>WI</td>
<td>128</td>
<td>134</td>
<td>226</td>
</tr>
</tbody>
</table>

(Data source: USDA, calculated by alternative year reports)

**TABLE 5-2**  Description Statistics for the Independent Variables

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5-3 The Hypotheses Discussion

There are some hypotheses that will be discussed in this study.

First, this analysis examines that if there exists displacement effect that happens on exiting hog producers, that displacement effect describes the relationship of exit and entry. If new entrants aggressively displace the incumbents, the crowding-out force might induce more incumbents to leave the business. In this study we observe the dependent variable, the exit rates, with the numbers of large producers. If the exit rate has a positive relationship with the independent variable, the number of large producer, this displacement might exist.

Second, Industrial concentration, observing by the large firm’s scale economies that reflect the production efficiency, is related to the exit rate. Exiting behaviors of small producers, instead of observing market shares of large producers, provide alternative and more direct facet for market concentration, linking by scale economies. If this result sustains, it supports the traditional idea that scale economies are one important source of large-firm efficiency, and therefore the industrial concentration. In addition, this
relationship also provides the supportive evidence for crowding-out effect for small producers.

Next, this study discusses the role of macroeconomic conditions on small producers’ exiting behaviors. Basically when macroeconomic conditions are relatively weak, the exit behavior tends to stay low, “conservative”, vice versa, if this phenomenon sustains, it shows that the voluntary exit behavior dominates; if this phenomenon is not clear or even exists negative relationship, it might imply that the involuntary exit behavior would be more significant in swine industry. In this hypothesis, this study chooses each State level’s unemployment rate. The unemployment rate not only reflects macroeconomic condition but also provides that exiting producers thinking of difficulties degree of potential job opportunities. It is the opportunity cost for quitting the swine industry.

Another hypothesis is if there is market-timing effect that interprets the exit behavior. Price is the crucial index for this effect. If price has the relationship with the exit pattern, then the marketing effect is involved. It implies that exiting behavior is not only driven by exogenous shocks, instead, it is driven by cost-related variables. If the hypothesis, marketing timing effect affecting on the exit behavior, sustains, this result indirectly supposes that the asymmetry of supply response by observing the whole hog producers’ specific exiting pattern, which can proxy the last inventories of willing-to-exit producers, that is related to expectation profitability and hog prices. One previous study predicts that poor price tends to increase the small producers’ exodus from the Canadian swine industry (Massow et al., 1992)
Finally, this study examines whether the technology improvements and exiting pattern are related in swine industry. The technology improvements affect the exit behavior in two directions. One is the technology availability and the other is spill-over effects of new technology. Although technology improvement favors large-scale hog operations, small-scale producers still can get benefits from it. New pigs-raising skill or innovation can decrease small-scale producers’ production costs, too. However, the accessibility of technology is the major consideration. Generally, the large producers usually easily get the industrial information and innovation. The more hog producers practice by new raising technology, the less hog producers consider of exiting the business. Agarwal and Audretsch (2001) point out that the products applied different degree of technology affect survival rates. From Agarwal and Audretsch’s (2001) conclusion, the advantages from entrant size seem to be less relevant in highly technical products.

This study uses fully recorded and quantitative description related to technology improvement, average slaughter weight, as a proxy of technological improvement.

Generality of small and large producers’ survivals are still far from making a conclusion (Agarwal and Audretsch, 2001). Most of reasons are new and incumbent firms’ dynamics and with the technological demands of that industry. Due to entrants’ different motivation responding to a different stimulus in the formative stages of the life cycle than in the mature stages, their role in industry dynamics is also different (Agarwal and Audretsch, 2001). From this viewpoint, the swine industry seems to be in the product mature stage, with the stage that technology still keeps growing.

5-4 Data Description

The data structure for this study is panel data set. Based on availability and compatibility, a panel data set is assembled comprising of time series from 1988-2003 for 14 major hog-raising states: Iowa, North Carolina, Minnesota, Illinois, Indiana, Missouri, Nebraska, Oklahoma, Kansas, Ohio, South Dakota, Pennsylvania, Michigan, Wisconsin.

Other variables that this study uses are the hog price per head, corn price, unemployment rate, percentage change of average slaughter weight, percentage change of average farm size per year, and percentage change of numbers of large operations. The whole data set is composed by state-level data. Also all the data are annual data that reflects the decision making of reality and data availability. There are several choices that can be used as the hog price index, such as price per head and price that producers received per cwt. There are also several choices that can be used as the hog cost index, such as corn price per bushel, corn meal price and hog feed price (14%-18% protein). This study will examine each one and find out the best indexes to use.
Chapter 6  EMPIRICAL RESULTS AND DISCUSSION

6-1 Comparison of Models

According to the model for testing the hypothesis discussed in previous chapter, the specifications are presented as follows:

\[
y_{it} = \alpha + \beta_1ch_{num\_large} + \beta_2ch_{size} + \beta_3un\_e\_rate + \beta_4p\_per\_head_{it-1} \\
+ \beta_5corn\_price + \beta_6ch\_avg\_slaughter + \mu_i + \lambda_i + \nu_{it} \quad (6-1)
\]

and

\[
y_{it} = \alpha + \beta_1ch_{num\_large} + \beta_2ch_{size\_s500} + \beta_3un\_e\_rate + \beta_4p\_per\_head_{it-1} \\
+ \beta_5corn\_price + \beta_6ch\_avg\_slaughter + \mu_i + \lambda_i + \nu_{it} \quad (6-2)
\]

The equation (6-1) is for the category of smallest producers (operations with 1-99 head); the equation (6-2) is for the category of second-smallest producers (operation with 100-499 head).

The panel data applications utilize a one-factor fixed-effects model for the disturbances with \( u_{it} = \mu_i + \nu_{it} \) and utilize a two-factor fixed-effects model for the disturbances: \( u_{it} = \mu_i + \lambda_i + \nu_{it} \). \( \mu_i \) denotes the unobservable individual specific effect (the state fixed effect) which captures other time-invariant influences on exit rate, \( \lambda_i \) is the year fixed effect and \( \nu_{it} \) denotes the error term.

Now we set the common panel data structure as follow for discussing the model specifications:
\[ y_{it} = \sum_{k=1}^{K} x_{itk} \beta_k + u_{it} \quad i = 1, \ldots, N; \ t = 1, \ldots, T_i \]

The total number of observations \( M = \sum_{i=1}^{N} T_i \). The \( X \) matrix without the intercept represent as \( X_s \).

As shown above, the specification for the one-factor fixed-effects model is

\[ u_{it} = \mu_i + \nu_{it} \]

where the \( \mu_i \) are nonrandom. The \( \mu_i \) estimates are reported under the restriction that \( \mu_N = 0 \) due to the redundancy of the existence of both the intercept and all the \( \mu_i \)s (SAS, 1999). Let \( Q_0 = \text{diag}(E_{T_i}) \), with \( J_{T_i} = J_{T_i} / T_i \) and \( E_{T_i} = I_{T_i} - J_{T_i} \)

The estimators for the intercept and the fixed effects are given by the usually OLS expressions. If \( \tilde{X}_s = Q_s X_s \) and \( \tilde{y} = Q_s y \), the estimator of the slope coefficients is given by

\[ \tilde{\beta}_s = (\tilde{X}_s'\tilde{X}_s)^{-1}\tilde{X}_s'\tilde{y} \]

The estimator of the error variance is

\[ \hat{\sigma}_e = \tilde{u}'Q_0\tilde{u} / (M - N - (K - 1)) \]

where the residuals \( \tilde{u} \) are given by \( \tilde{u} = (I_M - J_M J_M' / M)(y - X_s \tilde{\beta}_s) \)

The specification for the two-factor fixed-effects model is:

\[ u_{it} = \mu_i + \lambda_i + \nu_{it} \]

where the \( \mu_i \) and \( \lambda_i \) are nonrandom. Both \( \mu_N \) and \( \lambda_T \) are assumed to be zero.
Let \( X^* \) and \( y^* \) be the independent and dependent variables arranged by time and cross section within each time period. Let \( M_t \) be the number of cross section observed in year \( t \) and let \( \sum_t M_t = M \). Let \( D_t \) be the \( M_t \times N \) matrix obtained from the \( N \times N \) identity matrix from which rows corresponding to cross sections not observed at time \( t \) have been omitted. Consider

\[
Z = (Z_1, Z_2)
\]

where \( Z_1 = (D_1', D_2', ..., D_T')' \) and \( Z_2 = \text{diag}(D_1J_N, D_2J_N, ..., D_TJ_N) \). The matrix \( Z \) gives the dummy variable structure for the two-factor model. Let \( \Delta_N = Z'_1Z_1 \), \( \Delta_T = Z_2'Z_2 \), \( A = Z_2'Z_1 \); \( \bar{Z} = Z_2 - Z_1\Delta_N^{-1}A' \); \( Q = \Delta_T - A\Delta_N^{-1}A' \), then

\[
P = (I_M - Z_1\Delta_N^{-1}Z_1') - \bar{Z}Q\bar{Z}'
\]

The estimators for intercept and the fixed effects are given by the usual OLS expressions. Also the estimate of the regression slope coefficients is given by

\[
\tilde{\beta}_s = (X_{ws}'PX_{ws})^{-1}X_{ws}'Py_w
\]

where \( X_{ws} \) is the \( X_w \) matrix without the vector of 1s

The estimator of the error variance is

\[
\hat{\sigma}_e^2 = \tilde{u}'P\tilde{u}/(M - T - N + 1 - (K - 1))
\]

where the residuals are given by \( \tilde{u} = (I_M - J_MJ_M'/M)(y_w - X_{ws}\tilde{\beta}_s) \)

Analyzed by the econometrical computer software, SAS program version 8.2, the results are summarized in Table 6-1, 6-2, 6-3 and 6-4. This study uses the TSCSREG (Time Series Cross Section Regression) procedure in SAS program as a computing tool. This
procedure analyzes a set of linear econometric models that usually arise when time series and cross-sectional data are combined.

During the computing process, this study withdraws the Oklahoma’s data from the data set due to its transition of hog industrial structure is different from other main hog-raising states. Oklahoma has almost no traditional swine industry. This fact makes the exit rate of Oklahoma affect the whole data quality, even though Oklahoma is the major swine industry nowadays. After dropping the Oklahoma’s data, the quality of estimation results is improved.

This study creates the results of different panel data models: the one-factor fixed-effects, one-factor random effects, two-factor random-effects and two-factor fixed-effects models. Besides, this study uses two categories of exit rates, smallest and second-smallest producers, therefore, there are total 8 models that we will observe and evaluate.

The endogenous problem has been avoided by the data designs. By using the exit rate for dependent variable and the annual percentage changes of large operations (ch_num_large), the annual percentage changes of average slaughter weights (ch_avg_slaugt) and the annual percentage change of lager operations’ producer size (ch_size_s and ch_size_s500) for independent variables, exclusive of the smaller operations’ portions, the models decrease the possibilities of endogenous problems. Besides, these variables, waived the time-specific trends, become the parameters of time-invariant regressors. This procedure helps clarifying the effects from these variables themselves, decrease the interactions with time-specific effects.
There are some advantages in estimating both models. The Hausman (1978) chi-square test was developed to compare coefficients in the random and fixed effect solutions (Greene, 1992; Hsiao, 1986). It is a test of the overall difference between the $\beta$ coefficients estimated by the two methods. If the $\beta$ coefficients differ significantly on this test, specification errors of the type discussed above are likely and the fixed effects model is more appropriate (Allison, 1994; Hsiao, 1986). If the test is not significant, then the random effects solution is generally the best choice for the reasons mentioned above.

The difficulties in estimating the fixed-effects and the random-effects models are the determination of the true model. Another way to view the difference between these two approaches provides a more substantively meaningful way to choose between them (Allison, 1994). In this perspective, the decision to use fixed- or random-effects is based on the amount of confidence we have that our substantive model is correctly specified. If we believe that the model we are testing includes all variables that are likely to jointly influence both independent and dependent variables, so that there are no omitted sources of variation in the dependent variables, then the random-effects model would provide the better estimators (Allison, 1994).

It is not easy to show confidence that we have completely specified our model. The research is often aware of variables (either measured or unmeasured) that were not included in the equation but may affect both independent and dependent variables. Such variables would produce a specification error in the random-effects model because a correlation between the $\mu_i$ coefficient and the independent variables would result. If we cannot be assured that we have explicitly controlled for all such variables, then the fixed-effects
model would be preferred because it reduces the risk of the estimates being biased by specification errors stemming uncontrolled individual differences that do not vary over time. Mundalk (1978) argued that random-effects model assumes exogeneity of all the regressors and the random individual effects. In contrast, the fixed effect model allows for endogeneity of all the regressors and the individual effects.

Roughly speaking, for survey panel data, it would appear that random effects would be the estimators of choice. However, the issue of which estimator would be preferred for survey data models, has not been completely resolved in the literature. Our argument is that because one method treats the constant term as fixed and the other treats it as random, the choice of model should be based on which of these assumptions comes closest to the sample characteristics (Hsiao, 2003). According to this view, if we had a fixed sample of individuals (e.g., the assumption normally made in experimental designs) and could not generalize to a population, then the fixed effects model would be appropriate. If we assumed that the individuals were a random sample from a population (the norm in survey samples), and the analyst wanted to generalize to this population, then random effects model would be more appropriate (Johnson, 1995).

The standard Hausman test is the one popular acceptable test for choosing between the estimators of fixed-effects and random-effects models, which are built on the difference of assumptions in the two models. In the fixed effects model, the individual regressors do not need to be treated as uncorrelated with the individual effects, whereas in the random effects, the regressors must be uncorrelated with individual effects. The Hausman tests that the covariance of an efficient estimator with its difference from an inefficient estimator is
zero. It is distributed as $\chi^2$ with one degree of freedom. The Hausman specification test is the classical test of whether the fixed or random effects model should be used. The research question is whether there is significant correlation between the unobserved person-specific random effects and regressors. If there is no such correlation, then the random effects model may be more powerful and parsimonious. If there is such a correlation, the random effects model would be inconsistently estimated and the fixed effects model would be the model of choice.

The statistic of Hausman test is based upon a contrast between the fixed effect and random effect estimators. If this standard Hausman test rejects the null hypothesis that the conditional mean of the disturbances given the regressors is zero, the applied researcher reports the fixed estimator. Otherwise, the researcher reports the random effect estimator.

The results of one specification test for fixed effects and one specification test for random effects. For fixed effect, let $\beta_f$ be the n dimensional vector of fixed effects parameters. The specification test reported in the conventional F-statistic for the hypothesis $H_0 = \beta_f = 0$. The F-statistic with n, M – K degrees of freedom is computed as

$$\hat{\beta}_f \hat{S}_f^{-1} \hat{\beta}_f / n$$

where $\hat{S}_f$ is the estimated covariance matrix of the fixed effects parameters.

Hausman’s (1978) specification test or m-statistic can be used to test hypotheses in terms of bias or inconsistency of an estimator. It means that the independent variables are not related to different states. The test for this correlation is a comparison of the covariance matrix of the regressors in the LSDV model with those in the random effects model. The
null hypothesis is that there is no correlation. If there is no statistically significant difference between the covariance matrices of the two models, then the correlations of the random effects with the regressors are statistically insignificant. The Hausman test is a kind of Wald $\chi^2$ test with k-1 degrees of freedom (where k = number of regressors) on the difference matrix between the variance-covariance of the LSDV with that of the Random effects model.

(Baltagi, 2001) A critical assumption in the error component regression model is that $E(u_i/X_{it}) = 0$. This is important given that the disturbances contain individual invariant effect (the $\mu_i$), which are unobserved and may be correlated with the $X_{it}$. In this case, $E(u_i/X_{it}) \neq 0$ and the GLS estimator $\hat{\beta}_{GLS}$ becomes biased and inconsistent for $\beta$. However, the within transformation wipes out these $\mu_i$ and leaves the within estimator $\tilde{\beta}_{within}$ unbiased and consistent for $\beta$. Hausman (1978) suggests comparing $\hat{\beta}_{GLS}$ and $\tilde{\beta}_{within}$, both of which will have different under the null hypothesis $H_0 : E(u_i/X_{it}) = 0$, but which will have different probability limits if $H_0$ is not true. In fact, $\tilde{\beta}_{within}$ is consistent whether $H_0$ is true or not, while $\hat{\beta}_{GLS}$ is BLUE, consistent and asymptotically efficient under $H_0$, but is inconsistent when $H_0$ is false. A natural test statistic would be based on $\tilde{q}_1 = \hat{\beta}_{GLS} - \tilde{\beta}_{within}$. Under $H_0$, $p\lim \tilde{q}_1 = 0$ and $\text{cov}(\tilde{q}_1, \hat{\beta}_{GLS}) = 0$.

Greene (2003) calls the random effects model a regression with a random constant term. One way to handle the ignorance or error is to assume that the intercept is a random outcome variable. The random outcome is a function of a mean value plus a random error.
But this cross-sectional specific error term \( v_i \), which indicates the deviation from the constant of the cross-sectional unit (in this example, country) must be uncorrelated with the errors of the variables if this is to be modeled. The time series cross-sectional regression model is one with an intercept that is a random effect.

Intuitively, the different states have their own production characteristics and surroundings. The Hausman test for the fixed and random-effects regressions are based on the parts of the coefficient vectors and the asymptotic covariance matrices that correspond to the slopes in the models. The hypothesis that the individual effects are uncorrelated with the other regressors in the model can not be rejected.

In the random effects specification, the null hypothesis of no correlation between effects are regressors implies that the OLS estimates of the slope parameters are consistent and inefficient but the GLS estimates of the slope parameters are consistent and efficient. This facilitates a Hausman specification. The reported \( \chi^2 \) statistic has degree of freedom equal to the number of slope parameters.

Because fixed-effects estimators depend only on deviations from their group means, they are sometimes referred to as with-groups estimators. If the cross-sectional effects are correlated with the regressors, then the cross-sectional effects will be correlated with the group means. Ordinary least squares estimation on the pooled sample would be inconsistent, even though the within-groups estimator would be consistent. If, however, the fixed effects are uncorrelated with the regressors, the within-groups estimator will not be efficient. If there is only variation between the group means, then it would be permissible to
use the between-groups estimator, but this would be inconsistent if the cross-sectional errors are correlated with the group means of the regressors.

Fixed-effects models have their own drawbacks. The fixed-effects models may frequently have too many cross-sectional units of observations requiring too many dummy variables for their specification. Too many dummy variables may sap the model of sufficient number of degrees of freedom for adequately powerful statistical tests (Yaffee, 2003). Moreover, a model with many such variables may be plagued with multicollinearity, which increases the standard errors and thereby drains the model of statistical power to test parameters. If these models contain variables that do not vary within the groups, parameter estimation may be precluded. The data this study uses has been avoided such statistical problems. Although the model residuals are assumed to be normally distributed and homogeneous, there could easily be country-specific (groupwise) heteroskedasticity or autocorrelation over time that would further plague estimation.

Under these circumstances, the random error $v_i$ is heterogeneity specific to a cross-sectional unit, in this study, state. This random error $v_i$ is constant over time. Therefore, $E[v_i^2 | x] = \sigma_i^2$, the random error $e_{it}$ is specific to a particular observation. For $v_i$, to properly specified, it must be orthogonal to the individual effects. Because of the separate cross-sectional error term, these models are sometimes called one-way random effects models. Owing to this intra panel variation, the random effects model has the distinct advantage of allowing for time-invariant variables to be included among the regressors.
In addition to Hausman test, this study also observes the F test, \( R^2 \), and the results of the estimators as the criteria for deciding the better models. Also, by comparing these models, we can evaluate the meanings behind these differentials. Next we compare the superiority and adequacy among the one-factor random-effects model, one-factor fixed-effects model, two-factor random-effects model, and two-factor fixed-effects model for both smallest category and second-smallest category of producers.

The one-factor fixed-effects model is not superior to the one-factor random-effects model for smallest category producers. From the result of Hausman test, the \( m \) value is 3.44. This value can not reject the hypothesis. It implies that the random effects exist. In addition, from the F-test’s result, the value of F-test is 0.78. This value also can not prove the fixed effect exists. It means that no fixed effects sustain. Besides, the \( R^2 \) does not significantly prove since fixed effects, state-specific factors in this study, are considered. The \( R^2 \) value is only up 4% after the fixed effect assumption is added. It means that the explanation abilities from state-specific factors are weak. Also, the t-values of all states’ estimates are not significant from zero in one-factor fixed-effect models. In addition, the estimations of both models, one-factor random-effects model and one-factor fixed-effects model for smallest category producers, are similar. It strengthens the evidences that the individual-specific effects, state characteristics in this study, do not play a crucial role for decision-makings of exit of smallest producers.

As for the models for the category of second-smallest producers, it shows that the similar results with the smallest producers’ category: It is clear that one-factor fixed-effects model for second-smallest category does not dominate one-factor random-effects model for
second-smallest category producers. Not only the Hausman test for random effect ($m = 4.42$) is not significant also F test for no fixed effect (F-value = 0.59) can not reject the hypothesis. It indicates the similarities of both one-factor random-effects and fixed-effects models. In addition, the significant independent variables ($ch\_size\_s500$, $un\_e\_rate$, $p\_per\_head$) are the same in both models. Therefore, the explanatory abilities of both models, the one-factor fixed and random-effects for second-smallest producers are almost the same, even though the $R^2$ of one-factor fixed-effects model for second-smallest category is slightly higher (5%) than one-factor random-effects model. However, the individual state factor has no significantly influences on the dependent variable. Therefore, there is no significantly difference to choose between one-factor fixed-effects model and one-factor random-effects model. As we know one-factor fixed-effects models can exploit the heterogeneity across individual facilities. If appropriate, the one-factor random-effects model is preferred to the one-factor fixed-effects model, which precludes estimation of two key, yet time-invariant, factors. However, the one-factor fixed-effects model does not dominate the one-factor random-effects model. Thus, heterogeneity across individual state is not evident, and inclusion of state-specific constant terms is ambiguous. Further speaking, these exiting behaviors of small producers are no different among states, even though each state might have its own policy or regulations to protect or discourage smaller producers.

Next, we evaluate the two-factor random-effects model and two-factor fixed-effects model for smallest category. The Hausman test for random effect rejects significantly (its $m$ value is 15.6): it implies that the two-factor random-effects model is not suitable for this data set. Its explanatory ability for data set is even worse than one-factor random effects
model by comparing the $R^2$ values. Meanwhile, the F-test for no fixed effects rejects the hypothesis. It means that the two-factor fixed model is better for analyzing this data set. The R-square increases from 0.09 to 0.35. The other auxiliary evidences, the significant estimates either state factor or year effect exists.

The same situation happens in the second-smallest category: the two factors fixed-effects model performs much better than the two-factor random-effects model by F-test and the Hausman test criteria. In addition, the R-square is the highest among these models. The R-square values increase from 0.14 (the two-factor random-effects model) to 0.46 (the one-factor fixed-effects model). It indicates that the two factors fixed-effects model results for factors involving time-variant factor such as annual pattern, states-specific factors such as environmental regulations, state-level agricultural policy-related specific deterrence, are distinctive from the two-factor random-effects model results in sign and statistical significance.

Among all models, the two-factor random-effects models have the worse explanatory abilities for both smallest and second-smallest categories of producers. Not only their R-squares ($R^2$) are the lowest among all models, also these models are rejected by Hausman tests and F tests. It means that states-specific effects or/and time-specific effects exist, especially time-specific effects. Also as shown in Table 6-2 and 6-3, the estimation results of two-factor random-effects models are not in accord with those of the one-factor random-effects model. Thus, inclusion of time-specific factors, year, significantly alter the previous conclusion. Moreover, two-factor fixed-effects models have the best explanatory abilities for both smallest and second-smallest categories of producers.
according to the better $R^2$ values for each category’s model. These results also support that state-specific effects and/or time-specific effects sustain and are not random.

From the discussions above, we use the estimators of one-factor random-effects models for both smallest and second-smallest producer as our major results and two-factor fixed-effects models as auxiliary results.

Table 6-1 Estimation Results of Exit Rate Functions (One-Factor Fixed Effect Model)

<table>
<thead>
<tr>
<th></th>
<th>Smallest category</th>
<th>Second-smallest category</th>
</tr>
</thead>
<tbody>
<tr>
<td>IA</td>
<td>0.029013 (0.0291)</td>
<td>-0.00684 (0.0362)</td>
</tr>
<tr>
<td>IL</td>
<td>0.032674 (0.0300)</td>
<td>0.042848 (0.0373)</td>
</tr>
<tr>
<td>IN</td>
<td>0.021752 (0.0287)</td>
<td>0.024775 (0.0356)</td>
</tr>
<tr>
<td>KS</td>
<td>-0.00746 (0.0291)</td>
<td>0.034937 (0.0360)</td>
</tr>
<tr>
<td>MI</td>
<td>-0.00343 (0.0308)</td>
<td>0.052311 (0.0382)</td>
</tr>
<tr>
<td>MN</td>
<td>-0.00697 (0.0291)</td>
<td>-0.01264 (0.0361)</td>
</tr>
<tr>
<td>MO</td>
<td>0.019108 (0.0299)</td>
<td>0.026371 (0.0370)</td>
</tr>
<tr>
<td>NC</td>
<td>0.030939 (0.0298)</td>
<td>0.017383 (0.0369)</td>
</tr>
<tr>
<td>NE</td>
<td>-0.00847 (0.0300)</td>
<td>-0.02562 (0.0373)</td>
</tr>
<tr>
<td>OH</td>
<td>0.0037 (0.0300)</td>
<td>0.03344 (0.0373)</td>
</tr>
<tr>
<td>PA</td>
<td>-0.0253 (0.0302)</td>
<td>-0.00048 (0.0375)</td>
</tr>
<tr>
<td>SD</td>
<td>0.014234 (0.0297)</td>
<td>0.0054 (0.0369)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.020461 (0.0577)</td>
<td>0.222199 (0.0720)</td>
</tr>
</tbody>
</table>
Table 6-2 Estimation Results of Exit Rate Functions (One-Factor Random Effect Model)

One-Factor Random Effects Model

<table>
<thead>
<tr>
<th></th>
<th>Smallest category</th>
<th>Second-smallest category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.04901 (0.0512)</td>
<td>0.222394 *** (0.0635)</td>
</tr>
<tr>
<td>ch_num_large</td>
<td>-0.00247 (0.0419)</td>
<td>0.03153 (0.0514)</td>
</tr>
<tr>
<td>ch_size</td>
<td>0.165783 *** (0.0440)</td>
<td>-----------</td>
</tr>
<tr>
<td>ch_size_s500</td>
<td>----------- (0.0597)</td>
<td>0.389248 *** (0.0597)</td>
</tr>
<tr>
<td>un_e_rate</td>
<td>-0.00875 ** (0.00446)</td>
<td>-0.01268 *** (0.00549)</td>
</tr>
</tbody>
</table>

Note: ***, **, and * indicate that the parameter is significant at the 1%, 5% and 10% level, respectively. The standard errors are shown in parentheses.

R-Square = 0.1802 and 0.2630, respectively
<table>
<thead>
<tr>
<th>Variable</th>
<th>Smallest category</th>
<th>Second-smallest category</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intercept</strong></td>
<td>0.10961</td>
<td>0.206449 **</td>
</tr>
<tr>
<td></td>
<td>(0.0785)</td>
<td>(0.1007)</td>
</tr>
<tr>
<td><strong>ch_num_large</strong></td>
<td>-0.03133</td>
<td>0.070116</td>
</tr>
<tr>
<td></td>
<td>(0.0445)</td>
<td>(0.0511)</td>
</tr>
<tr>
<td><strong>ch_size</strong></td>
<td>0.169618 ***</td>
<td>------------</td>
</tr>
<tr>
<td></td>
<td>(0.0470)</td>
<td>(0.0571)</td>
</tr>
<tr>
<td><strong>ch_size_s500</strong></td>
<td>------------</td>
<td>0.288734 ***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0571)</td>
</tr>
<tr>
<td><strong>un_e_rate</strong></td>
<td>-0.00175</td>
<td>-0.00392</td>
</tr>
<tr>
<td></td>
<td>(0.00527)</td>
<td>(0.00580)</td>
</tr>
<tr>
<td><strong>P_per_head</strong></td>
<td>-0.00046</td>
<td>-0.00133</td>
</tr>
<tr>
<td></td>
<td>(0.000686)</td>
<td>(0.000876)</td>
</tr>
<tr>
<td><strong>corn_price</strong></td>
<td>0.008622</td>
<td>0.002383</td>
</tr>
<tr>
<td></td>
<td>(0.0221)</td>
<td>(0.0274)</td>
</tr>
<tr>
<td><strong>ch_avg_slaught</strong></td>
<td>0.588416 ***</td>
<td>-0.28129</td>
</tr>
<tr>
<td></td>
<td>(0.2349)</td>
<td>(0.2723)</td>
</tr>
<tr>
<td><strong>Hausman Test (m)</strong></td>
<td>15.17</td>
<td>12.31</td>
</tr>
</tbody>
</table>

Note: ***, **, and * indicate that the parameter is significant at the 1%, 5% and 10% level, respectively. The standard errors are shown in parentheses. R-Square = 0.0922 and 0.1440 respectively.
<table>
<thead>
<tr>
<th></th>
<th>Smallest category</th>
<th>Second-smallest category</th>
</tr>
</thead>
<tbody>
<tr>
<td>IA</td>
<td>0.046587 *</td>
<td>0.01126</td>
</tr>
<tr>
<td></td>
<td>(0.0279)</td>
<td>(0.0331)</td>
</tr>
<tr>
<td>IL</td>
<td>0.018903</td>
<td>-0.00961</td>
</tr>
<tr>
<td></td>
<td>(0.0314)</td>
<td>(0.0372)</td>
</tr>
<tr>
<td>IN</td>
<td>0.038695</td>
<td>0.007451</td>
</tr>
<tr>
<td></td>
<td>(0.0281)</td>
<td>(0.0333)</td>
</tr>
<tr>
<td>KS</td>
<td>0.008123</td>
<td>0.040633</td>
</tr>
<tr>
<td></td>
<td>(0.0294)</td>
<td>(0.0346)</td>
</tr>
<tr>
<td>MI</td>
<td>-0.03646</td>
<td>-0.00502</td>
</tr>
<tr>
<td></td>
<td>(0.0335)</td>
<td>(0.0398)</td>
</tr>
<tr>
<td>MN</td>
<td>-0.00963</td>
<td>-0.00594</td>
</tr>
<tr>
<td></td>
<td>(0.0289)</td>
<td>(0.0343)</td>
</tr>
<tr>
<td>MO</td>
<td>0.022057</td>
<td>0.007842</td>
</tr>
<tr>
<td></td>
<td>(0.0304)</td>
<td>(0.0360)</td>
</tr>
<tr>
<td>NC</td>
<td>0.092085 ***</td>
<td>-0.01558</td>
</tr>
<tr>
<td></td>
<td>(0.0393)</td>
<td>(0.0467)</td>
</tr>
<tr>
<td>NE</td>
<td>0.035918</td>
<td>0.012787</td>
</tr>
<tr>
<td></td>
<td>(0.0300)</td>
<td>(0.0356)</td>
</tr>
<tr>
<td>OH</td>
<td>0.006543</td>
<td>-0.01229</td>
</tr>
<tr>
<td></td>
<td>(0.0303)</td>
<td>(0.0359)</td>
</tr>
<tr>
<td>PA</td>
<td>0.03994</td>
<td>-0.08196</td>
</tr>
<tr>
<td></td>
<td>(0.0457)</td>
<td>(0.0542)</td>
</tr>
<tr>
<td>SD</td>
<td>0.022527</td>
<td>0.041985</td>
</tr>
<tr>
<td></td>
<td>(0.0315)</td>
<td>(0.0373)</td>
</tr>
<tr>
<td>1989</td>
<td>0.031647</td>
<td>0.003545</td>
</tr>
<tr>
<td></td>
<td>(0.0318)</td>
<td>(0.0377)</td>
</tr>
<tr>
<td>1990</td>
<td>0.059038 *</td>
<td>0.023479</td>
</tr>
<tr>
<td></td>
<td>(0.0336)</td>
<td>(0.0399)</td>
</tr>
<tr>
<td>1991</td>
<td>0.039604</td>
<td>-0.01221</td>
</tr>
<tr>
<td></td>
<td>(0.0364)</td>
<td>(0.0433)</td>
</tr>
<tr>
<td>1992</td>
<td>-0.02565</td>
<td>-0.00729</td>
</tr>
<tr>
<td></td>
<td>(0.0393)</td>
<td>(0.0467)</td>
</tr>
<tr>
<td>1993</td>
<td>0.076983 ***</td>
<td>0.01966</td>
</tr>
<tr>
<td></td>
<td>(0.0305)</td>
<td>(0.0362)</td>
</tr>
<tr>
<td>Year</td>
<td>ch_num_large</td>
<td>Ch_size</td>
</tr>
<tr>
<td>------</td>
<td>--------------</td>
<td>---------</td>
</tr>
<tr>
<td>1994</td>
<td>0.066163**</td>
<td>0.013477</td>
</tr>
<tr>
<td></td>
<td>(0.0337)</td>
<td>(0.0400)</td>
</tr>
<tr>
<td>1995</td>
<td>0.241058***</td>
<td>-0.00883</td>
</tr>
<tr>
<td></td>
<td>(0.0700)</td>
<td>(0.0838)</td>
</tr>
<tr>
<td>1996</td>
<td>0.157545***</td>
<td>0.113944***</td>
</tr>
<tr>
<td></td>
<td>(0.0353)</td>
<td>(0.0418)</td>
</tr>
<tr>
<td>1997</td>
<td>0.157749***</td>
<td>0.076429</td>
</tr>
<tr>
<td></td>
<td>(0.0463)</td>
<td>(0.0548)</td>
</tr>
<tr>
<td>1998</td>
<td>0.055203</td>
<td>0.016544</td>
</tr>
<tr>
<td></td>
<td>(0.0519)</td>
<td>(0.0614)</td>
</tr>
<tr>
<td>1999</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>-0.00443</td>
<td>0.092099*</td>
</tr>
<tr>
<td></td>
<td>(0.0455)</td>
<td>(0.0541)</td>
</tr>
<tr>
<td>2001</td>
<td>0.065133</td>
<td>0.066079*</td>
</tr>
<tr>
<td></td>
<td>(0.0301)</td>
<td>(0.0357)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.33114</td>
<td>-0.2487</td>
</tr>
<tr>
<td>ch_num_large</td>
<td>-0.05101</td>
<td>0.1025*</td>
</tr>
<tr>
<td>Ch_size</td>
<td>0.148391***</td>
<td></td>
</tr>
<tr>
<td>Ch_size_s500</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Un_e_rate</td>
<td>0.015271*</td>
<td>0.008702</td>
</tr>
<tr>
<td>p_per_head</td>
<td>-0.00076</td>
<td>0.00037</td>
</tr>
<tr>
<td>corn_price</td>
<td>-0.14312**</td>
<td>0.097091</td>
</tr>
<tr>
<td>ch_avg_slaught</td>
<td>0.731069***</td>
<td>-0.3895</td>
</tr>
<tr>
<td>F-test (for no fixed effect)</td>
<td>1.99</td>
<td>2.68</td>
</tr>
</tbody>
</table>

Note: ***, **, and * indicate that the parameter is significant at the 1%, 5% and 10% level, respectively. The standard errors are shown in parentheses.

R-Square = 0.3455 and 0.4644, respectively.
6-2 Discussion of Empirical Results

According to the results shown in Tables 6-1, 6-2, 6-3, and 6-4, there are several findings in this research interpreted below:

First, the unemployment rate plays a guiding role for smallest and second-smallest producers’ decision-making of quitting hog business. For producers with 100-499 head of hogs, this effect shows in both in one-factor fixed-effects and one-factor random-effects models; for producers with less 100 head, this effect shows in one-factor random-effects model. It indicates that macroeconomic conditions affecting decision making of exiting behavior has sustained in this study, i.e. when macroeconomic conditions are relatively weak, small producers tend to stay in the industry; when economy situations are good, small producers might consider leaving the industry. The unemployment rate not only reflects macroeconomic conditions but also proxies exiting producers’ potential job opportunities. If the situation of the outside job markets is good, it speeds up the producers’ exiting behaviors. It also implies that small producers’ exit behaviors tend to be voluntary. The study from Roe, Irwin and Sharp (2002) by observing the traditional hog-raising states also found this relationship. They interpret hog production does not benefit from a robust local economy that attracts labor force leaving the swine industry. Moreover, Foltz (2004) also found the strongly positive and significant coefficient on the unemployment rate that outside labor opportunities and the lack of a local labor supply to hire for producer work influences local dairy producers’ exit.

Second, the significantly positive relationship between exit rate and the size change of larger operations is sustained in every model for both smallest and second-smallest
producers. These solid results mean that industrial concentration, by observing the large operations’ scale economies that reflect the production efficiency, is positively related to the exit rate. The more large operations expand, the more small producers exit. It indirectly proves that crowding-out effects sustain. If small producers have no intention to increase production size, they are facing more severe competition from the larger scale producers. This strong positive relationship supports that scale economies are one important source of large-firm efficiency, and therefore of industrial concentration due to the scale economy speeding up the exit behaviors and industrial concentration. This phenomenon strongly supports the U.S swine industry is under the process of restructure. And this result follows Eckard’s (1990) estimation of larger producer’ efficiency from scale economies that induce industrial concentration.

Next, hog price has a significant influence on a second-smaller producer’s decision for timing of leaving business. There is a negative relationship between hog price and exit rate. When hog prices are lower, more producers exit. The result is same with Lawrence and Wang’s survey (1998): low hog price is the top reason why hog producers in Iowa left the swine industry. This result also indirectly supports that the market timing effect also happens in the swine industry as in the cattle industry. Market timing effect interprets the exit behavior, i.e. exiting behavior is not only driven by exogenous shocks but also driven by cost-related variables. From the results of this study, marketing timing effect affecting on the exit behavior sustains by observing the statistical significances in both one-factor fixed-effects model and one-factor random-effects model. These results indirectly suppose that the asymmetry of supply response by observing the whole hog producers’ specific exiting pattern, which can proxy the last inventories of willing-to-exit producers, that is
related to expectation profitability and hog prices. The two-factor fixed-effects models also provide strong supportive evidences. We can observe that some specific years have robust relationships on second-smallest producers’ decision-making of exit.

The relationship among price per head, corn price and exit rate is worth discussing in detail here. For smallest producers, the corn price, which represents production costs, affects its exit rate; for second-smallest producers’ category, the corn price does not have significant influence on exit rate. Meanwhile, observing the price effect on exit rate, we can get the opposite results: price has the effect on second-smallest category of producers, but does not affect the smallest category of producers significantly. These results indicate that different sizes of producers have different considerations and prior criteria when small producers decide to leave the business. It might be related to small producers’ individual characteristics, such as retirement, financial difficulty, or off-farm employment etc. For example, empirically smallest producers might be part-time hog producers with other income sources, compared with the second-smallest producer with 100-499 head of hogs might be full-time hog producers. One finding can sustain empirically the previous papers (Tweenten, 1984 and Goddard et al., 1993) that summarized that unstable prices hurt mid-size farms the most due to better risk management of larger farms and more possible off-farm jobs involvement of small farms. This characteristic might be one of the reasons that the decision-making criteria are different for smallest and second-smallest producers: hog price for second-smallest producers; corn price for smallest producers.

The entrance of new producers, represented the percentage change of number of large producers, does not play any important factor on the smallest producers’ decisions. The number of producers with large inventories, over 1000, 2000, or 5000 head in different
time periods, has no relation with the exit rate of smallest operations. It implies the
displacement effect does not affect the smallest producers. However, the percentage
changes of numbers of large producers have a positive influence on the exit rate of
producers with 100-499 head of hogs in two-factor fixed-effects model. It means that new
entrants affect the second-smallest producer’s exit decisions, i.e. the displacement effect on
second-smallest producers sustains. It implies that the competitive power of this size of
operations is disappearing.

Technology improvement has a significantly positive relation with exit rate of
producers in smallest category from all assumptions of model types, even in the two-factor
fixed-effects model that abstracts the year-specific factors. It describes solidly one
phenomenon: the more production technology is improved, the more producers with less
than 100 head of hogs are considering leaving swine industry. There are two possible
explanations behind this result. One is that spillover effect of technology is not significant
i.e. it is not easy for smallest producers to receive newer production technology or
transferability; the other is that the costly investment for technology is a barrier for smallest
producers. However, we do not find this relationship on producers with 100-499 head this
category according to the insignificant results of the explanatory variable for technology
improvement in all models. It implies that production technology improvement is neutral to
exit decisions of second-smallest producers. Furthermore, technology improvement might
relieve the exit rate of second-smallest producers due to the negative sign between exit rate
and the variable, \textit{ch\_avg\_slaught} in every model. It means that the improvement of
production technology can create benefits and advantages for second-smallest producer
group to delay the second-smallest producers’ exit decisions. However, this effect is not robust.

From the fixed-effects models, one-factor and two-factors, we did not observe the state-specific factor has influence on the small or second-smallest producers’ exit behaviors, except Iowa and North Carolina (the largest and second largest hog production states, respectively). We can say that the smallest producers in these two states (Iowa and North Carolina) are facing more severe competition to survive. It means that the industrial concentration is more obvious in these two states. Also the superiorities of one-actor fixed-effects model and one-actor random-effect model are not clear. It means that large exodus is nationwide no matter what production locations are. In addition, this result also implies that the states’ unobservable factors, such as environmental regulations, production advantages, did not play the crucial reasons for small producers’ exit decisions. As shown in table 6-1 and table 6-2, the estimation results of the one-factor random-effects model are highly similar to those estimators in the one-factor fixed-effects models. We strengthen the evidence that state-specific factors are not major concerns for small producers’ decision-making of exit.

Finally, does the market timing influence the exit behavior? From the results of two-factor fixed-effects models, we can observe that some specific years have robust relationships with exit rates, both with smallest and second-smallest producers. Besides, for both categories, different years have different degrees of impacts. However, the timing effect is positive with small producers’ exit decisions.
In addition, in comparison of R-square values of smallest and second-smallest categories of producer’s exit behaviors, we find out that all the models have better explanation abilities for second-smallest category. It implies that the unobservable individual private factors, such as retirement, personal financial situations…etc, have more influences on smallest producers than industrial factors and macroeconomic conditions.

6-3 Results from the Pooled Model – Dummy Variable Technique

For the completeness and the creditability of this analysis, this study uses the pooled model to estimate the data. By using this model, we can include the third category that increases the observation numbers and includes the total change of all producers. The model structure is set up as:

\[ Y_{ijk} = \alpha + \beta X_{ijk} + D_s + D_{ss} + D_{MW} + \delta(D_s \times X_{ijk}) + \theta(D_{ss} \times X_{ijk}) + \varepsilon \]

Where \( Y_{ijk} \) represent the exit rate, \( i \) denotes the states, \( j \) denotes the time periods and \( k \) denotes three categories: the operations with 1-99 head, the operations with 100-499 head, and the operations with over 500 head. \( \varepsilon \) is error term. The total numbers of observations are 585.

The \( X_{ijk} \) are the state-level unemployment rates, annual percentage change of inventory of market share of the operations with over 1000 head, corn prices, the change of average slaughter weights, and price per head of previous year. Annual percentage change of inventory of market share of the operations with over 1000 head is defined as:
Also, this model establishes three dummy variables $D_{MW}$, $D_{S}$ and $D_{SS}$. The dummy, $D_{MW}$, is defined as the location characteristic:

$$D_{MW} = \begin{cases} 1 & \text{if the states are in the Midwest} \\ 0 & \text{otherwise} \end{cases}$$

The Midwest is composed of the states: Iowa, Illinois, Indiana, Michigan, Minnesota, Missouri, Ohio and Wisconsin. The dummy variables, $D_{S}$ and $D_{SS}$, indicate the characteristics of different categories:

$$D_{S} = \begin{cases} 1 & \text{if the category of operations with 1 – 99 head} \\ 0 & \text{otherwise} \end{cases}$$

$$D_{SS} = \begin{cases} 1 & \text{if the category of operations with 100 – 499 head} \\ 0 & \text{otherwise} \end{cases}$$

In addition, for observing the interaction of different size of the operations and other explanatory variables, $X_{ijk}$, this study set up the two groups of variables, $(D_{S} \times X_{ijk})$ and $(D_{SS} \times X_{ijk})$. This study also considered the dummies for states in this model. However, after experimenting with a number of different specifications, the results show these estimators are not robust, also have weak explanations for the model by observing the little change of R-square value. The results are shown in the Table 6-5. The table also displays
that estimated asymptotic covariance matrix of the estimates under the hypothesis of
heteroscedasticity.

Table 6-5 Estimation Results of Pooled Model

<table>
<thead>
<tr>
<th></th>
<th>Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.09538</td>
</tr>
<tr>
<td></td>
<td>[0.053786]</td>
</tr>
<tr>
<td>Ch_I_above1000</td>
<td>0.00497 **</td>
</tr>
<tr>
<td></td>
<td>[0.002533]</td>
</tr>
<tr>
<td>Un_e_rate</td>
<td>-0.01119 **</td>
</tr>
<tr>
<td></td>
<td>[0.005667]</td>
</tr>
<tr>
<td>P_per_head</td>
<td>-0.00097857 *</td>
</tr>
<tr>
<td></td>
<td>[0.000445]</td>
</tr>
<tr>
<td>corn_price</td>
<td>0.01001</td>
</tr>
<tr>
<td></td>
<td>[0.017254]</td>
</tr>
<tr>
<td>ch_avg_slaught</td>
<td>-0.06037</td>
</tr>
<tr>
<td></td>
<td>[0.148368]</td>
</tr>
<tr>
<td>D_MW</td>
<td>0.01917 **</td>
</tr>
<tr>
<td></td>
<td>[0.027667]</td>
</tr>
<tr>
<td>D_S</td>
<td>-0.11141</td>
</tr>
<tr>
<td></td>
<td>[0.081828]</td>
</tr>
<tr>
<td>D_SS</td>
<td>0.01824</td>
</tr>
<tr>
<td></td>
<td>[0.086752]</td>
</tr>
<tr>
<td>D_S*p_per_head</td>
<td>0.00137</td>
</tr>
<tr>
<td></td>
<td>[0.000683]</td>
</tr>
<tr>
<td>D_S*corn_p</td>
<td>0.03773</td>
</tr>
<tr>
<td></td>
<td>[0.023082]</td>
</tr>
<tr>
<td>D_S*ch_avg_slaught</td>
<td>0.72910 *</td>
</tr>
<tr>
<td></td>
<td>[0.202421]</td>
</tr>
<tr>
<td>D_S*ch_I_above1000</td>
<td>0.00101</td>
</tr>
<tr>
<td></td>
<td>[0.003343]</td>
</tr>
<tr>
<td>D_S*un_e_rate</td>
<td>-0.00191</td>
</tr>
<tr>
<td></td>
<td>[0.007525]</td>
</tr>
<tr>
<td>D_SS*p_per_head</td>
<td>0.00006359</td>
</tr>
<tr>
<td></td>
<td>[0.000716]</td>
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<tr>
<td>D_SS*corn_p</td>
<td>0.02243</td>
</tr>
<tr>
<td></td>
<td>[0.028395]</td>
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<tr>
<td>D_SS*ch_avg_slaught</td>
<td>-0.05832</td>
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<tr>
<td></td>
<td>[0.2827]</td>
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<tr>
<td>D_SS*ch_I_above1000</td>
<td>0.00951 **</td>
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<td></td>
<td>[0.00373]</td>
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<tr>
<td>D_SS*un_e_rate</td>
<td>-0.00386</td>
</tr>
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<td></td>
<td>[0.007712]</td>
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</tbody>
</table>

Note: ***, **, and * indicate that the parameter is significant at the 1%, 5% and 10% level, respectively. The heteroscedasticity-robust standard errors are shown in brackets, [ ].

R-Square = 0.2519; Adjust R-Square = 0.2281
Overall, from this model, we still can conclude that swine industry in U.S. is restructuring. The positive sign of intercept can depict that the number of hog producers still decreases also prove the trend of concentration of hog production.

Increasing market share of inventory of large producers (operations with over 1000 head) has positive relationship with producers’ exit behaviors. The independent variable, ch_I_above1000, we use in this model instead of the variable, ch_size500, as a proxy for larger producers’ scale effects. It still has the significant result. It implies that the large-scale producers might have an influence on small-scale producer’s exiting. This scale hypothesis is consistent with basic economic theory, competition force the small high cost operations to be out of market, also consistent with other empirical studies of other manufacturing industries (Deily, 1991; Fleischmann and Prentice, 2001). However, the demand side of hog market in this study is relatively stable, not a declining industry, this characteristic strengthens and isolates the explanation of scale economy effect. In addition, the variable, $D_{SS} \times ch_I_{aove1000}$, shows that the operations with 100 – 499 head are facing more pressure from large-scale operations. One possibility of this phenomenon is that higher ratio of income sources form hog-raising in this category of producers.

Higher hog prices alleviate the hog producers’ exit behaviors. When hog prices go up, the exit rates decrease vice versa. This study conveys that the hog price is one major criteria of timing to leave the swine industry. Meanwhile, Corn price has no determination on producers’ exiting behaviors according to this model. The supportive evidence is from Lawrence and Wang (1998)’s survey of Iowan farmers. Their paper pointed out that 80% of the farmers did not know their production cost regardless of economic factors that are
important to quitting behaviors. In addition, the diverse cost functions among different categories of hog producers: the low fixed cost and high variable cost operations, representing small producers that their feed cost (variable cost) is the major part of the total cost; the high fixed cost and low variable cost operations, representing large producers, especially producers with mega operations, that their capital cost (fixed cost) is the main part of the total cost. Therefore, the dummies, $D_s$ and $D_{ss}$, can represent as the different cost structures of different groups (Fleischmann and Prentice, 2001). It also supports that cost factors are unclear for exit of small hog producers in this empirical study by the estimators insignificantly different from zero.

The macroeconomic conditions have the negative influences on hog producers’ exit behaviors. The proxy estimator, unemployment rate, indicates this relationship. It interprets that more job opportunities from outside swine industry attract producers leave the hog-raising activities. It also implies that hog producers are more self-employment that makes staying in hog-raising more appealing when economy is during a recession. This result, the pattern of leaving swine industry, also indirectly shows that some small hog producers are waiting for the timing, good economy conditions, to leave the unappealing business for them.

The spillover effect of technology improvements do not happen on the exit behaviors in all categories, but technology improvements facilitate the decision-making of exit of smallest producers from the robust estimator ($D_s \times \text{ch_avg_slaught}$).

By observing the variable, $D_{MW}$, we conclude that restructuring of swine industry are significant in the states in Midwest. It implies that the number of hog operations is
decreasing robustly in Midwest. The competitions of survival for small-scale producers in Midwest states are even more severe. This result does not clearly show in panel data models, except Iowa. This model does not conflict with panel data models in this study. Moreover, this model provides the auxiliary evidences for supporting panel data models. They have very similar results, even though the R square is less in this pooled model.

In addition, the economic importance from one-factor random-effect model is shown in Table 6-6. Hog price and corn price are the two major reasons to affect the exit rates in smallest and second-smallest categories of hog operations. For hog producers in second-smallest category, average hog price can lead almost 10% of hog producers to stay in the business; the increase of corn price contributes exit rate increase 8% in the smallest category. Meanwhile, the average unemployment rates affect almost 5% and 7% of hog producers’ leaving decisions of smallest and second-smallest categories, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Smallest category</th>
<th>Second-smallest category</th>
</tr>
</thead>
<tbody>
<tr>
<td>ch_num_large</td>
<td>-0.0001729</td>
<td>0.002207</td>
</tr>
<tr>
<td>ch_size</td>
<td>0.0149702***</td>
<td>-----------</td>
</tr>
<tr>
<td>ch_size_s500</td>
<td>-----------</td>
<td>0.022849***</td>
</tr>
<tr>
<td>un_e_rate</td>
<td>-0.0485914 **</td>
<td>-0.07042***</td>
</tr>
<tr>
<td>P_per_head</td>
<td>-0.0021726</td>
<td>-0.09632***</td>
</tr>
<tr>
<td>corn_price</td>
<td>0.0806218***</td>
<td>0.025228</td>
</tr>
<tr>
<td>ch_avg_slaugt</td>
<td>0.0030760***</td>
<td>-0.00052</td>
</tr>
</tbody>
</table>
Chapter 7  CONCLUSIONS

7-1 Policy Issues and Application

Understanding the pattern of producer’s exiting behavior provides some policy-related information and discussion. Whether the exiting behaviors of producers, especially for smaller producers, are volunteering or forcing to leave, that is related to the fairness of competition within the industry. Some corn-belt states has law designed to protect the more traditional-size producer operated by a family (Rhodes, 1998). This study can offer the supportive result for the small producer policy in the states.

Should the government encourage this concentration trend of the swine industry or take opposite actions? In this study we find out new large-scale entrants do not displace the incumbents. It means that the crowding-out force does not happen between large-scale producers and small-scale producers. Alternatively, we find out that the expanding larger producers’ hog operation sizes pressure the small producers to leave swine industry. As for this expanding is benign or hurtful, this study does not provide the evidences to judge.

However, technology improvement affects the survival space for smallest hog producers. It implies that smallest category of producers have difficulty to access the improvement technology. Furthermore, technology improvement plays a buffer role for producers with scale of 100-499 head of hogs. It implies that for producers in this category need to change its efficient capacity, match the necessity of improved technology and/or raise the management skills to survive in this business. If any government’s action aimed at reducing concentration of the swine industry must consider the trade-off between welfare
gains from the reduction of market power and welfare losses from foregone technological efficiency improvements (Anderson et al., 1998).

Illustrate the exiting behaviors might increase the forecasting precision of supply for the whole industry, especially established the relationship between exit behaviors and supply, that might help clarifying further hog cycles. In this study we conclude that hog price is the factor to affect the incentives of raising-hogs of producers with scale of 100-499 head.

In addition, from this study, we do not observe that state-specific factors affect the exit behaviors of small producers strongly enough. It implies that state-level public programs or policies, such as environmental regulations, do not have crucial influence on small producers’ exodus. Supporting evidence from Lawrence and Wang’s survey (1998) for Iowa hog producers, it shows that over 50% of hog producers did not think that increased environmental regulations is the important reason why they left swine industry.

7-2 Limitations and Further Study

The data used in this research does not come from the individual level. The individual-level data is unavailable under such large-scale interstate comparison. Therefore not wanting to take larger risks or to supervise non-family labors, or because further expansion seems irrational given the producer’s age or poor health, wanting more leisure time and lack of family successor (Rhodes, 1995; Lawrence and Wang, 1998) such personal reasons can not show in our data and estimations. The personal-specific reasons could be the major factors to leave the swine industry. Meanwhile, the cost of tracking such individual-level data is considerably high and beyond this study’s limitation. However, the
state-level aggregate data, considered as an efficient method, still provides useful information. Especially calculating the exit rate can be treated as a reasonable and feasible way to detect the ordinary small producers’ willingness of exiting this business.

Another flaw of this aggregate data set is that we can not track the patterns of exiting hog production, either leaving gradually by reducing capacity or leaving instantly by dealing with all production equipment and estate. Meanwhile, The production types of hog operations (farrow-to-finish, farrow-to-feeder pig, and feeder pig-to-finish) cannot be separated from this data set. This drawback might affect the precision of willingness of quitting industry of small producers. However, the reasons of quitting behaviors still can be observed and caught properly.

In addition, these models treat all the hogs that have the same quality. Therefore, hog quality or marketing does not play the important factors to increase the small producers’ competition abilities with larger producers. However, it is believed that hog quality or marketing could raise the smaller producers’ survival abilities. Another limitation in this study is the information of vertical integration and contract production do not reveal in this data. Contracted production might be the possible strategy to the survival of the small producers.
REFERENCES


(www.ssu.missou.edu/faculity/jikerdpapers/EconFallacies-Hogs.htm) visited at 1/31/05


