INNOVATION ACROSS SUB-DISCIPLINES OF AGRICULTURAL ECONOMICS: THE COST OF INSECT RESISTANCE TO PESTICIDE IN STORED GRAIN, THE DEMAND FOR COLLEGE COURSES, AND MEASURES OF SCHUMPETERIAN ACTIVITY

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AND MEASURES OF SCHUMPETERIAN ACTIVITY

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TABLE OF CONTENTS

Chapter Page

I. INNOVATION AND AGRICULTURAL ECONOMICS..1

II. RESISTANT PESTS AND STORED GRAIN CONTROL COSTS 6

Introduction..6
Objectives 7
Literature..8
Conceptual Framework...11
Cost Model...14
Population Dynamics Model..15
Factors Driving Resistance and Costs..19
Methodology...21
Data and Simulation Parameters..30
Results and Discussion 32
Summary and Conclusion...38
References...42
Tables...46
Figures..61

III. STUDENTS' PREFERENCES FOR COLLEGE CREDIT COURSES...............65

Introduction..65
Background...69
Methods and Procedures...72
Data...80
Results and Discussion 82
Summary and Conclusion...85
References...88
Tables...93
Figures..101

Chapter Page

IV. CHARACTERISTICS OF STUDENTS SELECTING ONLINE COURSES....103

Introduction....103
Background....106
Methods and Procedures....110
Data....112
Results and Discussion....113
Summary and Conclusion....117
References....120
Tables....122

V. DEVELOPING A MEASURE OF SCHUMPETERIAN ACTIVITY....127

Introduction....127
Background....132
Methods and Procedures....137
Results and Discussion....143
Conclusion and Recommendations....150
References....154
Tables....159
Figures....169

VI. CONCLUSION....174
References....176

APPENDEX....177
IRB Letter....178

LIST OF TABLES

Table Page

1 Treatment Cost for Stored Wheat 46

2 Discount for Insect Damage Kernels (IDK) 47

3 Non-parametric Bootstrap of Grain Management Strategy
Costs for Oklahoma City - 1% Discount Rate (Non-stabilized)........................48

4 Non-parametric Bootstrap of Grain Management Strategy
Costs for Goodland - 1% Discount Rate (Non-stabilized)................................49

5 Non-parametric Bootstrap of Grain Management Strategy
Costs for Oklahoma City - 10% Discount Rate (Non-stabilized)......................50

6 Non-parametric Bootstrap of Grain Management Strategy
Costs for Goodland - 10% Discount Rate (Non-stabilized)...............................51

7 Non-parametric Bootstrap of Grain Management Strategy
Costs for Oklahoma City - 1% Discount Rate (Stabilized) 52

8 Non-parametric Bootstrap of Grain Management Strategy
Costs for Goodland - 1% Discount Rate (Stabilized) 53

9 Non-parametric Bootstrap of Grain Management Strategy
Costs for Oklahoma City - 10% Discount Rate (Stabilized) 54

10 Non-parametric Bootstrap of Grain Management Strategy
Costs for Goodland - 10% Discount Rate (Stabilized) 55

11 Parametric Bootstrap of Grain Management Strategy Costs
for Oklahoma City (Non-stabilized) 56

12 Parametric Bootstrap of Grain Management Strategy Costs
for Goodland (Non-stabilized)...57

Table	Page

13 Parametric Bootstrap of Grain Management Strategy Costs for Oklahoma City (Stabilized) 58

14 Parametric Bootstrap of Grain Management Strategy Costs for Goodland (Stabilized) 59

15 Discounted Aeration-Based IPM Costs 60

16(a) Online and Face-to-Face Course Attribute Options in Choice Questions 93

16(b) Demographics of Students Completing the Surveys 94

17(a) Conditional Logit Parameter Estimates for College Course Attributes (Survey 1) 95

17(b) Estimated WTP and 95% CI for College Course Attributes (Survey 1) 96

17(c) Conditional Logit Parameter Estimates for College Course Attributes (Survey 2) 97

17(d) Estimated WTP and 95% CI for College Course Attributes (Survey 2) 98

18 Course Attributes Used to Simulate Online and F2F Course Demand 99

19 Simulation of Impact of Additional Attribute Information on Student Demand 100

20 Summary Statistics of Student Characteristics Questions 122

21 Comparison of Student Demographics 123

22 Frequency of Students Taking Online Courses by Age 124

23 Comparison of Ordered logit Parameter Estimates of Student Characteristics in Likelihood to Take Online Course Model 125

24 Identification and Source of Sub-indicators Used to Generate CEI 159

25 Summary Statistics of 2002 CEI Inputs 160

26 Summary Statistics of 2007 CEI Inputs..161

27 Comparison of Different Measures of Entrepreneurship (2002)........................162

28 Comparison of Different Measures of Entrepreneurship (2007)........................163

29 Weights of Sub-indicators Contribution to OEI 164

30 Weights of Categories, within Category Sub-indicator, and
Overall Sub-indicator Contribution to MEI...165

31 Pearson Correlation of Different Measures of
Entrepreneurship (2002) 166

32 Pearson Correlation of Different Measures of
Entrepreneurship (2007...167

33 Correlation of the Goetz and Freshwater EC and Other
Measures of Entrepreneurship (1996)..168

LIST OF FIGURES

Figure Page

1 Hypothesized Population Dynamics of Lesser Grain Borer in Stored Wheat..61

2 Resistance Development and Costs of Calendar-Based Fumigation for Oklahoma City, Under Scenario 1, Stabilized, Non-parametric Model, with 95% F, ω = 0.35, δ =0.8, and 3% Allele Starting Frequencies 62

3 Resistance Development and Costs of Calendar-Based Fumigation for Oklahoma City, Under Scenario 1, Stabilized, Non-parametric Model, with Moderate F, ω = 0.35, δ =0.8, and 3% Allele Starting Frequencies 63

4 Resistance Development and Costs of Calendar-Based Fumigation for Oklahoma City, Under Scenario 1, Stabilized, Non-parametric Model, with Low F, ω = 0.35, δ =0.8, and 3% Allele Starting Frequencies 64

5 Example of Course Choice Questions in Survey 1...101

6 Example of Course Choice Questions in Survey 2...102

7 Conceptual Design the Scoreboard Approach for Developing a Composite Entrepreneurship Indicator 169

8 Pearson Correlation Map of the 2002 CEI Model Inputs and Categories of Inputs 170

9 Pearson Correlation Map of the 2007 CEI Model Inputs and Categories of Inputs 171

10 Negative Trend – Firm Births vs. Schumpeterian Activity (2002)....................172

11 Negative Trend – Firm Births vs. Schumpeterian Activity (2007)....................173

CHAPTER I

INNOVATION AND AGRICULTURAL ECONOMICS

Agricultural economics research tends to focus on microeconomic problems and utilizes a broad array of tools to address research concerns (Penson, Capps, and Rosson 2002). Many of the tools that are used originated in other academic disciplines. For example, developments in computer science, genetics, engineering, and statistics have been applied to the problem solving process, allowing new insights to microeconomic phenomena. Additionally, the areas of concentration for modern agricultural economics research include traditional topics, such as production economics or agribusiness management, and cross into other sub-disciplines, such as education economics and entrepreneurship.

A key feature of agricultural economics research is the concept of innovation. Schumpeter (1947) described innovation as “doing new things or doing things already being done in a new way” (p. 151). However, Schumpeter’s ideas were primarily about innovation that occurs in business and industry enterprises. From Ruttan’s (1959) perspective, innovation should be emphasized as a broader concept that could occur anywhere, whether in science, technology or art. It is this broader context that embodies the way innovation is viewed in agricultural economics research.

Based on this perspective, the incorporation of innovation into in agricultural economics research can vary considerably. For example, an innovative way of addressing a problem may be proposed, research may be focused on the impact of innovation in a particular area of concentration, or innovation itself may be the thing that is measured. Therefore, innovation, in the broadest sense, is a unifying aspect among much of the agricultural economics research conducted today.

In the spirit of Ruttan's (1959) view of innovation, this work is composed of studies in agribusiness management, education economics, and entrepreneurship. More specifically, four studies cover the following topics:

1) The impact of resistant pests on the costs of stored grain management;

2) Students' preferences for online and face-to-face college courses and course attributes;

3) The characteristics of students selecting online courses; and

4) Measures of Schumpeterian activity in the US.

In each study, the framework of innovation may include a new way to model a particular phenomenon, a new application of an established methodology, examining the impact due to a change in understanding resulting from innovation, or measuring an aspect of innovation itself.

Although innovation in agricultural economics is the unifying theme among the studies included in this work, there is another motivation for the compilation of these particular studies. In short, these studies also demonstrate the wide array of modeling techniques as well as the different sources of data used in agricultural economics. For example, modeling the specific phenomena may occur via mathematical programming, econometric or statistical methods, while the data in each study may be simulated, primary, or secondary in nature.

An overview of each study

In chapter 2, *Resistant Pests and Stored Grain Costs*, a consideration is made in an empirical cost model for a potential change in costs due to a change in the amount of pest resistance. Within the agricultural and applied economics literature, there are a number of models that conceptually demonstrate how changes in cost can occur. However, the models are only conceptual in nature. They do not consider the specific genetic nature of resistance in stored grain pest, nor can they account for the population dynamics of stored grain pests. In fact, one might consider that the biological nature such that it allows pests to innovate a means of pesticide survival.

The data in this particular study was simulated since it currently does not exist. Recent discoveries regarding the genetic mechanisms of resistance in stored grain pests were incorporated into the model. Changes in the cost of stored grain management resulting from increases in pest resistance were modeled using mathematical programming. Some of the inputs for this model are stochastic, specifically the weather influencing pest growth and the actual resistance expressed by groups of pests. The resulting model is dynamic since the choices made affect the results in the succeeding storage seasons.

In chapter 3, *Students' Preferences for College Credit Courses*, the make-up of effective college level courses, given the potential features and attributes of various courses, is examined from the students' perspectives. In chapter 4, *Characteristics of Students Selecting Online Courses*, some of the potential reasons that students select online courses are considered. In both of these chapters, the framework is from the student's perspective and relies on the information and experience that students have prior to selecting particular courses. More specifically, college courses are treated as goods while the students are treated as consumers of the goods. This re-frames the discussion about college level courses in the context of students making choices for learning based on their individual preferences and needs.

In these two studies, primary data were obtained from a survey of university students. In chapter 3, a choice experiment was employed to obtain the necessary response data. In chapter 4, students' responses to Likert item and rating questions made up the data set. In each case, logistic regression models (a conditional logit model in chapter 3 and an ordered logit model in chapter 4) were constructed and used to estimate parameters for students' preferences and characteristics.

In chapter 5, *Developing a Measure of Schumpeterian Activity*, an argument is constructed that demonstrates the need for an improved measure of Schumpeterian activity. Innovation is at the core of Schumpeterian activity; however, much of the entrepreneurship literature uses entrepreneurship proxies that do not match up with their Schumpeterian-type definitions. In fact, the actual measures used may be capturing other dominant types of entrepreneurship that behave differently from Schumpeterian-type definitions. In the US, there is also a belief that only Schumpeterian-type entrepreneurs should be encouraged by US policy. The main challenge regarding this idea is that there are no widely measures for the activity related to this kind entrepreneurship.

The data used in this study is from secondary, publicly available sources. The inputs used to construct the measure of Schumpeterian activity were based on the economic and entrepreneurship literature. In order to consolidate the range of inputs into a single measure for Schumpeterian activity, principle component analysis (PCA) techniques, popular in the statistics literature, were employed.

The presentation of each study is as follows. Each study is “self-contained” within the context of a particular chapter. More precisely, each chapter is presented in the format of a journal style article and includes the main body of the study, followed by the references, tables and figures. The main body of each study includes an introduction to the problem, a literature review or background, a conceptual framework and methodology (or methods and procedures), a discussion of the data used, a presentation and discussion of results, and a summary and conclusion.

CHAPTER II

RESISTANT PESTS AND STORED GRAIN CONTROL COSTS

Introduction

Insect resistance to phosphine, the primary fumigant used to combat stored grain pests, is a major problem in many countries such as Australia, Brazil, China and India (Collins et al. 2005; Daglish 2004; Rajendran 1999; Sartori and Vilar 1991; and Zeng 1999). The development of resistance in these countries is believed to have resulted from poor fumigation practices over time. Inadequate insect exposure to phosphine made multiple treatments necessary, allowing pests to develop resistance (Semple et al. 1992). Fumigation selects for resistant pests, and once the genes responsible for resistance were present in an insect population, increased phosphine use resulted in higher proportions of resistant pests (Emery, Collins and Wallbank 2003; Collins et al. 2005; Daglish 2004; Newman 2010; Schlipalius et al. 2008). As the levels of resistance increase, the frequency, concentration, and/or duration of fumigation must also increase. Additionally, the problem of pest resistance developing has been compounded by the Montreal Protocol which mandated that methyl bromide be phased out (Van Graver and Banks 1997). For many uses, phosphine has been the only economically available alternative.

Although there currently are no economical alternatives to phosphine as a stored grain fumigant (Collins et al. 2005), other grain management strategies, such as integrated pest management (IPM), have been adopted that help slow the development of phosphine resistance (Lorini and Filho 2004; Mori et al. 2006). IPM combines different tools in a way that is intended to reduce need for fumigation. IPM is a balanced use of multiple control tactics – biological, chemical, and cultural – as is most appropriate for a particular situation in light of careful study of all factors involved (Way 1977).

For example, a storage manager may sample grain to determine if fumigation is necessary instead of using a calendar-based approach of routinely and automatically fumigating. In some countries where insect resistance is problematic, stored grain managers have had success combating resistance by using IPM (Lorini and Filho 2004; Mori et al. 2006).

Although concerns about phosphine-resistant pests have been primarily focused on Australia, Brazil, China, India and a number of other developing nations, recently, phosphine resistance has reportedly been detected in the US (Bonjour 2010). Stored grain managers in the U.S. can learn from the experience gained in countries currently combating phosphine resistance. More specifically, stored grain managers in the U.S. could potentially adopt some of the available IPM tools if they can be shown to be cost effective. In order to make this determination, however, a model that includes the costs associated with increased pest resistance to phosphine is needed. It is hypothesized that accounting for resistance costs will increase the economic attractiveness of IPM approaches relative to conventional fumigation approaches.

Objectives

The overall objective is to determine how phosphine resistance affects cost of controlling *Rhyzopertha dominica*, or lesser grain borer (LGB), in stored grain.

The specific objectives are to:

1) Determine the effect of reduced fumigation frequency on costs of LGB control in stored grain when resistance genes are present.
2) Determine how assumptions about emigration to refuge populations and immigration from secondary populations affect growth of resistant populations of LGB and their control costs in stored grain.
3) Determine how alternative rates of fumigation effectiveness affect control costs of LGB populations in stored grain when resistance genes are present.
4) Determine how alternative beginning levels of phosphine resistant phenotypes affect control costs of LGB populations in stored grain.
5) Determine how weather affects LGB control costs in stored grain when phosphine resistant populations are present.

In this study, additional costs associated with changes in pest resistance are modeled and included in the cost-benefit analysis of a calendar-based fumigation strategy, sampling-based IPM, and aeration-based IPM.

The model is applied to the weather and grain conditions in two locations representative of major US wheat-growing areas, Oklahoma City, OK, and Goodland, KS, representative of major wheat-growing areas.

Literature Review

Pest Resistance Models

Most researchers recognize that pest resistance is a global problem (Collins et al. 2005; Laxminarayan 2003; Semple et al. 1992); however, the economic costs of pest resistance remain unclear. Many view pest susceptibility to an insecticide as a common property resource (Carlson 1977; Cowan and Gundy 1996; Hueth and Regev 1974; Fleischer 1998; Laxminarayan 2003). Since many firms contribute to the resource depletion over a long time horizon, it is difficult for individual firms to internalize their contribution to the total cost. However, much of the work leading to the view of pest susceptibility as a common property resource has occurred with crop pests. Campbell et al. (2007) has provided some evidence that individual stored grain firms bear a large portion of the cost associated with resistant LGB because LGB do not migrate far. Thus, there may be an incentive for stored grain firms to manage levels of phosphine resistance within their firms.

Several conceptual models have been proposed to explain how pest management strategies impact pest resistance. For example, Hueth and Regev (1974) demonstrated how farm level decision makers can influence changes in the resistance levels of a crop-pest population. Their model included a single crop with one pest and one gene responsible for resistance. Analysis centered on the economic threshold for pesticide application, the known point when a pesticide must be used to prevent economic loss from crop damage. They showed that the economic threshold is variable depending on decisions made in the current year. In some cases, however, it increases in succeeding years. Therefore, pest resistance should be modeled dynamically because changes in resistance are the direct result of previous choices. This result was supported by Lichtenberg and Zilberman (1986) who showed that use of products contributing to resistance increases the future amounts of product needed to achieve earlier results. This increased product use leads to increased treatment costs.

Hurley, Babcock, and Hellmich (2001) incorporated the Hardy-Weinberg principle (which states that the proportion of particular genotypes remain constant in a population unless there is a disturbance) into an economic model that was designed to determine optimal crop refuge size. Refuge is the designated portion of the crop land where pesticide application does not occur. The purpose of the refuge is to maintain some level of pest susceptibility as a means to control the development of pest resistance. They found that the levels of susceptibility are significantly affected by pest mobility and the ability of refuge and non-refuge pests to mate.

Genetics of Pest Resistance

To date, economic models used to demonstrate the development of pest resistance have assumed that a single gene (or allele at two levels) is responsible for resistance to a fumigant. However, these conceptual models may oversimplify the problem of resistance in stored grain pests. For example, Daglish (2004) identified two levels of LGB resistance to phosphine. Collins et al. (2005) found that LGB exhibiting strong resistance to phosphine had an additional mechanism not present in the weak resistant LGB. These two results led to the discovery by Schlipalius et al. (2008) that two different alleles are responsible for LGB resistance. Further, the genotypes possible from each allele interact in such a way that LGB exhibit four different levels of phosphine resistance (phenotypes) which range from about 2.5 to more than 250 times the resistance of susceptible LGB. These three studies are of potential significance for economic modeling, especially since the level of fumigation effectiveness impacts the surviving phenotypes. In other words, when fumigation effectiveness is low, weak resistant pests would dominate the population; when fumigation effectiveness is high, strong (and some moderate) resistant pests would dominate.

A common finding reported by Collins et al. (2005), Daglish (2004), and Schlipalius et al. (2008) is that phosphine resistant LGB did not suffer any fitness cost associated with the increased resistance. In essence, fitness costs are the tradeoffs that result when one genetic trait is given up for another. However, Sousa et al. (2009) reported that resistant LGB, in the absence of phosphine exposure, may indeed suffer fitness costs compared to susceptible LGB. Further, the fitness costs associated with resistant pests may allow previous levels of susceptibility to be regained once phosphine use is substantially reduced. Therefore, use of phosphine-reducing strategies such as IPM may do more than slow resistance development: they may actually reverse it.

Conceptual Framework

This paper estimates the cost of controlling LGB in stored wheat under alternative specifications of phosphine resistance and insect population dynamics. According to Schlipalius et al. (2008), LGB resistance is the result of two different alleles, each at two levels, which leads to the five possible phenotypes (susceptible LGB, plus four different levels of resistance). They found that one of the alleles responsible for resistance can occur as a heterozygote (weak 1 resistance level, which is 2.5-12.5 times more resistant than susceptible LGB), while the other must occur as homozygote in order for resistance to be expressed (weak 2 resistance level, which is 12.5-25 times more resistant than susceptible LGB). When no resistant genes are present, or when the alleles responsible for the weak 2 resistance level occur as a heterozygote, then the LGB phenotype is susceptible. Schlipalius et al. also found that when the alleles responsible for weak1 resistance level occur as a heterozygote and those responsible for weak 2 resistance level occur as a homozygote, moderate resistance results (25-50 times more resistant than susceptible). However, they discovered that an interaction between the two alleles occurs when the genes responsible for weak 1 and weak 2 resistance levels both occur as homozygotes. This results in a strong resistance (250 times more resistant than susceptible LGB).

One consideration made in this study is that differences in fumigation effectiveness may affect which of the five phenotypes dominates the population and, therefore, has the strongest impact on costs. For example, where fumigation effectiveness is high enough to eliminate the susceptible and weak resistant pests, strong resistant LGB (and potentially some moderately resistant LGB) would eventually dominate the population, and be the main driver of changes in cost. However, if fumigation effectiveness were low enough, only some susceptible pests and a small fraction of weak and moderate pests would be eliminated. The result in this case would be that weak and moderately resistant pests would eventually dominate the population (the primary driver of changes in cost) and strong resistant pests would remain in relatively small proportions.

This paper also considers the impact of three grain management strategies on levels of LGB resistance, and the effect that changes in resistance have on the strategy costs. In particular, changes in costs of calendar-based fumigation, sampling-based IPM, and aeration-based IPM resulting from LGB resistance are compared. A typical practice used for wheat in the U.S. Great Plains region is calendar-based fumigation, under which a grain elevator manager fumigates all structures at approximately the same time every year. In contrast, a sampling-based IPM approach is to periodically sample the grain in a storage structure, and to fumigate only if the information, combined with known insect growth patterns, possibly using decision support software, suggests that insects are likely to cause damage in the future (Flinn et al., 2007). The assumption with this IPM strategy is that some or all bins within a storage structure might have sufficiently low insect population growth that fumigation is not required.

Insect population growth in a grain storage structure depends on environmental conditions (particularly grain temperature and moisture), condition of the grain, and rate of immigration of grain-damaging insects into the structure (which itself depends on environmental conditions such as wind and temperature as well as cleanliness and structural integrity of the facility). The effectiveness of insect control treatments depends on environmental conditions, cleanliness and structural integrity of the facility, and on how thoroughly and carefully a particular practice is implemented.

If the insect population in stored grain is not controlled effectively, the insects will damage grain, which in turn triggers large discounts. *Rhyzopertha dominica*. in particular, cause insect damaged kernels (IDK). *R. dominica* larvae feed inside the kernel until they mature into adults and burrow out of the kernel, which results in an IDK. The life cycle of *R. dominica* is approximately five weeks at 32°C, so there is approximately a five-week lag between immigration of an adult insect until appearance of new adults.

Also, if two or more live insects are detected in a one-kilogram grain sample at time of sale, the U.S. Department of Agriculture (USDA) does not permit the grain to be sold for human consumption. Since this prohibition can be overcome by fumigating to kill the live insects, this results in a live insect discount that is commonly larger than the cost of fumigating itself. Often, in practice, this discount is imposed by commercial firms even if only one live grain-damaging insect is detected in a one-kg sample.

The model specified below includes costs of discrete insect management and control activities that can be combined into both IPM and non-IPM strategies. Using the model together with a population dynamics model, we simulate and compare costs of alternative insect control strategies, including conventional, calendar-based fumigation approaches and IPM sampling-based approaches to managing stored-grain insects.

Cost Model

The strategy cost of insect control in time *p* can be expressed as

$$SC_p = C\left(F_p, S_p, A_p, IDK_p, INF_p\right), \quad 1(a)$$

where $C(\cdot)$ is a function of the number of fumigations (*F)*, number of samplings (*S*), use of aeration (*A*), and insect damaged kernels (*IDK*) and infestation discount (INF) at the end of period *p*. The net present value (NPV) of costs over P periods is:

$$NPV = \sum_{p=1}^{P} \frac{SC_p}{(1+d)^{p-1}}, \quad 1(b)$$

where *d* is the discount rate.

The cost of treatment is estimated using economic engineering methods in a partial-budgeting approach, and the cost of failing to control insects is estimated by simulating insect growth under various environmental conditions and treatments. Adding these costs provides an estimate of the total cost of using each insect control strategy (IPM vs. calendar-based).[1]

[1] In a partial budgeting approach, only cost components that might differ between approaches are evaluated. For example, although the cost of loading and unloading grain is an important storage cost, it is

The elevator manager using calendar-based fumigation is assumed to fumigate at nearly the same time every year, with its associated costs. Under a sampling-based approach, however, it is assumed a manager samples the grain, and fumigates a particular bin only if the number of insects from a sample of that bin exceeds a threshold level.

Population Dynamics Model

The development of LGB resistance to phosphine in Australia (see Emery, Collins, and Wallbank 2003; Newman 2010) appears more similar to scenarios of crop-pest resistance development when a refuge population is present (see Hurley, Babcock, and Hellmich 2001), than to scenarios with no refuge (see Hueth and Regev 1974). However, there are currently no economic studies in the context of stored grain that depict the potential movement of LGB populations with different proportions of resistance phenotypes.

Implementing a model based on this proposition is difficult, though, because there is uncertainty regarding: 1) how many LGB with each level of resistance exist in and around a stored grain facility; and 2) the manner in which insects from each of these levels combine in and around the storage facility. For example, after fumigation the population inside the stored grain would have proportions of phosphine resistance different from those of the population nearby the facility. There may also be LGB that linger within the stored grain facility after grain is removed and that population would have proportions of resistance levels different from those of the population nearby the facility. Further, when grain is moved there may be an opportunity for some LGB in the grain to flee back outside the facility. Finally, when new grain is received, LGB

not considered here because it is assumed to be the same for both the calendar-based and the sampling-based approaches.

immigrating into the stored grain could be coming from populations of LGB that potentially have different proportions of resistance levels.

Consider the following model:

2(a) $$\boldsymbol{a_p} = (\boldsymbol{\alpha_{p-1}} + \omega\boldsymbol{\gamma_p})(1+\omega)^{-1}$$

2(b) $$\boldsymbol{\gamma_p} = \boldsymbol{\lambda_p}[\boldsymbol{I^T}\boldsymbol{\lambda_p}]^{\boldsymbol{-1}}$$

2(c) $$\boldsymbol{\lambda_p^T} = (1-F)^{n_p}[(1+\delta)^{\boldsymbol{-1}}(\boldsymbol{\alpha_{p-1}} + \delta\boldsymbol{\gamma_{p-1}})]^{\boldsymbol{T}}\boldsymbol{R}^{n_p}$$

$$s.t.\ \lambda_{jp} \le (1+\delta)^{-1}(\alpha_{j,p-1} + \delta\gamma_{j,p-1})$$

- $\boldsymbol{a_p}$ is a vector of the resistant proportions of the LGB population (based on Schlipalius et al. 2008)
- *p* is the storage period (only one period is allowed per year), for $p = 1, \dots, P$
- $\boldsymbol{\alpha_{p-1}}$ is a vector of the resistance proportions at the end of the previous period and represents the refuge proportion of the pest population
- $\alpha_{j,p-1}$ is the proportion of LGB with resistance level j, for $j = 1, \dots, 5$, and $\sum_j \alpha_{j,p-1} = 1$
- $\boldsymbol{\gamma_p}$ is a vector of the resistant proportions inside the stored grain at the end of period p
- ω is the ratio at which the inside and refuge populations mix
- $\boldsymbol{\lambda_p}$ is a vector of the proportions of the *j* resistance levels remaining at the end of the period
- λ_{jp} is the proportion of resistance level j surviving fumigation, and $\boldsymbol{\lambda_p}$ is not standardized to one, i.e. $\sum_j \lambda_{jp} \le 1$

- F is the fumigation effectiveness and is defined as the proportion of susceptible LGB that are eliminated during fumigation; and the proportion of resistant LGB eliminated is based on their level of phosphine resistance relative to susceptible pests
- n_p is the number of fumigations
- δ is the ratio by which the two populations inside the stored grain mix
- $\boldsymbol{R_p}$is a diagonal matrix of the resistance levels based on Schlipalius et al. (2008) and each level, r_{jp}, is defined in terms of a distribution such that r_{jp}~N(μ_j, σ_j^2),where j is the resistance level, $\mu_j = \frac{lower\ limit_j + upper\ limit_j}{2}$, and $\sigma_j = \frac{upper\ limit_j - lower\ limit_j}{6}$
- $\boldsymbol{I}$ is a vector of ones

The insect population dynamics model presented here is sufficiently general to permit three different scenarios about refuge populations. The first scenario identifies three distinct LGB populations (see Figure 1). The primary (refuge) population (α_p) is similar to a refuge population described by Hurley, Babcock, and Hellmich (2001) and exists within a region where one or more stored grain facilities operate. A portion of this refuge population immigrates into new grain after it is stored. A secondary population (γ_{p-1}) remains inside the stored grain facility after grain is moved. When new grain shipments arrive, this population also immigrates into the new grain. A tertiary population (γ_p) grows inside newly stored grain and is a mix (at rate δ) of the refuge and secondary populations. When grain is sold and removed from storage, a portion of the tertiary (in-bin) population emigrates (at rate ω) back to the refuge population, and the remaining portion of the population makes up the secondary population.

A distinction between the three populations is important when proportions of resistance are considered since each population would have different proportions of resistance levels. The tertiary (in-bin) population is the only population exposed to phosphine; therefore, that population would have the highest levels of resistance. The secondary population only exists after the storage-bin is emptied and would have the same levels of resistance as the tertiary population in the previous period. The refuge population would have the lowest levels of resistance.

This first scenario appears to best model the situation in Australia. Without the presence of an "accidental" refuge of LGB near Australian stored grain facilities as suggested by Emery, Collins, and Wallbank (2003) and Newman (2010), the Hueth and Regev (1974) model predicts that susceptible LGB would have disappeared much more rapidly (in just a few seasons) and LGB populations would only be composed of weak and strong phosphine resistant LGB (see also Hurley, Babcock, and Hellmich 2001). Avoiding this type of occurrence was the primary motivation behind utilizing crop refuges (Hurley, Babcock, and Hellmich 2001). Further, as the number of fumigations and/or the concentrations of fumigant increased, the proportion of weak resistant LGB would have dwindled, allowing strong resistant LGB to dominate the population. Based on the evidence provided by Emery, Collins, and Wallbank (2003) and Newman (2010), this was not the case.

The second scenario considers only two populations, the refuge and the tertiary population. In this case, no secondary population exists (and $\delta = 0$). The third scenario considers three populations but assumes that no portion of the tertiary population returns back to the refuge (i.e. $\omega = 0$). Instead, it makes up the secondary population. This scenario allows for a steady state of resistance level proportions since the refuge acts to continually dilute the tertiary population, while the proportion of the resistant levels in the refuge population never change.

Factors Driving Resistance and Costs

Higher frequencies of phosphine application by stored grain managers result in more rapid development of resistant LGB (Collins et al. 2005; Hueth and Regev 1974; Lichtenberg and Zilberman 1986). As the resistance to phosphine increases, more frequent applications are needed to control economic damage. Therefore, factors that contribute to more rapid resistance development should also contribute to higher costs. There are five different factors considered in this study that potentially affect the speed of resistance development, which in turn impacts insect control strategy costs: fumigation effectiveness, the relative proportion of the tertiary population returning back to the refuge (ω), the relative proportion of the secondary population entering the grain (δ), starting proportions of resistance levels, and the weather.

Schlipalius et al. (2008) identified four different levels of resistance and depending on the fumigation effectiveness (and potentially the weather which drives LGB growth) rapid development of resistance could occur by one of two ways. If fumigation effectiveness was high enough, only strong (and some moderate) resistant LGB would survive. Therefore, the costs associated with increased resistance would be the result of increased strong resistance LGB. On the other hand, if fumigation effectiveness was low enough then higher portions of weak resistant LGB, relative to strong resistant LGB, would survive. In this case, the costs associated with resistance would initially be attributed to weak resistant LGB, and later with strong resistant LGB (as the number of fumigations per period increased).

Under scenarios 1 and 2, the higher the rate of emigrating (ω in Figure 1) tertiary LGB, the faster the refuge develops resistance. This also depends on the fumigation effectiveness (i.e. the surviving proportions of resistance levels) as well as the weather. Similarly, under scenarios 1 and 3, higher rates of immigration (δ in Figure 1) of the secondary population would lead higher proportions of strong and moderate resistant pests inside the grain. This would also potentially lead to to faster rates of resistance development. Again, this will depend on the fumigation effectiveness and weather. The rates of emigration and immigration are potentially important considerations if other conditions, such as fumigation effectiveness and weather, are such that one grain management strategy is more cost effective than the other. However, the specific threshold for each of these other considerations (fumigation effectiveness, and weather) must also be determined.

When the proportion of weak, moderate and strong LGB resistance is very low in the LGB population, there is a potential opportunity for cost differentiation between grain management strategies that fumigate at different rates per period. In other words, it may be possible that the strategy which fumigates the least would also cost the least if LGB resistance is not well established. This is one of the motivating factors for using sampling-based IPM (Adam et al. 2006). However, the difference in the frequency of fumigations under each strategy, in this case calendar-based and sampling-based, would have to be such that the costs associated with the sampling-based IPM would be less than those associated with calendar-based fumigation over a limited time horizon.

In general, warmer weather encourages LGB growth in stored grain (Flinn et al. 2004). Therefore, strategies that are cost effective in cooler climates may not have the same cost benefit in warmer climates. For example, Adam et al. (2010) demonstrated that sampling-based IPM was only cost effective in cooler climates, or when grain was stored for a shorter period of time. This was because LGB growth was high enough in the locations considered that fumigation was always necessary. Although the present study only considered a single storage season (1989-1990), it may be the case that using sampling-based IPM will never be cost effective in warmer climates (where LGB growth is potentially higher) when storage periods are longer. However, in warmer climates with moderate storage periods and once LGB resistance is introduced into the model, sampling-based IPM may be cost effective over a time horizon.

Methodology

The objective in this study is to determine how the cost of grain management is impacted by the proposed LGB population dynamics model, fumigation effectiveness, starting proportions of LGB resistance, and weather. The proposed LGB population dynamics model considers three scenarios: (1) after grain is sold, LGB surviving fumigation emigrate (at rate ω) to a refuge population, and then immigrate into new grain while a secondary population remains in the storage facility that also immigrates (at rate δ) into new grain, (2) after grain is sold, LGB surviving fumigation emigrate to a refuge population and no secondary population exists ($\gamma_{p-1} = 0, \delta = 0$), (3) after grain is sold, LGB surviving fumigation do not emigrate ($\omega = 0$) to the refuge population, but become the secondary population (se Figure 1). It is important to point out that the impact on cost from immigration of a general LGB population into stored grain was demonstrated by Adam et al. (2010). In their study, the term "immigration" referred to the rate at which LGB entered the stored grain. Their immigration rate generated an actual number of pests per kg and was based on the Flinn et al. (2004) model. In this study, immigration and emigration are relative terms and used to describe the proportions of each LGB populations relative to the refuge population.

Since the same LGB growth model (Flinn et al. 2004) is used in this study, immigration based on the Adam et al. (2010) definition is considered part of the LGB growth rate. Additionally, a fixed immigration rate of "low," based on the Flinn et al. (2004) model was used for all LGB growth. The reason this "low" rate was used is because Adam et al. (2010) had previously demonstrated that fumigation was always necessary in warmer climates and when immigration into the grain was "normal." Therefore, when LGB resistance is included in the model, the only case where calendar-based fumigation and sampling-based IPM impact changes in the development of resistance differently is when the immigration rate used in the Flinn et al. model is low.

To accomplish the objective set out in this study, a simulation was designed such that each scenario could be examined given variations of the five factors (model parameters). In the simulation, grain is received and stored shortly after harvest. LGB enter the grain according to what the Flinn et al. (2004) model predicts, and based on the specific scenario and set of factors (model parameters) used.

Under calendar-based fumigation, grain is fumigated at the same time each season. At the conclusion of the storage period, grain is moved. Since the development of

LGB resistance is included in the model, at some point in time the residual LGB remaining after fumigation will trigger the need for additional fumigation. In the simulation, if residual LGB population is greater than the acceptable threshold at the time grain is sold, the simulation adds an additional fumigation for all subsequent crop years. Once an additional fumigation event is added, under calendar-based fumigation it will always occur, so the number of times fumigation occurs per period only increases and never decreases.

Under sampling-based fumigation, the process of receiving grain and LGB growth is the same as under calendar-based fumigation. In place of automatic fumigation, however, grain is automatically sampled. Fumigation will only occur if sampling determines it is necessary to avoid LGB growth reaching the acceptable threshold. Similar to calendar-based fumigation, at some point in time additional sampling and fumigation becomes necessary due to the increase of LGB resistance. In place of one additional sampling event occurring automatically, the initial sampling will determine if fumigation and the further sampling is necessary. Once the threshold is reached, if sampling determines fumigation is necessary then one an additional sampling is also necessary. However, if the initial sampling determined fumigation was unnecessary then no further action is taken during the particular period. As was the case with calendar-based fumigation, this is a stepwise process. Therefore only the addition of one sampling and fumigation is allowed per period.

The specific simulation parameters and the sources for model inputs are described in the next section (Data and Simulation Parameters). What follows in this section is the specification and explanation of the general model used in the simulation as well as a discussion about how the LGB population genetics was handed in the simulation.

Change in Levels of Resistance from Fumigation

Determining periodic changes in grain storage costs from corresponding increases in LGB resistance to phosphine depends on identifying how resistance increases the number of fumigations (or fumigations and sampling) needed per period. Hueth and Regev (1974) demonstrated that use of a pesticide in period P to control crop pests would reduce the proportion of susceptible pests in period $P + 1$ making pesticide use in successive periods less effective. Greater amounts of pesticide would be necessary to achieve the same level of pest control obtained in previous periods thereby increasing the cost of crop pest control. Similarly, an increase in the cost of stored grain management during any period would result from additional fumigation or additional fumigation and sampling.

Although fumigation selects for resistant pests, the impact of a single fumigation also depends on the effectiveness of pesticide application (fumigation effectiveness), the proportions of pest resistance levels in the population, and the genetic mechanisms responsible for resistance. The analysis by Hueth and Regev (1974) assumed that a single allele was responsible for resistance. However, for *R. dominica* Schlipalius et al. (2008) have identified two loci, each with two alleles, responsible for resistance. The possible combinations of their alleles result in four levels of LGB phosphine resistance, plus full susceptibility.

As previously discussed, the specific population dynamics that account for LGB phosphine resistance levels within the framework of stored grain management are unclear. The model proposed in equations 2(a)-2(c) is similar to what Hurley, Babcock and Hellmich (2001) have described with crop-pests: that LGB surviving fumigation in a given period mix with another population not fumigated (refuge population) in the same period. In this case, the overall change in resistance is diluted down, relative to what Hueth and Regev (1974) predicts. To set up the model following the proposed LGB population dynamics, an initial LGB refuge population with specific proportions of each resistance level is defined, $\boldsymbol{a_p}$ (also see Figure 1). Then LGB immigrate into the stored grain, potentially from two sources if the secondary population ($\boldsymbol{\gamma_{p-1}}$) exits, and are defined by, $\boldsymbol{\gamma_p}$. This population in the stored grain will potentially have different proportions of resistance levels relative to $\boldsymbol{a_p}$. If fumigation occurs, then the surviving pests inside the grain will have different proportions of resistance levels relative to $\boldsymbol{a_p}$. Once grain is sold and depending on the particular scenario considered, a portion of the population inside the stored grain may return to the refuge (at rate ω), while the remainder will make-up the secondary population for the next period.

Based on the model's construction, the secondary population and the refuge will mix at rate δ during the fumigation step in equation 2(c). This is simply for convenience. The restriction in the model assures that the proportion of a particular resistance level after fumigation is not greater than what is actually possible. Additionally when $\delta = 0$, the model fits scenario 2, and when $\omega = 0$ and $\delta > 0$ the model fits scenario 3. Equation 2(a) is used to develop the recursive model that is used to identify changes in proportions of resistance over the time-horizon of P periods:

2(d) $$\boldsymbol{a_P} = \boldsymbol{\alpha_0}(1+\omega)^{-P} + \omega \sum_{p=1}^{P} \boldsymbol{\gamma_p}(1+\omega)^{-P+p-1}$$

where $\boldsymbol{\alpha_0}$ is a vector of the initial resistance proportions at the start of the simulation.

Determining the Number of Fumigations

A distinction is made between the number of fumigations for calendar-based fumigation and sampling-based IPM. Under a calendar-based approach, fumigation occurs regularly and the number of fumigations will increase by up to one per storage period, as the number of LGB surviving fumigation is at, or above, a predetermined economic threshold. This threshold is based on the acceptable number of pests that are found in the grain on a per kg basis (Adam et al. 2010). Under a calendar-based strategy the number of fumigations per period is determined as follows:

3(a) $$n_p = \begin{Bmatrix} n_{p-1} + 1 \;\; if \;\; G_{p-1}\boldsymbol{I^T}\boldsymbol{\lambda_{p-1}} \geq \tau \\ n_{p-1} \;\; otherwise \end{Bmatrix}$$

where G_p is the LGB growth based on Flinn et al. (2004) and τ is the economic threshold. For sampling-based IPM, the number of fumigations is determined by sampling in the current period as well as the number of fumigations in the previous period and whether or not pest growth exceeded τ in the previous period, that is:

3(a) $$m_p = m(n_p | s_p, n_{p-1}, \tau)$$

where m_p is the number of fumigation under sampling-based IPM and s_p is the number of samplings. As n_{p-1} increases, the number of potential sampling and fumigation increases. For example, if $n_{p-1} = 3$ and $G_{p-1}\boldsymbol{I^T}\boldsymbol{\lambda_{p-1}} \geq \tau$ then the possible number of sampling is $s_p \in \{1,2,3,4\}$, while the possible number of fumigations is $n_p \in \{0,1,2,3,4\}$. Note that $n_p \leq s_p \; \forall \; p$. For this same example of $n_{p-1} = 3$, if the first sampling determines that fumigation is not necessary during period p, then $s_p = 1$ and $n_p = 0$. On the other hand, if the first sampling determines fumigation is necessary, then the number of samplings in period p will continue to increase until $s_p = 3$ (and the number of fumigations will also continue to increase until $n_p = 3$) or until sampling determines no more fumigation is necessary.

Aeration-based IPM

In this study, aeration-based IPM is also examined in the context of resistance and compared to the other two strategies. Under an aeration-based strategy, grain is cooled shortly after it is received in order to suppress pest growth. Previous simulations of LGB growth under aeration-based IPM and with a “low” rate immigration (based on the Adam et al. 2010 definition of immigration), demonstrated that fumigation would not ever occur (see Adam et al 2006; Flinn et al. 2004). This is the case because aeration, under the conditions given above, is able to suppresses pest growth well below τ. Since fumigation is not needed under these particular circumstances, LGB resistance remains constant. Therefore, the costs associated with aeration-based IPM are also constant.

Adam et al. 2010 also pointed out that many grain storage facilities in Oklahoma and Kansas (the course of weather data used in this model) are not properly equipped to aerate grain. Therefore the costs associated with aeration under the conditions or low aeration is simply for comparison.

Estimating Costs

The specific cost for calendar-based fumigation in period p is determined as follows:

$$4(a) \qquad SC_p = C_F n_p + \boldsymbol{C_{D1}^T D1_p} + \boldsymbol{C_{D2}^T D2_p}$$

where SC_p is the strategy cost, C_F is costs of fumigation, $\boldsymbol{C_{D1}}$ and $\boldsymbol{C_{D2}}$ are vectors of IDK and infestation costs respectively, and $\boldsymbol{D1_p}$ and $\boldsymbol{D2_p}$ are vectors of indicator variables for IDK and infestation respectively. Similarly, the cost of IPM is given by:

$$4(b) \qquad SC_p = (1-A)C_F m_p + (1-A)C_s s_p + C_A A + \boldsymbol{C_{D1}^T D1_p} + \boldsymbol{C_{D2}^T D2_p}$$

where C_s is the cost of sampling, C_A is the cost of aeration, and A is an indicator variable for the use of aeration.

In this study, changes in the NPV of costs are examined under three different pest population scenarios, $\omega > 0$ and $\delta > 0$ (scenario one), $\omega > 0$ and $\delta = 0$ (scenario two), and $\omega = 0$ and $\delta > 0$ (scenario three), and utilizing one of three grain management strategies (calendar-based fumigation, sampling-based IPM, and aeration-based IPM). In the third scenario, the primary population (refuge population) is unchanged after grain is sold and only the secondary population experiences changes in resistance levels. This allows for a potential steady state of resistance level proportions which are dependent on F and δ.

Stabilizing Allele Frequencies after Fumigation

In the basic Hueth and Regev (1974) model the effect of the remaining allele frequencies, after fumigation, on the genetic make-up of future pest population is not a necessary consideration since the model only considers one gene responsible for resistance. Since the findings of Schlipalius et al. (2008); however, there is a need for a two-allele (each at two levels) economic model to determine the impact of changes in LGB resistance on the cost of stored grain management over a time horizon. One of the challenges in developing such a model is determining how quickly the LGB population stabilizes after fumigation based on the remaining allele frequencies. The main concern is that stabilizing the population under the circumstances of fumigation and different groups of populations mixing violates the Hardy-Weinberg principle (Lush 1994). Additionally, Hurley, Babcock and Hellmich (2001) demonstrated how a violation of the Hardy-Weinberg principle, non-random mating, might also occur when pest populations made up of different resistance levels (the refuge population and the population where fumigation has occurred) are unable to combine due to their proximity to one another.

In the case of stored grain in this study, it is assumed that mating only occurs inside the stored grain and after the population has sufficiently mixed (random mating). Further, fumigation effectiveness is not 100% successful meaning that some susceptible LGB will remain after fumigation. The distribution throughout the grain of all LGB, both susceptible and resistant is assumed to be random. Since the allele frequency stabilization after fumigation and potential violations of the Hardy-Weinberg principle are beyond the scope of this paper, two extreme cases will be examined: 1) no stabilizing and 2) stabilization after every shock.

If one were to assume that allele frequencies remain constant after fumigation and until the next round of pesticide is applied (one extreme), then the increase in resistance occurs much faster compared to when allele frequencies in the population are stabilized after each shock (fumigation or mixing) (see Lush 1994). Stabilizing the population after each shock also assumes that at least one generation of reproduction occurs and that the population is large enough for stabilization to occur. In the first extreme, the five proportions of resistance levels only change when fumigation occurs or when the two populations mix. However, the levels of resistance are never stabilized based on allele frequencies (Lush 1994). For the second extreme, the allele frequencies are assumed to stabilize after each shock (fumigation or populations mixing). In this case, the genotypes have a multinomial distribution (see Lush 1994) and are grouped into their respective phenotypes based on the results of Schlipalius et al. (2008).

Data and Simulation Parameters

LGB growth was simulated with the Flinn et al. (2004) model for Oklahoma City, OK, using NOAA weather data for years 1961-1990 and Goodland, KS, using NOAA weather data for years 1997-2004. The storage facility and grain condition inputs for the growth model as well as grain management costs and τ were identical to what Adam et al. (2010) (see Tables 1 and 2) specified. The rate of LGB immigration (based on the Adam et al. 2010 definition) into the grain was assumed to be low. Although ω is unknown, pre-test simulations with large values of ω (>0.5) resulted in development of resistance that far exceeded what was observed by Emery, Collins and Wallbank (2003) and Newman (2010). However, parameter values in the model were still determined *ad hoc* since there are no other studies to support choosing different values. The particular parameter values selected in this study were based on pre-testing attempts to replicate the development of resistance in Australia, given the model presented in equation 2(a)-(c). During pre-testing, it was determined that the rate at which the development of resistance occurred was due to a combination of all parameters considered (including weather). Therefore, it was possible to replicate the Australian data presented by Emery, Collins and Wallbank (2003) and Newman (2010) by different combinations of parameters and parameter values. The range of values used in this study includes these values, as well as values that result in resistance developing more slowly (specifcally low ω and δ). The reason for the use of low values in this study is because resistance in the U.S. has potentially occurred more slowly than in Australia. Therefore, parameters reflecting this possibility were selecting and included.

Values for ω of 0.05, 0.20 and 0.35 were used in scenarios 1 and 2. For each scenario, low (0.65), medium (0.80) and high (0.95) values of F were used. For scenarios (1) and (3), low (0.20) and high (0.80) values for δ were used. Additionally, starting values for the allele frequency of the gene responsible for resistance at each locus were set at either 1% for each resistant gene (lower levels of resistance) or at 3% for each resistant gene (higher levels of resistance).

Two methods were considered to simulate grain management cost and changes in LGB phosphine resistance. The first method utilized a non-parametric bootstrap and simulated LGB growth for two different storage periods in each location, June 1 - February 1 and June 1 - April 1. An LGB growth year was selected at random and with replacement from the pool of simulated values for each city to create a 25-year period of estimated changes in phosphine resistance. Then, 1,000 25-year periods were generated and used to estimate a mean NPV of costs for each location and under each strategy, scenario and set of model parameters.

For the second method, a frequency of fumigation (i.e. having to fumigate about 71% of the time) given τ was selected and the distribution of LGB growth for each location that matched the frequency of fumigation was estimated. The storage periods that matched the frequency of fumigation were June 1-January 27 (Oklahoma City) and June 1-February 9 (Goodland). Using a parametric bootstrap procedure, the growth distribution was used to create a 25-year period. Again, 1,000 25-year periods were generated and used to estimate a mean NPV of costs for each location and combination of strategy, scenario, and model parameters.

Results and Discussion

Impact of Fumigation Effectiveness

In general, higher fumigation effectiveness resulted in lower cost relative to moderate and low fumigation effectiveness (see Tables 3-14). However, the type of LGB resistance driving costs was different depending on fumigation effectiveness. To demonstrate this difference, three plots (one for each level of fumigation effectiveness) were generated showing the proportions of resistance levels and the corresponding average period costs over a 35-season time horizon (Data in Tables 3-15 are based on a 25-season time horizon, but this extended time horizon for the three plots was necessary to clearly see what happens when the fumigation effectiveness level is high.) Figures 2-4 show how average costs per period change as the proportions of the five phenotypes (susceptible plus the four resistant levels) under a calendar-based strategy. The specific parameters used to generate these figures are based on scenario 1: LGB population stabilized after each shock, Oklahoma City weather, a storage period July 1 to February 1, high (Figure 2), medium (Figure 3) and low (Figure 4) values of fumigation effectiveness (F), high tertiary population emigration (ω), high secondary population immigration (δ), and a 3% beginning frequency of each gene responsible for resistance (also see Figure 1).

When fumigation effectiveness is high (Figure 2), a change in the average cost does not occur until the end of the time-horizon (about period 25). The main driver for these changes is the rapid increase in the proportion of the strong resistance phenotype (and to a lesser extent the moderate resistance phenotype). The changes in cost under calendar-based fumigation are the result of an increase in the number of fumigations each period. The change in the number of fumigations per period is triggered once the residual LGB (LGB renaming after fumigation) and their offspring are at or above the acceptable number of pests per kg of grain (τ). When fumigation effectiveness is high, only strong resistant LGB can survive in large proportions and it's the strong resistant LGB that are responsible for the increase in residual LGB.

When fumigation effectiveness is moderate and low (Figures 3 and 4, respectively), the weak 1 resistant phenotype is driving the increase in the average cost per period. In fact, the other resistant phenotypes (including strong resistance) do not account for a significant proportion of the total LGB resistance. This is the case since large proportions of weak 1 resistant LGB are able to survive fumigation when the effectiveness is low or moderate. It is also important to point out in Figures 3 and 4 that by season 20, the simulation reaches is preset maximum limit of possible fumigations per period (10 fumigations).

In all three figures the proportion of susceptible LGB falls substantially within the first 5-10 seasons (below 25%). Further, susceptible LGB are replaced by weak 1 as the dominant phenotype by period 5. This is an important point, especially when fumigation effectiveness is high, since this shift dramatically increases the rate at which strong resistant LGB are produced.

Although these snapshots (Figure 2-4) may not accurately characterize how grain managers in Oklahoma would respond over the time horizon, piecing together these figures can potentially explain, at least in part, what occurred in Australia as well as other countries where LGB resistance is problematic. The development of pest resistance is believed to have occurred as the result of low and repeated pest exposure to fumigants (Semple et al. 1992). As weak LGB resistance became problematic (as demonstrated in Figures 3 and 4), improvements resulting in increased fumigation effectiveness occurred (see Emery, Collins and Wallbank 2003; Newman 2010). Based on the results in Figure 2, high proportions of weak resistant LGB combined with high fumigation effectiveness resulted in a rapid increase in the proportions of strong resistant LGB.

Impact of immigration (ω) and/or emigration (δ)

When values for immigration (ω) and/or emigration (δ) were increased, costs also increased (this result is a generalization that can be seen in Tables 2-14). However, the rate at which costs increased depended on fumigation effectiveness as well as on the interaction between immigration (ω) and emigration (δ). For example, as emigration (δ) is increased from zero to high and/or when immigration (ω) is increased from low to high, weak 1 resistance is able to develop much more rapidly for low and moderate values of fumigation effectiveness. However, under scenario 3 when immigration (ω) was zero, a steady state of resistance proportions was possible and per period costs stabilized (or began to stabilize, since in some cases a time horizon longer than 25-season was needed to see this result). In this third scenario, costs were lowest when the fumigation effectiveness was high.

In cases when the residual LGB and offspring remained consistently below the acceptable threshold τ (see results for Goodland with the storage period of July 1 to February 1), the effect of immigration (ω) and/or emigration (δ) on costs were negligible. This result occurred regardless of the fumigation effectiveness or grain management strategy. Given the 25-season time horizon and low LGB growth in these cases, resistance was not able to develop in sufficient proportions to necessitate additional fumigation.

Comparison of Scenarios

Scenario 1 resulted in the highest potential costs since the combination of immigration (ω) and emigration (δ) allowed for the most rapid development of resistance. However, when immigration (ω) and emigration (δ) are low, the costs across the three scenarios are very close to one another (especially when the phenotype population was stabilized in the model). When the phenotype population was stabilized in the model, costs for all three scenarios are also relatively close when the storage period is July 1 to February 1, and the fumigation frequency was high. When the storage period was expanded (July 1 to April 1), resistance was able to further develop and the costs under each scenario diverged.

Distinguishing the highest cost scenario between scenarios 2 and 3 is not as straightforward. Under scenario 2, costs, in some cases, are higher (relative to scenario 3) when the storage period is July 1-February 1. Under scenario 3, costs are frequently higher (relative to scenario 2) when the storage period is extended to April 1.

Grain Management Strategy, Location, and Sale Date

In this study, selecting an optimal grain management strategy supported many of the findings of Adam et al. (2010). When the storage period was July 1 to February 1 (February 28 in Adam et al. 2010), sampling-based IPM was optimal when Goodland weather data was used (relatively cooler weather). Calendar-based fumigation was frequently optimal when Oklahoma City weather data was used (with relatively warmer weather). In some cases under scenarios 1 and 2, however, use of a sampling-based IPM strategy with Oklahoma City weather data resulted in enough slowed LGB resistance development (compared to calendar-based fumigation) that the costs between the two strategies were very close. This was even true with the higher discount rate (10%). This occurrence can be seen in the results tables with both the stabilized and non-stabilized LGB population models as well as allele frequencies of 1% and 3%.

Regarding aeration-based IPM, the findings in this study support the results of Adam et al. (2006) and Adam et al. (2010). With a "low" immigration rate used to determine LGB growth, aeration frequently cost less than sampling-based IPM and always cost less than calendar-based fumigation (see Table 15). However, many storage facilities in Oklahoma and Kansas are not equipped with aeration.

Comparing Costs at the Two Locations

The non-parametric results (Tables 3-10) demonstrate that, in general, locations with cooler weather will experience lower grain management costs regardless of the strategy employed. This result occurs because LGB growth is lower where weather is cooler and the rate at which additional fumigation is needed is also lower relative to where weather is warmer. However, these results do not distinguish between the impacts of mean LGB growth and the frequency of pesticide use on the development of resistance. To make this distinction, the use of a common fumigation frequency, 71% (or 0.71 probability that fumigation was needed), was used to compare strategies and scenarios across the two locations (see Tables 11-14). The common fumigation frequency was based on the distribution of the LGB growth data for each location (the corresponding storage periods were June 1 to January 27 for Oklahoma City, and June 1 to February 9 for Goodland).

The average untreated LGB growth is higher in Oklahoma City (1.17 LGB per kg) than in Goodland (1.11 LGB per kg). Therefore, the number of LGB surviving fumigation needed to trigger additional fumigation is lower in Oklahoma City than Goodland (holding other factors the same). As a result, resistance (and costs) develop more rapidly in Oklahoma City. As was the case with many earlier results, when fumigation effectiveness, immigration (ω) and emigration (δ) are low, costs in the two locations are very close. However, as immigration (ω) and emigration (δ) are increased, the difference in costs between the two locations also increases. This observance is most pronounced under the parametric scenario 1 and less so in the parametric scenario 2. In the parametric scenario 3, the costs for the two locations remained close despite the increase in immigration (ω) and emigration (δ). This is because LGB growth is still low enough that very little resistance develops over the 25-season time horizon.

Allele Frequencies and Population Stabilization

A stark contrast can be drawn between the results where the proportions of resistant allele frequencies were stabilized and those where they were not stabilized. Where allele frequencies were not stabilized, LGB resistance developed much faster, especially as the immigration (ω), emigration (δ) and fumigation effectiveness were increased. The increased rate of resistance development between the stabilized and non-stabilized allele frequencies was also reflected in increased costs.

For example, the discounted cost of $22.52 reported in Table 7 reflects the impact of stabilized allele frequencies after every shock, under a calendar-based fumigation strategy, with a starting allele frequency of 1%, a storage period of July 1 to February 1, and with high levels of immigration (ω), emigration (δ) and fumigation effectiveness. The corresponding cost when allele frequencies were not stabilized (but all other parameters remained the same) is $67.82 (see Table 3). When the starting allele frequency was increased to 3%, the difference between costs of stabilized and non-stabilized allele frequency results is much greater. On the other hand, when the model parameters are adjusted such that resistance development occurs slowly due to low levels of immigration (ω) and emigration (δ) the cost differences between the stabilized and non-stabilized allele frequency results are very small. Additionally, the costs diverged much more rapidly when the allele frequencies were not stabilized and as the rate of resistance increased compared to when allele frequencies were stabilized.

Summary and Conclusion

The primary motivation for this study is that recently pest resistance in stored grain has been detected in parts of the US (Bonjour 2010). Significant economic damage from LGB resistance to phosphine has already occurred in countries such as Australia and Brazil (Emery, Collins, and Wallbank 2003; Collins et al. 2005; Daglish 2004; Newman 2010). Currently there are no economical alternatives to phosphine as a fumigant against stored grain pests (Collins et al. 2005). The main challenge is to extend the useful life of phosphine by developing and adopting strategies that can reduce pest exposure to the fumigant. However, grain managers in the US have been reluctant to adopt many of these strategies potentially since many of these strategies have not been shown to be cost effective, especially in all climates (Adam et al. 2010).

The overall objective of this study was to determine how the cost of controlling LGB in stored grain is affected by LGB resistance. Three scenarios were proposed that depicted LGB population dynamics. Under each scenario, changes in specific parameters were examined in the context of their individual impact on LGB resistance and the corresponding change in the costs of controlling LGB. The particular parameters considered were: rates of LGB emigration from the stored grain to a refuge population; rates of LGB immigration from a secondary population into stored grain; levels of fumigation effectiveness; weather; grain storage periods; and starting levels of the frequency of alleles responsible for resistance. Additionally, changes in costs resulting from changes in LGB resistance were modeled and incorporated into the cost benefit analysis of three grain management strategies (calendar-based fumigation, sampling-based IPM, and aeration-based IPM).

When costs associated with LGB resistance are incorporated into the cost model, results from the simulation suggest that in Oklahoma, where the weather is considered warm relative to what encourages pest growth, sampling-based IPM is only cost-effective when the development of LGB is much slower relative to what occurs under calendar-based fumigation. In Kansas, where the weather is cool relative to what encourages pest growth, sampling-based IPM is cost-effective much more frequently. Additionally, aeration-based IPM was found to be the most cost-effective strategy since LGB growth was suppressed enough that fumigation was never found to be necessary. Although these results only reflect the case of “low” immigration (based on the definition used by Adam et al. 2010 and Flinn et al. 2004), they justify further research into the application of different IPM technologies and the impact of such technologies on LGB resistance and the corresponding costs from changes in resistance.

The results also indicate that high fumigation effectiveness has a potential long-term externality associated with the type of LGB resistance that develops. In short, large portions of strong resistant LGB survived when the fumigation effectiveness was high. Given a particular value for “high” fumigation effectiveness (in this study 95%), once strong resistant LGB have a foothold, the value of “high” will have to be increased in order to maintain the same level of effectiveness. However, increasing fumigation effectiveness will only delay the development of strong resistant LGB.

Another strategy may be to incorporate alternative means, such as aeration, to suppress pest growth. Although aeration will not eliminate the need for fumigation in all regions (especially where weather is favorable to insect growth), it could further extend the useful life of phosphine. The use of aeration may also make sampling-based IPM more useful in warm and hot climates. Combined, these two strategies could potentially extend the useful life of phosphine further than either strategy alone.

Another important consideration is the population dynamics of LGB in and around stored grain facilities. Although the impacts on resistance development from emigrating LGB back to a refuge population and the immigrating LGB into grain from a secondary population are intuitive, they present another area that could be exploited by grain mangers to control pest populations. For example, when emigration and immigration were low, the development of resistance occurred much slower compared to when these levels were high. Controlling the entry and exits of pests as well as controlling the potential multiple pest populations may have added benefit when resistance is taken into account. Although the proposed scenarios of LGB population dynamics are hypothetical, the potential cost savings from reduced resistance development justify more research into this area.

For grain managers, one symptom of increased pest resistance is the need for increased fumigation effectiveness (via more frequent fumigations or higher concentrations). If controls are in place such that the fumigation effectiveness is relatively high (see the example in Figure 2), then the symptoms of pest resistance may be initially over looked. In warmer climates where sampling-based IPM has been shown to be too expensive, grain managers may be unaware of current levels of resistance. If the development of LGB resistance is on the threshold, such as the example of Figure 1 near the end of the 35-season storage period, then the current strategies employed may lead to significant economic loss. Once past this threshold, the options for grain managers to make alternative strategy decisions are further reduced.

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Table 1. Treatment Cost for Stored Wheat

Treatment	Cost ($/t)
Fumigation	0.911
Sampling	0.345
Aeration	0.671

source: Adam et al. (2010)

Table 2. Discount for Insect Damage Kernels (IDK)

# of insect damage kernels (IDK)	Discount ($)
1 < IDK 5	0.00
6 < IDK 20	0.367 x #IDK in sample
21 < IDK 31	0.735/IDK in sample
32 < IDK 70	14.47 cleaning charge
71 < IDK 100	22.05 cleaning charge
101 < IDK 140	33.07 cleaning charge
140 < IDK	0.367 x #IDK in sample

source: Adam et al. (2010)

Table 3. NPV of Grain Management Strategy Costs ($/t): Oklahoma City, 1% Discount Rate, Non-parametric Bootstrap, Non-stabilized

			Calendar-based fumigation				Sampling-based IPM			
			ω = 0	ω = 0.05	ω = 0.2	ω = 0.35	ω = 0	ω = 0.05	ω = 0.2	ω = 0.35
Beginning resistance alleles present at 1%										
June 1 to February 1	δ = 0	65% F	-	27.34	42.14	66.93	-	29.41	33.98	63.46
		80% F	-	21.48	54.49	85.31	-	27.18	55.86	98.74
		95% F	-	20.84	30.83	44.69	-	27.02	33.13	46.96
	δ = 0.2	65% F	26.69	27.44	53.46	79.40	29.23	29.23	44.54	82.78
		80% F	20.84	24.10	72.11	96.20	27.00	27.97	77.32	113.19
		95% F	20.84	22.26	39.55	53.09	27.02	27.37	40.57	55.44
	δ = 0.8	65% F	28.25	38.65	82.61	100.11	29.39	32.57	86.20	116.09
		80% F	27.30	44.62	98.22	111.18	28.93	36.90	113.96	134.87
		95% F	24.43	31.86	56.46	67.82	28.12	31.54	58.06	72.14
June 1 to April 1	δ = 0	65% F	-	131.67	155.64	159.38	-	173.28	211.80	217.46
		80% F	-	130.14	154.40	158.78	-	174.73	210.56	216.29
		95% F	-	47.63	113.35	126.68	-	51.21	151.83	171.50
	δ = 0.2	65% F	139.14	154.35	159.67	161.42	155.39	209.83	218.04	220.45
		80% F	134.56	152.08	158.25	159.14	144.34	207.30	215.80	216.92
		95% F	53.43	105.85	126.79	133.53	47.60	139.30	171.94	181.67
	δ = 0.8	65% F	160.15	160.57	161.79	162.48	219.09	219.67	221.07	221.95
		80% F	154.95	155.21	157.76	158.92	211.88	212.27	215.50	217.08
		95% F	132.55	134.80	138.34	140.69	179.76	183.74	188.77	191.91
Beginning resistance alleles present at 3%										
June 1 to February 1	δ = 0	65% F	-	27.68	55.74	84.88	-	29.41	46.42	89.61
		80% F	-	23.21	71.13	97.89	-	27.78	74.71	114.85
		95% F	-	20.91	35.21	52.69	-	27.03	36.64	54.43
	δ = 0.2	65% F	26.69	28.84	69.69	94.84	29.23	29.58	65.25	106.87
		80% F	20.84	27.99	84.69	106.86	27.00	29.31	94.12	127.75
		95% F	20.84	22.78	45.11	61.74	27.02	27.56	45.57	64.79
	δ = 0.8	65% F	28.39	47.48	96.54	112.09	29.43	36.92	107.11	133.67
		80% F	27.97	53.20	106.98	119.16	29.29	42.12	125.89	145.78
		95% F	24.98	34.79	65.15	79.88	28.27	32.79	66.76	84.95
June 1 to April 1	δ = 0	65% F	-	151.68	164.11	166.40	-	205.38	224.24	227.32
		80% F	-	145.56	161.09	162.91	-	197.82	220.15	222.55
		95% F	-	67.67	126.94	137.60	-	76.56	170.97	186.90
	δ = 0.2	65% F	158.94	163.47	166.39	167.05	204.76	223.54	227.40	228.19
		80% F	153.05	159.39	162.75	164.49	193.28	217.99	222.42	224.70
		95% F	64.23	119.68	137.38	143.01	54.92	159.13	186.96	195.01
	δ = 0.8	65% F	165.96	165.91	166.58	167.07	227.07	227.00	227.62	228.21
		80% F	160.32	160.46	161.60	161.83	219.34	219.54	220.79	221.06
		95% F	142.06	143.60	146.40	148.44	193.72	196.04	200.01	202.75

Table 4. NPV of Grain Management Strategy Costs ($/t): Goodland, 1% Discount Rate, Non-parametric Bootstrap, Non-stabilized

			Calendar-based fumigation				Sampling-based IPM			
			ω = 0	ω = 0.05	ω = 0.2	ω = 0.35	ω = 0	ω = 0.05	ω = 0.2	ω = 0.35
Beginning resistance alleles present at 1%										
June 1 to February 1	δ = 0	65% F	-	20.84	20.84	22.33	-	10.67	10.68	10.64
		80% F	-	20.84	21.53	26.72	-	10.68	10.77	10.69
		95% F	-	20.84	20.90	21.95	-	10.65	10.70	10.69
	δ = 0.2	65% F	20.84	20.84	20.84	24.23	10.67	10.67	10.68	10.64
		80% F	20.84	20.84	22.97	29.10	10.68	10.68	10.71	10.69
		95% F	20.84	20.84	21.14	22.68	10.65	10.65	10.64	10.69
	δ = 0.8	65% F	20.84	20.84	23.68	29.28	10.68	10.68	10.65	10.67
		80% F	20.84	20.84	27.50	33.31	10.71	10.70	10.65	10.68
		95% F	20.84	20.84	22.31	24.75	10.64	10.71	10.65	10.66
June 1 to April 1	δ = 0	65% F	-	83.93	138.21	147.33	-	109.08	188.88	201.57
		80% F	-	83.45	133.11	141.55	-	84.95	175.62	190.57
		95% F	-	23.53	88.43	108.16	-	30.96	119.01	147.11
	δ = 0.2	65% F	40.34	125.39	145.75	149.93	55.20	169.24	199.31	205.10
		80% F	37.03	117.30	140.79	144.76	41.82	151.50	190.27	196.47
		95% F	20.84	64.86	107.57	118.12	28.52	84.41	145.85	161.05
	δ = 0.8	65% F	146.47	147.85	150.09	151.27	200.39	202.29	205.34	206.96
		80% F	143.35	145.35	148.06	149.63	193.65	197.27	202.30	204.52
		95% F	108.10	118.05	125.59	128.95	144.73	160.18	171.23	176.07
Beginning resistance alleles present at 3%										
June 1 to February 1	δ = 0	65% F	-	20.84	20.84	24.23	-	10.67	10.68	10.64
		80% F	-	20.84	22.99	29.10	-	10.68	10.77	10.69
		95% F	-	20.84	20.95	22.48	-	10.65	10.70	10.69
	δ = 0.2	65% F	20.84	20.84	21.87	26.45	10.67	10.67	10.68	10.64
		80% F	20.84	20.84	24.54	32.25	10.68	10.68	10.71	10.69
		95% F	20.84	20.84	21.34	23.49	10.65	10.65	10.64	10.69
	δ = 0.8	65% F	20.84	20.84	25.52	32.31	10.68	10.68	10.65	10.68
		80% F	20.84	20.84	28.88	35.10	10.71	10.70	10.65	10.68
		95% F	20.84	20.84	22.92	26.13	10.64	10.71	10.65	10.66
June 1 to April 1	δ = 0	65% F	-	114.39	150.74	155.54	-	150.74	206.01	212.79
		80% F	-	109.35	146.51	151.43	-	135.74	197.31	206.12
		95% F	-	28.67	103.18	120.35	-	36.30	139.48	163.91
	δ = 0.2	65% F	72.25	142.18	154.56	157.54	67.64	192.95	211.45	215.50
		80% F	59.96	137.11	150.12	153.98	53.66	183.67	204.41	210.30
		95% F	20.84	77.16	119.32	128.77	28.52	100.24	162.37	175.65
	δ = 0.8	65% F	154.73	155.02	156.25	156.33	211.69	212.10	213.78	213.88
		80% F	152.63	153.59	155.88	157.57	208.61	210.02	213.26	215.58
		95% F	120.87	129.05	135.09	138.20	163.11	175.29	184.45	188.88

Table 5. NPV of Grain Management Strategy Costs ($/t): Oklahoma City, 10% Discount Rate, Non-parametric Bootstrap, Non-stabilized

			Calendar-based fumigation				Sampling-based IPM			
			$\omega = 0$	$\omega = 0.05$	$\omega = 0.2$	$\omega = 0.35$	$\omega = 0$	$\omega = 0.05$	$\omega = 0.2$	$\omega = 0.35$
Beginning resistance alleles present at 1%										
June 1 to February 1	$\delta = 0$	65% F	-	11.29	13.74	19.13	-	12.89	13.55	19.07
		80% F	-	9.46	15.51	22.86	-	12.18	17.08	26.52
		95% F	-	9.36	11.17	14.15	-	12.18	13.27	16.01
	$\delta = 0.2$	65% F	11.08	11.41	15.73	21.42	12.78	12.87	15.41	22.75
		80% F	9.36	10.01	19.65	26.12	12.17	12.35	21.28	30.50
		95% F	9.36	9.62	12.92	15.85	12.15	12.24	14.65	17.73
	$\delta = 0.8$	65% F	11.33	13.49	22.89	27.55	12.80	13.48	24.18	30.91
		80% F	10.85	14.69	27.14	31.44	12.60	14.30	31.01	37.79
		95% F	10.20	11.49	16.67	19.36	12.42	12.94	18.20	21.37
June 1 to April 1	$\delta = 0$	65% F	-	41.97	52.77	54.93	-	54.11	71.62	74.93
		80% F	-	40.76	52.11	54.31	-	54.14	70.90	73.92
		95% F	-	14.74	31.97	37.30	-	17.09	42.50	50.26
	$\delta = 0.2$	65% F	45.66	52.54	55.08	55.95	52.48	71.17	75.17	76.42
		80% F	43.98	51.14	53.96	54.57	49.47	69.48	73.50	74.37
		95% F	16.92	29.61	37.27	40.15	17.24	38.55	50.29	54.59
	$\delta = 0.8$	65% F	55.67	55.88	56.57	56.71	76.14	76.43	77.32	77.48
		80% F	52.12	52.47	53.61	54.28	71.23	71.74	73.27	74.15
		95% F	40.19	41.00	42.91	43.93	54.45	55.71	58.43	59.93
Beginning resistance alleles present at 3%										
June 1 to February 1	$\delta = 0$	65% F	-	11.38	16.34	23.33	-	12.89	15.69	24.86
		80% F	-	9.87	19.39	26.57	-	12.32	20.90	30.88
		95% F	-	9.37	12.06	15.95	-	12.18	13.88	17.62
	$\delta = 0.2$	65% F	158.94	11.67	19.25	25.95	12.78	12.92	19.31	28.78
		80% F	153.05	11.00	23.17	29.77	12.17	12.67	25.37	35.12
		95% F	64.23	9.70	14.22	17.80	12.15	12.27	15.71	19.70
	$\delta = 0.8$	65% F	165.96	15.50	26.98	31.82	12.82	14.41	29.57	36.62
		80% F	160.32	16.81	30.44	34.77	12.71	15.51	34.98	42.12
		95% F	142.06	12.08	18.87	22.10	12.47	13.19	20.24	24.41
June 1 to April 1	$\delta = 0$	65% F	-	51.29	57.86	59.30	-	68.95	79.07	81.06
		80% F	-	48.01	55.94	57.05	-	64.77	76.46	77.97
		95% F	-	19.68	37.75	42.38	-	22.61	50.41	57.35
	$\delta = 0.2$	65% F	55.09	57.95	59.36	59.63	71.55	79.22	81.16	81.49
		80% F	52.63	55.23	56.86	57.91	67.45	75.50	77.75	79.13
		95% F	19.95	34.78	42.33	44.90	19.31	45.66	57.36	61.17
	$\delta = 0.8$	65% F	59.21	59.21	59.35	59.45	81.01	81.01	81.13	81.22
		80% F	55.38	55.61	55.91	56.08	75.76	76.08	76.42	76.62
		95% F	44.85	45.55	47.22	48.15	61.03	62.10	64.47	65.80

Table 6. NPV of Grain Management Strategy Costs ($/t): Goodland, 10% Discount Rate, Non-parametric Bootstrap, Non-stabilized

			Calendar-based fumigation				Sampling-based IPM			
			ω = 0	ω = 0.05	ω = 0.2	ω = 0.35	ω = 0	ω = 0.05	ω = 0.2	ω = 0.35
Beginning resistance alleles present at 1%										
June 1 to February 1	δ = 0	65% F	-	9.36	9.36	9.57	-	4.81	4.79	4.79
		80% F	-	9.36	9.44	10.34	-	4.82	4.82	4.78
		95% F	-	9.36	9.36	9.55	-	4.82	4.82	4.80
	δ = 0.2	65% F	9.36	9.36	9.36	9.97	4.81	4.73	4.79	4.79
		80% F	9.36	9.36	9.68	10.82	4.78	4.75	4.78	4.80
		95% F	9.36	9.36	9.41	9.68	4.80	4.78	4.73	4.77
	δ = 0.8	65% F	9.36	9.36	9.77	10.89	4.81	4.81	4.77	4.73
		80% F	9.36	9.36	10.59	11.95	4.82	4.79	4.79	4.78
		95% F	9.36	9.36	9.63	10.03	4.82	4.75	4.77	4.76
June 1 to April 1	δ = 0	65% F	-	25.84	43.88	48.36	-	33.97	59.95	66.17
		80% F	-	24.00	40.67	44.84	-	24.88	52.45	59.50
		95% F	-	9.78	23.78	30.06	-	13.20	32.01	40.77
	δ = 0.2	65% F	17.40	38.38	47.35	49.50	23.81	51.39	64.76	67.71
		80% F	15.01	34.60	44.72	46.44	17.33	43.49	59.87	62.61
		95% F	9.36	18.27	29.81	33.62	12.80	23.99	40.37	45.75
	δ = 0.8	65% F	47.53	48.40	49.54	50.04	65.03	66.22	67.78	68.46
		80% F	45.87	46.61	47.97	49.00	61.45	62.92	65.36	66.95
		95% F	30.82	33.56	36.84	38.40	41.22	45.40	50.12	52.38
Beginning resistance alleles present at 3%										
June 1 to February 1	δ = 0	65% F	-	9.36	9.36	9.97	-	4.81	4.79	4.79
		80% F	-	9.36	9.69	10.87	-	4.82	4.82	4.78
		95% F	-	9.36	9.38	9.66	-	4.82	4.82	4.80
	δ = 0.2	65% F	72.25	9.36	9.50	10.38	4.81	4.73	4.79	4.79
		80% F	59.96	9.36	9.97	11.50	4.78	4.75	4.78	4.80
		95% F	20.84	9.36	9.44	9.82	4.80	4.78	4.73	4.77
	δ = 0.8	65% F	154.73	9.36	10.10	11.62	4.81	4.81	4.77	4.73
		80% F	152.63	9.36	10.89	12.38	4.82	4.79	4.79	4.78
		95% F	120.87	9.36	9.73	10.29	4.82	4.75	4.77	4.76
June 1 to April 1	δ = 0	65% F	-	35.00	50.22	52.89	-	45.51	68.48	72.36
		80% F	-	32.15	47.57	50.28	-	38.70	63.44	68.00
		95% F	-	10.71	28.33	34.84	-	14.15	38.24	47.35
	δ = 0.2	65% F	26.10	46.10	52.14	53.99	27.79	62.34	71.33	73.84
		80% F	21.39	43.21	49.66	51.80	21.58	57.07	67.35	70.62
		95% F	9.36	21.23	34.22	38.25	12.80	27.68	46.40	52.08
	δ = 0.8	65% F	52.11	52.34	52.84	52.94	71.29	71.61	72.29	72.44
		80% F	51.02	51.30	52.61	53.83	69.69	70.17	71.97	73.65
		95% F	35.68	38.02	41.23	42.62	47.85	51.58	56.17	58.21

Table 7. NPV of Grain Management Strategy Costs ($/t): Oklahoma City, 1% Discount Rate, Non-parametric Bootstrap, Stabilized

			Calendar-based fumigation				Sampling-based IPM			
			ω = 0	ω = 0.05	ω = 0.2	ω = 0.35	ω = 0	ω = 0.05	ω = 0.2	ω = 0.35
Beginning resistance alleles present at 1%										
June 1 to February 1	δ = 0	65% F	-	27.29	36.47	55.43	-	29.41	32.04	48.00
		80% F	-	21.35	41.31	70.02	-	27.12	39.46	73.04
		95% F	-	20.84	21.25	21.84	-	27.02	27.28	27.42
	δ = 0.2	65% F	26.69	27.27	44.29	66.13	29.23	29.23	37.47	62.62
		80% F	20.84	23.80	55.91	82.32	27.00	27.88	52.92	90.40
		95% F	20.84	20.84	21.51	22.08	27.02	27.02	27.33	27.52
	δ = 0.8	65% F	28.19	35.93	70.74	89.58	29.38	31.77	66.75	98.29
		80% F	26.43	39.64	85.78	100.71	28.71	34.16	92.59	117.91
		95% F	20.84	20.94	22.05	22.52	27.12	27.18	27.50	27.65
June 1 to April 1	δ = 0	65% F	-	127.48	154.13	158.53	-	166.65	209.89	216.28
		80% F	-	124.73	152.87	157.46	-	166.28	208.22	214.38
		95% F	-	29.11	40.42	44.06	-	34.89	50.37	54.75
	δ = 0.2	65% F	132.74	152.73	158.99	160.90	148.06	207.50	217.06	219.77
		80% F	125.50	148.89	156.39	158.22	133.53	202.52	213.15	215.48
		95% F	26.25	34.45	42.80	45.93	30.70	41.94	53.12	56.69
	δ = 0.8	65% F	159.47	160.15	160.98	162.08	218.12	219.08	219.97	221.45
		80% F	153.15	153.51	155.73	157.11	208.75	209.63	212.53	214.42
		95% F	38.04	41.88	46.27	47.82	44.00	51.49	57.10	58.75
Beginning resistance alleles present at 3%										
June 1 to February 1	δ = 0	65% F	-	27.58	44.96	70.27	-	29.41	37.82	65.35
		80% F	-	23.15	53.56	80.78	-	27.77	48.62	87.17
		95% F	-	20.84	21.46	22.03	-	27.02	27.33	27.50
	δ = 0.2	65% F	26.69	28.20	56.00	81.24	29.23	29.46	47.45	82.69
		80% F	20.84	26.55	68.14	92.73	27.00	28.89	65.31	103.86
		95% F	20.84	20.85	21.65	22.31	27.02	27.02	27.38	27.64
	δ = 0.8	65% F	28.31	42.51	84.31	101.22	29.40	34.65	84.11	115.37
		80% F	27.89	45.24	93.81	108.45	29.23	36.93	103.56	128.21
		95% F	20.87	21.04	22.41	23.33	27.12	27.20	27.68	28.12
June 1 to April 1	δ = 0	65% F	-	147.46	162.30	165.10	-	198.85	221.74	225.55
		80% F	-	139.72	159.30	161.65	-	189.19	217.61	220.69
		95% F	-	32.78	43.42	49.57	-	39.04	53.36	59.62
	δ = 0.2	65% F	154.15	161.50	165.61	166.66	196.06	220.74	226.40	227.70
		80% F	145.64	156.72	161.36	162.51	179.50	213.92	220.36	221.84
		95% F	28.15	37.06	47.19	57.27	31.63	45.09	56.82	67.39
	δ = 0.8	65% F	165.21	165.50	166.35	166.73	226.02	226.44	227.32	227.79
		80% F	158.76	158.59	160.68	160.53	216.43	216.62	219.36	219.09
		95% F	67.38	59.07	68.80	79.91	66.56	65.41	80.67	95.97

Table 8. NPV of Grain Management Strategy Costs ($/t): Goodland, 1% Discount Rate, Non-parametric Bootstrap, Stabilized

			Calendar-based fumigation				Sampling-based IPM			
			$\omega = 0$	$\omega = 0.05$	$\omega = 0.2$	$\omega = 0.35$	$\omega = 0$	$\omega = 0.05$	$\omega = 0.2$	$\omega = 0.35$
Beginning resistance alleles present at 1%										
June 1 to February 1	$\delta = 0$	65% F	-	20.84	20.84	20.94	-	10.67	10.68	10.64
		80% F	-	20.84	20.84	23.40	-	10.68	10.77	10.69
		95% F	-	20.84	20.84	20.84	-	10.65	10.70	10.69
	$\delta = 0.2$	65% F	20.84	20.84	20.84	21.77	10.67	10.67	10.68	10.64
		80% F	20.84	20.84	21.13	25.20	10.68	10.68	10.71	10.69
		95% F	20.84	20.84	20.84	20.84	10.65	10.65	10.64	10.69
	$\delta = 0.8$	65% F	20.84	20.84	21.71	25.45	10.68	10.68	10.65	10.67
		80% F	20.84	20.84	24.21	30.01	10.71	10.70	10.65	10.68
		95% F	20.84	20.84	20.84	20.84	10.64	10.71	10.65	10.66
June 1 to April 1	$\delta = 0$	65% F	-	74.71	135.84	146.33	-	94.15	185.31	200.14
		80% F	-	73.69	129.80	139.01	-	72.00	171.21	186.27
		95% F	-	21.11	29.56	32.48	-	28.71	37.72	41.48
	$\delta = 0.2$	65% F	40.34	119.50	143.57	148.39	55.20	160.45	196.18	202.91
		80% F	37.03	111.30	138.18	142.37	41.08	141.72	185.97	193.02
		95% F	20.84	23.14	31.23	33.66	28.52	30.29	39.76	42.91
	$\delta = 0.8$	65% F	144.41	146.32	147.95	150.34	197.38	200.20	202.39	205.69
		80% F	140.20	142.21	146.62	146.70	189.02	192.38	199.99	199.84
		95% F	21.97	29.21	33.96	35.17	29.17	36.09	42.89	44.64
Beginning resistance alleles present at 3%										
June 1 to February 1	$\delta = 0$	65% F	-	20.84	20.84	21.76	-	10.67	10.68	10.64
		80% F	-	20.84	20.84	24.31	-	10.68	10.77	10.69
		95% F	-	20.84	20.84	20.84	-	10.65	10.70	10.69
	$\delta = 0.2$	65% F	20.84	20.84	20.84	23.28	10.67	10.67	10.68	10.64
		80% F	20.84	20.84	21.74	26.23	10.68	10.68	10.71	10.69
		95% F	20.84	20.84	20.84	20.84	10.65	10.65	10.64	10.69
	$\delta = 0.8$	65% F	20.84	20.84	22.76	27.57	10.68	10.68	10.65	10.67
		80% F	20.84	20.84	24.94	31.26	10.71	10.70	10.65	10.68
		95% F	20.84	20.84	20.84	20.85	10.64	10.71	10.65	10.66
June 1 to April 1	$\delta = 0$	65% F	-	103.77	148.00	154.63	-	134.64	201.92	211.52
		80% F	-	99.20	142.73	149.08	-	119.72	191.95	202.36
		95% F	-	21.77	30.93	33.85	-	29.18	39.27	43.10
	$\delta = 0.2$	65% F	67.11	136.95	153.13	155.67	66.74	184.60	209.42	212.95
		80% F	49.00	130.20	147.46	151.64	51.90	173.35	200.57	206.79
		95% F	20.84	24.30	32.42	35.86	28.52	31.25	41.15	45.23
	$\delta = 0.8$	65% F	152.93	154.46	155.64	156.29	209.12	211.33	212.91	213.83
		80% F	148.99	150.44	152.78	153.74	202.66	205.42	208.78	209.90
		95% F	23.85	31.18	39.11	46.34	31.07	38.39	46.72	54.69

Table 9. NPV of Grain Management Strategy Costs ($/t): Oklahoma City, 10% Discount Rate, Non-parametric Bootstrap, Stabilized

			Beginning resistance alleles present at 1%							
			Calendar-based fumigation				Sampling-based IPM			
			ω = 0	ω = 0.05	ω = 0.2	ω = 0.35	ω = 0	ω = 0.05	ω = 0.2	ω = 0.35
June 1 to February 1	δ = 0	65% F	-	11.28	12.81	16.80	-	12.89	13.26	16.26
		80% F	-	9.43	13.20	19.15	-	12.17	14.40	20.70
		95% F	-	9.36	9.43	9.53	-	12.18	12.22	12.20
	δ = 0.2	65% F	11.08	11.38	14.11	18.62	12.78	12.87	14.22	18.78
		80% F	9.36	9.96	16.24	22.47	12.17	12.33	16.81	24.75
		95% F	9.36	9.36	9.46	9.59	12.15	12.16	12.22	12.22
	δ = 0.8	65% F	11.32	13.00	20.08	24.47	12.80	13.33	20.20	26.17
		80% F	10.72	13.66	23.63	28.06	12.55	13.77	25.61	32.44
		95% F	9.36	9.38	9.57	9.72	12.18	12.16	12.21	12.27
June 1 to April 1	δ = 0	65% F	-	40.48	52.09	54.59	-	51.90	70.68	74.48
		80% F	-	38.70	51.36	53.51	-	51.02	69.80	72.79
		95% F	-	11.32	14.78	16.15	-	14.14	18.81	20.55
	δ = 0.2	65% F	43.52	51.65	54.71	55.67	50.19	69.78	74.69	76.04
		80% F	40.69	49.68	53.29	54.19	45.56	67.37	72.56	73.85
		95% F	11.05	12.92	15.75	16.85	13.49	16.07	20.05	21.48
	δ = 0.8	65% F	55.30	55.64	56.16	56.50	75.62	76.10	76.76	77.21
		80% F	51.28	51.92	52.59	53.73	69.96	70.90	71.81	73.39
		95% F	14.68	15.75	17.36	18.02	17.67	19.89	22.02	22.83
			Beginning resistance alleles present at 3%							
June 1 to February 1	δ = 0	65% F	-	11.35	14.46	20.07	-	12.89	14.33	19.77
		80% F	-	9.85	15.88	22.11	-	12.32	16.26	24.05
		95% F	-	9.36	9.46	9.58	-	12.18	12.23	12.21
	δ = 0.2	65% F	154.15	11.56	16.53	22.44	12.78	12.90	16.16	23.32
		80% F	145.64	10.69	19.19	25.53	12.17	12.58	19.30	28.43
		95% F	28.15	9.36	9.49	9.65	12.15	12.16	12.22	12.23
	δ = 0.8	65% F	165.21	14.50	23.61	28.26	12.81	13.97	24.22	31.13
		80% F	158.76	15.04	26.33	30.94	12.70	14.49	28.75	36.05
		95% F	67.38	9.39	9.62	9.88	12.18	12.16	12.23	12.37
June 1 to April 1	δ = 0	65% F	-	49.34	56.80	58.50	-	65.94	77.62	79.97
		80% F	-	45.36	55.13	56.30	-	60.91	75.32	76.92
		95% F	-	12.58	16.06	17.79	-	15.31	20.26	22.23
	δ = 0.2	65% F	52.89	56.70	58.93	59.45	67.75	77.47	80.59	81.27
		80% F	49.66	54.08	56.28	56.89	62.14	73.82	76.91	77.73
		95% F	11.58	14.04	17.17	19.27	13.76	17.27	21.45	23.91
	δ = 0.8	65% F	58.86	58.97	59.29	59.22	80.53	80.68	81.07	80.94
		80% F	54.48	55.06	55.50	55.75	74.35	75.25	75.81	76.16
		95% F	20.47	19.31	21.99	24.29	22.22	23.08	26.87	29.89

Table 10. NPV of Grain Management Strategy Costs ($/t): Goodland, 10% Discount Rate, Non-parametric Bootstrap, Stabilized

			Calendar-based fumigation				Sampling-based IPM			
			ω = 0	ω = 0.05	ω = 0.2	ω = 0.35	ω = 0	ω = 0.05	ω = 0.2	ω = 0.35
Beginning resistance alleles present at 1%										
June 1 to February 1	δ = 0	65% F	-	9.36	9.36	9.37	-	4.81	4.79	4.79
		80% F	-	9.36	9.36	9.75	-	4.82	4.82	4.78
		95% F	-	9.36	9.36	9.36	-	4.82	4.82	4.80
	δ = 0.2	65% F	9.36	9.36	9.36	9.49	4.81	4.73	4.79	4.79
		80% F	9.36	9.36	9.39	10.06	4.78	4.75	4.78	4.80
		95% F	9.36	9.36	9.36	9.36	4.80	4.78	4.73	4.77
	δ = 0.8	65% F	9.36	9.36	9.48	10.11	4.81	4.81	4.77	4.73
		80% F	9.36	9.36	9.89	11.07	4.82	4.79	4.79	4.78
		95% F	9.36	9.36	9.36	9.36	4.82	4.75	4.77	4.76
June 1 to April 1	δ = 0	65% F	-	24.13	42.69	47.87	-	31.23	58.23	65.46
		80% F	-	21.84	39.35	43.68	-	22.49	50.73	57.67
		95% F	-	9.39	11.31	12.34	-	12.82	14.81	16.04
	δ = 0.2	65% F	17.40	36.26	46.40	48.77	23.81	48.34	63.33	66.67
		80% F	15.01	32.54	43.67	45.41	17.11	40.34	58.25	61.30
		95% F	9.36	9.71	11.93	12.87	12.80	13.07	15.50	16.68
	δ = 0.8	65% F	46.52	47.49	48.45	49.47	63.57	64.98	66.29	67.69
		80% F	44.68	45.33	47.31	48.01	59.85	60.93	64.37	65.37
		95% F	9.63	11.41	13.11	13.68	12.96	14.59	16.86	17.68
Beginning resistance alleles present at 3%										
June 1 to February 1	δ = 0	65% F	-	9.36	9.36	9.49	-	4.81	4.79	4.79
		80% F	-	9.36	9.36	9.89	-	4.82	4.82	4.78
		95% F	-	9.36	9.36	9.36	-	4.82	4.82	4.80
	δ = 0.2	65% F	67.11	9.36	9.36	9.77	4.81	4.73	4.79	4.79
		80% F	49.00	9.36	9.48	10.24	4.78	4.75	4.78	4.80
		95% F	20.84	9.36	9.36	9.36	4.80	4.78	4.73	4.77
	δ = 0.8	65% F	152.93	9.36	9.64	10.54	4.81	4.81	4.77	4.73
		80% F	148.99	9.36	10.05	11.43	4.82	4.79	4.79	4.78
		95% F	23.85	9.36	9.36	9.36	4.82	4.75	4.77	4.76
June 1 to April 1	δ = 0	65% F	-	31.76	48.82	52.43	-	40.92	66.42	71.73
		80% F	-	29.20	45.79	49.03	-	34.30	60.87	66.16
		95% F	-	9.48	11.83	12.84	-	12.89	15.35	16.59
	δ = 0.2	65% F	24.87	43.82	51.44	52.85	27.54	58.70	70.36	72.31
		80% F	18.92	40.27	48.62	50.79	20.94	52.74	65.86	69.16
		95% F	9.36	9.96	12.40	13.52	12.80	13.26	15.99	17.38
	δ = 0.8	65% F	51.11	52.02	52.67	52.91	69.90	71.17	72.06	72.40
		80% F	49.51	50.14	50.97	52.16	67.47	68.46	69.64	71.30
		95% F	10.12	12.07	14.25	15.72	13.40	15.30	17.84	19.50

Table 11. NPV of Grain Management Strategy Costs ($/t): Oklahoma City, Parametric Bootstrap, Non-stabilized

			Calendar-based fumigation				Sampling-based IPM			
			$\omega = 0$	$\omega = 0.05$	$\omega = 0.2$	$\omega = 0.35$	$\omega = 0$	$\omega = 0.05$	$\omega = 0.2$	$\omega = 0.35$
1% Discount Rate										
Beginning resistance alleles present at 1%	$\delta = 0$	65% F	-	20.84	26.49	92.11	-	22.59	22.96	27.80
		80% F	-	20.84	40.72	135.13	-	22.56	26.84	43.86
		95% F	-	20.84	26.53	73.07	-	22.46	23.26	26.53
	$\delta = 0.2$	65% F	20.84	20.90	35.39	57.92	22.59	22.59	24.48	33.56
		80% F	20.84	21.10	53.86	78.06	22.56	22.57	32.44	53.19
		95% F	20.84	20.97	32.30	42.96	22.46	22.46	24.62	29.34
	$\delta = 0.8$	65% F	20.98	27.14	61.83	78.83	22.52	22.85	35.57	51.59
		80% F	20.95	33.71	78.50	93.76	22.56	23.69	50.50	69.75
		95% F	20.84	25.57	45.39	54.80	22.57	22.99	29.69	36.15
Beginning resistance alleles present at 3%	$\delta = 0$	65% F	-	20.93	37.00	62.84	-	22.59	25.28	37.20
		80% F	-	20.92	52.23	79.28	-	22.56	32.29	54.72
		95% F	-	20.84	29.36	42.48	-	22.46	23.87	29.07
	$\delta = 0.2$	65% F	20.84	21.62	49.97	74.46	22.59	22.64	29.35	45.97
		80% F	20.84	22.19	65.08	88.10	22.56	22.63	39.65	64.25
		95% F	20.84	21.05	36.47	49.73	22.46	22.46	25.88	33.03
	$\delta = 0.8$	65% F	21.83	33.92	76.41	92.10	22.57	24.01	46.52	66.16
		80% F	21.29	39.88	87.78	101.84	22.58	24.94	59.45	80.10
		95% F	20.86	27.11	52.23	63.42	22.57	23.19	33.06	41.58
10% Discount Rate										
Beginning resistance alleles present at 1%	$\delta = 0$	65% F	-	9.36	10.28	13.87	-	10.10	10.13	11.01
		80% F	-	9.36	13.01	18.66	-	10.05	10.43	13.63
		95% F	-	9.36	10.32	12.34	-	10.14	10.22	10.78
	$\delta = 0.2$	65% F	9.36	9.36	11.94	16.48	10.05	10.12	10.45	11.98
		80% F	9.36	9.40	15.64	21.76	10.11	10.12	11.75	16.04
		95% F	9.36	9.37	11.51	13.58	10.11	10.06	10.43	11.30
	$\delta = 0.8$	65% F	9.38	10.53	17.45	21.77	10.10	10.14	12.32	15.62
		80% F	9.39	11.70	21.97	26.20	10.05	10.32	15.50	20.10
		95% F	9.36	10.18	14.14	16.21	10.14	10.11	11.44	12.56
Beginning resistance alleles present at 3%	$\delta = 0$	65% F	-	9.37	12.30	17.58	-	10.10	10.58	12.86
		80% F	-	9.37	15.43	21.77	-	10.05	11.79	15.90
		95% F	-	9.36	10.81	13.49	-	10.14	10.37	11.25
	$\delta = 0.2$	65% F	9.36	9.47	14.90	20.45	9.74	10.12	11.37	14.38
		80% F	9.36	9.58	18.33	24.63	9.77	10.12	13.12	18.77
		95% F	9.36	9.37	12.29	15.12	9.77	10.06	10.65	11.96
	$\delta = 0.8$	65% F	9.58	12.09	21.32	25.81	9.86	10.37	14.61	19.05
		80% F	9.51	12.99	24.53	29.08	9.80	10.57	17.78	22.89
		95% F	9.36	10.47	15.70	18.32	9.79	10.14	12.10	13.75

Table 12. NPV of Grain Management Strategy Costs ($/t): Goodland, Parametric Bootstrap, Non-stabilized

			1% Discount Rate							
			Calendar-based fumigation				Sampling-based IPM			
			No ω	Low ω	Medium ω	High ω	No ω	Low ω	Medium ω	High ω
Beginning resistance alleles present at 1%	δ = 0	65% F	-	20.84	22.22	69.79	-	22.67	22.62	24.44
		80% F	-	20.84	31.46	113.49	-	22.64	23.99	35.45
		95% F	-	20.84	23.02	59.89	-	22.55	22.83	24.52
	δ = 0.2	65% F	20.84	20.84	26.81	45.26	22.67	22.67	22.94	27.55
		80% F	20.84	20.85	40.57	66.48	22.64	22.64	26.71	43.28
		95% F	20.84	20.84	26.48	34.76	22.55	22.55	23.23	26.16
	δ = 0.8	65% F	20.84	21.56	46.42	66.46	22.59	22.59	28.08	41.15
		80% F	20.84	23.21	63.30	83.28	22.64	22.63	38.86	58.65
		95% F	20.84	21.45	34.78	44.01	22.65	22.68	25.88	30.77
Beginning resistance alleles present at 3%	δ = 0	65% F	-	20.84	26.98	47.96	-	22.67	23.11	29.18
		80% F	-	20.84	38.91	66.82	-	22.64	26.47	43.65
		95% F	-	20.84	24.44	33.74	-	22.55	22.99	25.77
	δ = 0.2	65% F	20.84	20.84	34.76	58.80	22.67	22.67	24.57	34.97
		80% F	20.84	20.89	49.48	75.66	22.64	22.64	30.55	52.13
		95% F	20.84	20.85	28.64	39.27	22.55	22.55	23.70	28.06
	δ = 0.8	65% F	20.84	23.17	57.90	78.70	22.59	22.68	34.25	52.79
		80% F	20.84	24.98	71.48	90.53	22.64	22.84	45.41	67.93
		95% F	20.84	21.77	39.43	50.71	22.65	22.70	27.47	34.30
			10% Discount Rate							
Beginning resistance alleles present at 1%	δ = 0	65% F	-	9.36	9.59	11.77	-	10.14	10.14	10.46
		80% F	-	9.36	11.12	16.09	-	10.09	10.24	12.13
		95% F	-	9.36	9.71	11.02	-	10.18	10.22	10.43
	δ = 0.2	65% F	9.36	9.36	10.32	13.73	10.10	10.16	10.23	10.88
		80% F	9.36	9.36	12.90	18.74	10.15	10.15	10.73	13.83
		95% F	9.36	9.36	10.33	11.83	10.16	10.10	10.22	10.71
	δ = 0.8	65% F	9.36	9.46	14.01	18.35	10.14	10.11	10.97	13.34
		80% F	9.36	9.73	17.78	22.79	10.09	10.14	13.05	17.35
		95% F	9.36	9.45	12.08	13.79	10.18	10.08	10.70	11.51
Beginning resistance alleles present at 3%	δ = 0	65% F	-	9.36	10.37	14.30	-	10.14	10.23	11.30
		80% F	-	9.36	12.66	18.48	-	10.09	10.73	13.64
		95% F	-	9.36	9.95	11.80	-	10.18	10.25	10.66
	δ = 0.2	65% F	9.36	9.36	11.81	16.70	9.77	10.16	10.49	12.25
		80% F	9.36	9.36	14.64	21.27	9.79	10.15	11.43	15.75
		95% F	9.36	9.36	10.75	12.81	9.80	10.10	10.30	11.06
	δ = 0.8	65% F	9.36	9.74	16.57	21.78	9.79	10.13	12.10	15.85
		80% F	9.36	10.10	20.02	25.29	9.76	10.18	14.43	19.58
		95% F	9.36	9.50	12.94	15.30	9.81	10.09	11.03	12.22

Table 13. NPV of Grain Management Strategy Costs ($/t): Oklahoma City, Parametric Bootstrap, Stabilized

			Calendar-based fumigation				Sampling-based IPM			
			No ω	Low ω	Medium ω	High ω	No ω	Low ω	Medium ω	High ω
1% Discount Rate										
Beginning resistance alleles present at 1%	δ = 0	65% F	-	20.84	24.73	75.66	-	22.59	22.82	25.45
		80% F	-	20.84	32.70	107.04	-	22.56	24.59	33.01
		95% F	-	20.84	20.84	41.70	-	22.46	22.64	22.54
	δ = 0.2	65% F	20.84	20.88	30.83	47.46	22.59	22.59	23.72	28.60
		80% F	20.84	21.03	42.73	64.09	22.56	22.56	27.34	39.76
		95% F	20.84	20.84	20.84	20.85	22.46	22.46	22.57	22.54
	δ = 0.8	65% F	20.92	25.76	51.90	67.90	22.52	22.77	30.28	40.94
		80% F	20.92	30.43	66.66	81.83	22.56	23.32	39.22	54.22
		95% F	20.84	20.84	20.85	20.86	22.57	22.57	22.51	22.47
Beginning resistance alleles present at 3%	δ = 0	65% F	-	20.92	31.60	50.05	-	22.59	24.24	30.21
		80% F	-	20.88	39.80	62.68	-	22.56	26.93	39.13
		95% F	-	20.84	20.84	20.87	-	22.46	22.64	22.54
	δ = 0.2	65% F	20.84	21.50	40.50	60.79	22.59	21.50	40.50	60.79
		80% F	20.84	21.74	50.26	72.96	22.56	21.74	50.26	72.96
		95% F	20.84	20.84	20.85	20.93	22.46	20.84	20.85	20.93
	δ = 0.8	65% F	21.62	30.76	63.76	80.14	22.56	30.76	63.76	80.14
		80% F	21.14	34.41	74.12	88.96	22.57	34.41	74.12	88.96
		95% F	20.84	20.84	20.95	21.28	22.57	20.84	20.95	21.28
10% Discount Rate										
Beginning resistance alleles present at 1%	δ = 0	65% F	-	9.36	9.99	12.42	-	10.10	10.12	10.63
		80% F	-	9.36	11.51	15.71	-	10.05	10.27	11.80
		95% F	-	9.36	9.36	9.36	-	10.14	10.17	10.10
	δ = 0.2	65% F	9.36	9.36	11.15	14.50	10.05	10.12	10.34	11.13
		80% F	9.36	9.38	13.48	18.49	10.11	10.12	10.89	13.32
		95% F	9.36	9.36	9.36	9.36	10.11	10.06	10.08	10.11
	δ = 0.8	65% F	9.38	10.24	15.40	19.14	10.10	10.13	11.44	13.54
		80% F	9.37	11.11	18.90	22.90	10.05	10.24	13.30	16.68
		95% F	9.36	9.36	9.36	9.36	10.14	10.05	10.08	10.10
Beginning resistance alleles present at 3%	δ = 0	65% F	-	9.37	11.34	15.04	-	10.10	10.40	11.59
		80% F	-	9.36	12.98	17.95	-	10.05	10.87	13.02
		95% F	-	9.36	9.36	9.36	-	10.14	10.16	10.10
	δ = 0.2	65% F	9.36	9.44	13.20	17.51	9.74	9.44	13.20	17.51
		80% F	9.36	9.49	15.25	20.81	9.77	9.49	15.25	20.81
		95% F	9.36	9.36	9.36	9.36	9.77	9.36	9.36	9.36
	δ = 0.8	65% F	9.53	11.39	18.44	22.63	9.84	11.39	18.44	22.63
		80% F	9.44	11.91	21.15	25.28	9.77	11.91	21.15	25.28
		95% F	9.36	9.36	9.37	9.41	9.79	9.36	9.37	9.41

Table 14. NPV of Grain Management Strategy Costs ($/t): Goodland, Parametric Bootstrap, Stabilized

			Calendar-based fumigation				Sampling-based IPM			
			No ω	Low ω	Medium ω	High ω	No ω	Low ω	Medium ω	High ω
1% Discount Rate										
Beginning resistance alleles present at 1%	δ = 0	65% F	-	20.84	21.51	57.06	-	22.67	22.60	23.33
		80% F	-	20.84	25.50	80.66	-	22.64	23.10	26.92
		95% F	-	20.84	20.84	41.68	-	22.55	22.72	22.64
	δ = 0.2	65% F	20.84	20.84	24.02	34.68	22.67	22.67	22.74	24.67
		80% F	20.84	20.84	31.04	49.23	22.64	22.64	24.11	30.70
		95% F	20.84	20.84	20.84	20.84	22.55	22.55	22.65	22.64
	δ = 0.8	65% F	20.84	21.27	36.92	51.94	22.59	22.58	25.17	31.42
		80% F	20.84	22.40	48.95	67.04	22.64	22.58	29.67	41.70
		95% F	20.84	20.84	20.84	20.84	22.65	22.66	22.60	22.56
Beginning resistance alleles present at 3%	δ = 0	65% F	-	20.84	24.02	35.60	-	22.67	22.82	25.15
		80% F	-	20.84	29.10	47.08	-	22.64	23.85	29.90
		95% F	-	20.84	20.84	20.85	-	22.55	22.72	22.64
	δ = 0.2	65% F	20.84	20.84	28.32	43.57	22.67	22.67	23.44	27.61
		80% F	20.84	20.86	35.19	56.21	22.64	22.64	25.44	34.58
		95% F	20.84	20.84	20.84	20.88	22.55	22.55	22.65	22.64
	δ = 0.8	65% F	20.84	22.33	44.40	62.06	22.59	22.62	27.93	37.46
		80% F	20.84	23.55	55.21	73.59	22.64	22.68	32.75	47.11
		95% F	20.84	20.84	20.88	21.10	22.65	22.66	22.60	22.60
10% Discount Rate										
Beginning resistance alleles present at 1%	δ = 0	65% F	-	9.36	9.47	10.64	-	10.14	10.14	10.28
		80% F	-	9.36	10.10	12.80	-	10.09	10.19	10.76
		95% F	-	9.36	9.36	9.36	-	10.18	10.21	10.14
	δ = 0.2	65% F	9.36	9.36	9.89	11.88	10.10	10.16	10.19	10.42
		80% F	9.36	9.36	11.17	14.85	10.15	10.15	10.32	11.54
		95% F	9.36	9.36	9.36	9.36	10.16	10.10	10.12	10.15
	δ = 0.8	65% F	9.36	9.43	12.19	15.32	10.14	10.11	10.54	11.63
		80% F	9.36	9.61	14.81	18.83	10.09	10.13	11.39	13.87
		95% F	9.36	9.36	9.36	9.36	10.18	10.08	10.11	10.14
Beginning resistance alleles present at 3%	δ = 0	65% F	-	9.36	9.88	12.05	-	10.14	10.18	10.61
		80% F	-	9.36	10.81	14.38	-	10.09	10.36	11.31
		95% F	-	9.36	9.36	9.36	-	10.18	10.21	10.14
	δ = 0.2	65% F	9.36	9.36	10.69	13.74	9.77	10.16	10.32	10.96
		80% F	9.36	9.36	12.07	16.57	9.79	10.15	10.56	12.34
		95% F	9.36	9.36	9.36	9.36	9.80	10.10	10.12	10.15
	δ = 0.8	65% F	9.36	9.61	13.98	17.77	9.79	10.12	11.03	12.84
		80% F	9.36	9.82	16.23	20.64	9.76	10.15	12.04	15.07
		95% F	9.36	9.36	9.36	9.39	9.81	10.08	10.11	10.14

Table 15. Discounted Aeration-Based IPM Costs

1% Discount	10% Discount
14.93	6.70

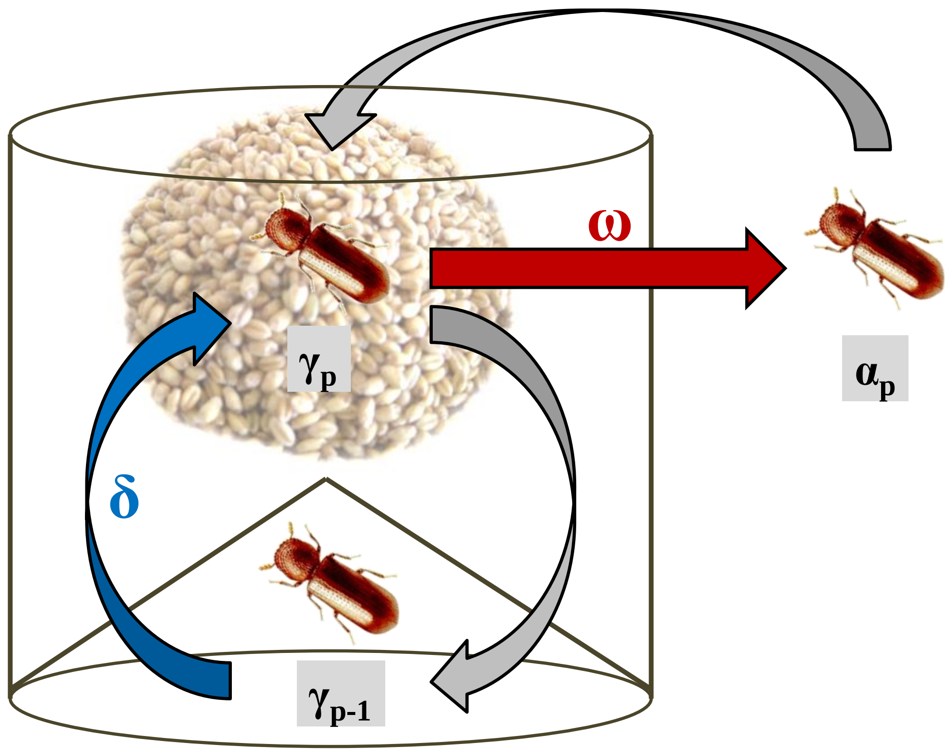

Figure 1. Hypothesized Population Dynamics of Lesser Grain Borer in Stored Wheat.

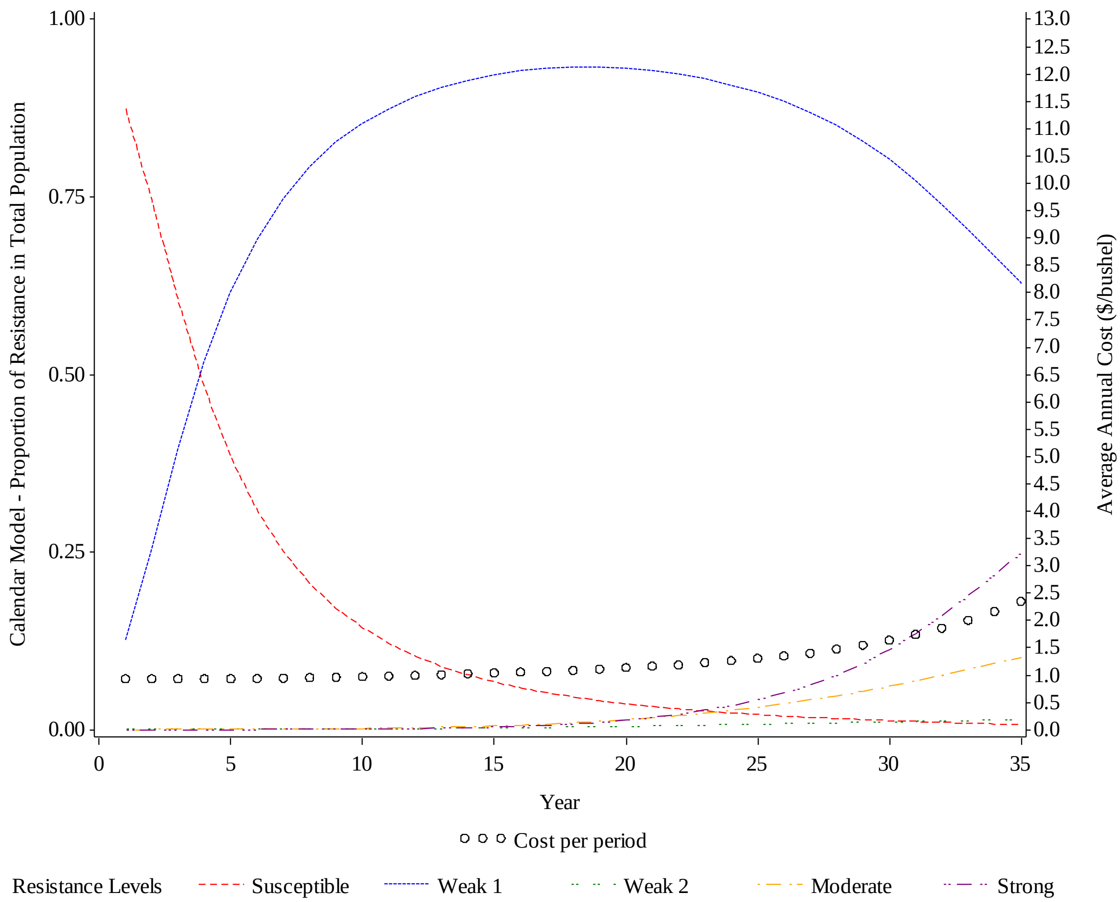

Figure 2. Resistance Development and Costs of Calendar-Based Fumigation for Oklahoma City, Under Scenario 1, Stabilized, Non-parametric Model, with 95% F, ω = 0.35, δ =0.8, and 3% Allele Starting Frequencies

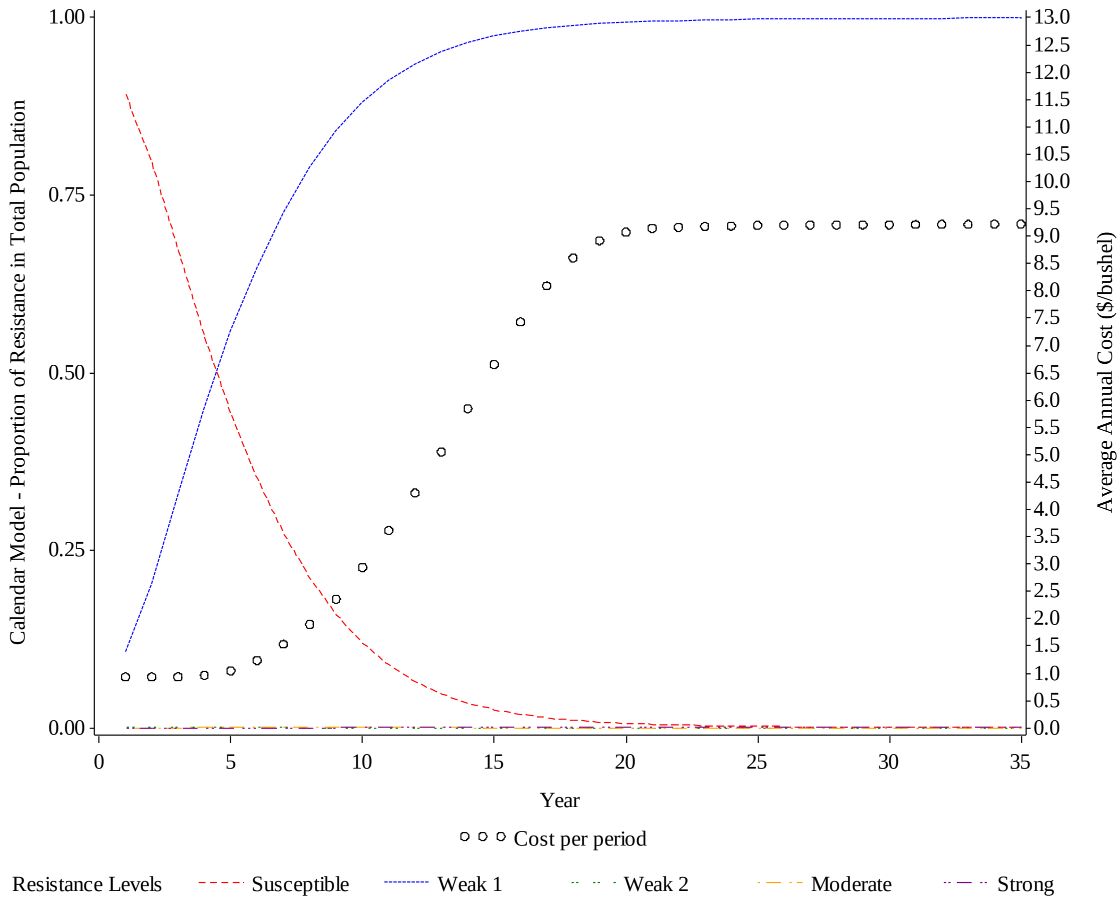

Figure 3. Resistance Development and Costs of Calendar-Based Fumigation for Oklahoma City, Under Scenario 1, Stabilized, Non-parametric Model, with 80% F, ω = 0.35, δ =0.8, and 3% Allele Starting Frequencies

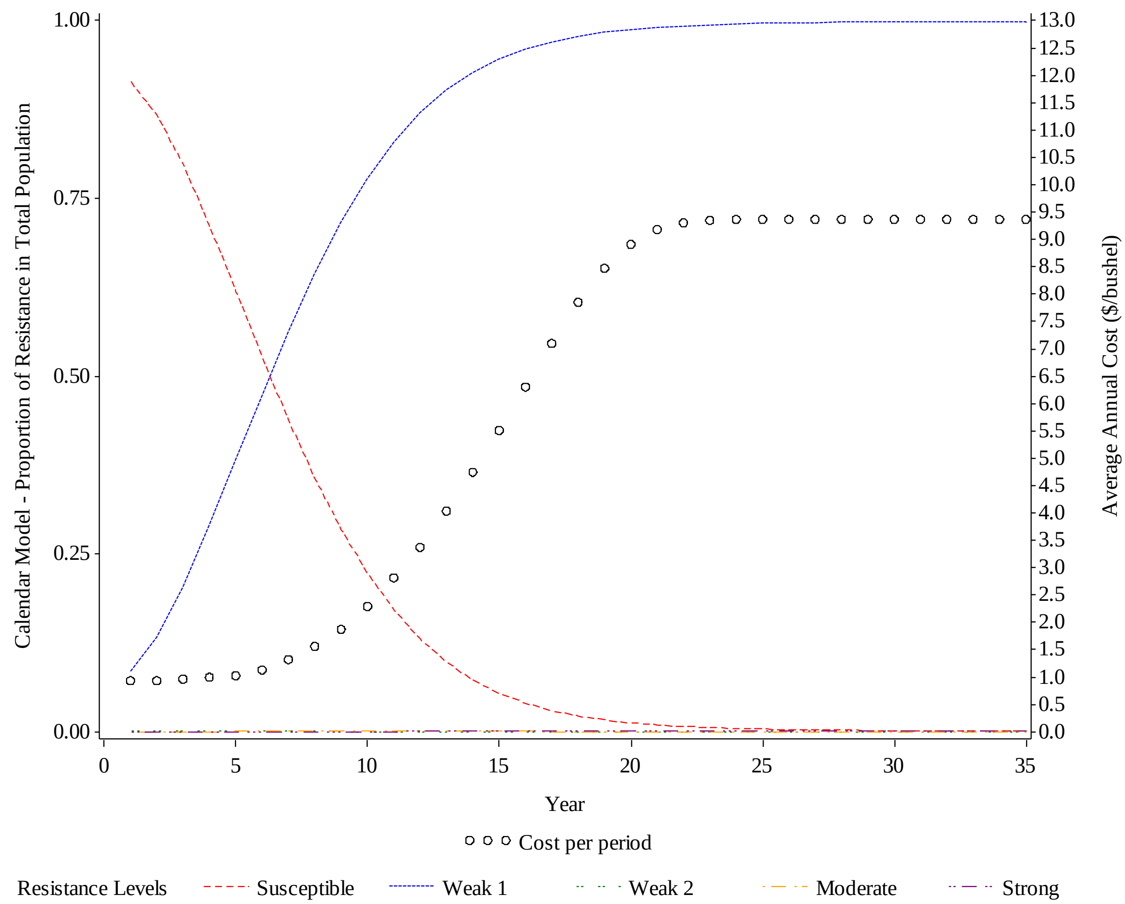

Figure 4. Resistance Development and Costs of Calendar-Based Fumigation for Oklahoma City, Under Scenario 1, Stabilized, Non-parametric Model, with 65% F, ω = 0.35, δ =0.8, and 3% Allele Starting Frequencies

CHAPTER III

STUDENT PREFERENCES FOR COLLEGE CREDIT COURSES

Introduction

The market for college-credit courses is in the process of a dramatic transition. This transition is the combined result of growing student demand for college courses and the availably of computer technology and the internet. In order to meet the growing student demand, many institutions are now including online courses and programs as part of their regular course offerings (Allen and Seaman 2010). However, the demand for online courses has recently been outpacing that for face-to-face (F2F) courses. As a result, many public and private institutions of higher education have significantly increased the number of online course offerings. In fact, between 2002 and 2008 distance education (DE) course enrollment grew from 9.6% to 25.3% of the total enrollment (Allen and Seaman 2010). Interestingly, this rise in demand for DE has not necessarily come from DE students. Many students living on college campuses chose to take distance courses (Bejerano 2008). Additionally, undergraduates have accounted for the majority of online course enrollment and this has been especially true for large public institutions (Allen and Seaman 2010).

While popularity for the online format has exploded, the debate over online course effectiveness has been still brewing. Although a small number of studies have reported that online courses are not suitable replacements for their face-to-face (F2F) counterparts (Anstine and Skidmore 2005; Brown and Liedholm 2002), the majority found that online courses are at least as effective as the F2F versions of the courses (Campbell et al. 2008; Coates et al. 2004; Lou, Bernard, and Abrami 2006; Means et al. 2009; Russell 1999; Summers, Waigandt, and Whittaker 2005). For traditional students at many institutions today, it has become common practice to substitute online courses for F2F versions of the same courses (Bejerano 2008).

There has been a lot of research about the advantages and disadvantages associated with online courses relative to their F2F counterparts (Anderson 2004; Ausburn 2004; Bernard et al. 2009; Campbell et al. 2008; Lou, Bernard, and Abrami 2006; Picciano 2002; Swan 2001). Although most researchers agree about what constitutes an effective online course, there are some potential misconceptions about online courses. In particular, it is commonly assumed that some level of uniformity exists across online courses and formats relative to their F2F counterparts (Russell 1999). Depending on the specific course features implemented, however, online learning environments can vary considerably from one another (Bernard et at. 2009). For example, the access students have to the course instructor or other students may not be equal across all online formatted courses.

Another concern is that most of the DE research has relied heavily on studies using measures of effectiveness (grades or satisfaction reports) to determine if online courses are substitutable for F2F courses. This eliminates the possibility that students' can directly contribute to the design of online courses before they are launched. Koehler et al. (2004) argued that collaboration between faculty and students is necessary to develop effective online courses. Because physical interactions and communication in the online learning environment is limited, these types of feedback are expected to help identify ways to reduce much of the uncertainly that faculty and students experience in the online environment.

Additionally, the tech-savvy millennial generation is very knowledge and have made significant contributions to a variety of modern information and communication technologies, such as web-based social networks, blogs, and streaming video (web 2.0 technologies) (Haythornthwaite and Andrews 2011; Jenkins et al. 2011). Many of these technologies are identical to design features of online courses. Further, texting, instant messaging, and emailing have become the primary means of communication for many young people. Therefore, college age students can provide valuable insight regarding online course inputs and their effects on the learning outcome.

Given the increase in the popularity of the online courses among both distant and on-site student population, and considering the limited published literature addressing what effect online courses have in common in terms of structure and format, the primary goal of this study is to identify student's preferences for online versus F2F course courses. More specifically, students' preferences and willingness to pay (WTP) for different attributes of online and F2F college-level courses are determined. Students' stated preferences are then used to determine how well online courses are perceived as substitutes for their F2F counterparts. As a secondary goal of this study, the impact on course selection based on the amount of online course information available to students during enrollment is determined.

In order to accomplish these objectives, a methodology allowing students to express preferences for specific course attributes is designed. One approach that can be used to evaluate student preferences for course attributes is the use of a choice experiment (CE) where college courses are considered goods with unique attributes and students are treated as the consumers of these goods. Within this framework, students can be exposed to a number of college course attributes and make choices based on their preferences.

This study is organized as follows. The background section includes a brief synopsis of the debate over the effectiveness of online versus F2F course. This is followed by an overview of the conceptual components of an effective online course including the empirical investigation of these concepts by Bernard et al. (2009). This section concludes with a brief discussion of others efforts to identify students WTP for features of F2F courses that are similar in nature to online courses. In the methodology section, the model used to estimate students WTP based on the CE is developed. This includes the construction of a utility model based on the online course characteristics as wells at the estimation procedure of a conditional logit model. In the data section, the survey instrument used to collect students' responses is describes and the some of the data collection challenges are identified. In the results and discussion section, the estimated model parameters for online and F2F courses are compared and the major trends are highlighted. In this section, the results are also compared to the findings of Bernard et al. (2009) as well as to those of the F2F students WTP studies. This paper is concluded with a brief summary of the findings and the potential policy implications based on these results.

Background

Defining an effective online course

Russell (1999) was one of the first researchers to review studies that had compared DE courses with F2F courses. From his study he concluded that there was no indication of a quantifiable difference regarding learning effectiveness, regardless of the method used, between the two types of formats. Although his work is more of a literature review, it was a platform that elevated the discussion about comparing online and F2F courses. Although the bulk of studies following Russell's work have supported his belief, a series of studies have since focused on evaluating online course effectiveness on student learning (Coates et al. 2004; Campbell et al. 2008; Lou, Bernard, and Abrami 2006; Means et al. 2009; Summers, Waigandt, and Whittaker 2005).

The core of most of these studies have been the evaluation of types of student interaction encouraged in online and F2F courses, and the effectiveness of each of these interactions on accomplishing the goals of the course. Moore (1989) was the first to define three types of student interactions: student-content (SC), student-instructor (SI), and student-student (SS). He believed that these interactions are necessary for the DE learning environment. Historically, SC interactions had been perceived as the most essential form of interaction as it was believed that this type of interaction was at the core of learning (Moore 1989).

Following the work of Moore (1989), Anderson (2004) identified student interactions, as they occur in the DE environment, in terms of specific DE technology.

Base on Anderson's (2004) descriptions, the following are examples of how three student interactions (SC, SI, and SS) first defined by Moore (1989) can occur using online course design technology: 1) course lecture notes made available to students via the online delivery platform (SC); 2) communication with the course instructor via email (SI); and 3) and group projects in which students communicate via email or threaded discussions (SS). Although Moore (1989) believed that SC interactions were the most important types of interaction in DE, much of the empirical research that followed have reported SI interactions followed closely by SS interactions were more important for online course success (Ausburn 2004; Campbell et al. 2008; Lou et al. 2006; Picciano 2002; Swan 2001).

As an effort to more broadly addresses the issue of which student interactions were most important for DE success, Bernard et al. (2009) conducted a meta-analysis of the DE literature. They investigated the differences in student interaction types among online courses and the impact that these differences had on students' grades and satisfaction reports. In their study, student interactions types were not categorized by specific technological attributes such as the instructor email communication or threaded discussion lead by the instructor, both of which are examples of SI interactions. Instead, they were grouped together based on the conceptual definitions of SC, SI, or SS provided by Moore (1989). Therefore, all interactions that occurred as SI were categorized the same regardless of the technology used to encourage it. What Bernard et al. found was that increasing SC interactions in the presence of low SI and SS interactions increased course effectiveness. However, increases in SI or SS interactions in the presence of low SC interactions did not necessarily improve course effectiveness. These results supported

Moore's original conclusions about the significance of SC interactions. One major consideration not addressed in this study is how differences within a particular interaction type, such as the SI interaction used above, may impact course effectiveness based on the specific technology used to facilitate the interaction. In other words, does the use of email correspondence with the instructor impact course effectiveness differently than participating in an instructor led threaded discussion?

Students' willingness-to-pay for course attributes

Only two studies were found that estimated students WTP for design features similar to those used in online courses (Boyer, Briggeman, and Norwood 2009; Flores and Savage 2007). However, both studies used data from students enrolled in F2F courses and only considered attributes allowing SC interactions. Flores and Savage (2007) considered two teaching alternatives and estimated students' WTP for recorded lecture videos (recorded during the same semester). The teaching alternatives were based on students attending class with and without access to the recorded lecture video. Their data was from a survey of 39 undergraduate students in an intermediate microeconomics course who were asked about their use of the recorded lecture videos during the summer 2005 semester. Flores and Savage reported that 77% of the students actually watched the videos and students were willing to pay about $74 for access.

Boyer, Briggeman, and Norwood (2009) estimated students' WTP for seven course attributes, including price and three others similar to the features of online courses (web-based study guide, electronic class notes, and pod casts of the lecture videos). Their survey data included responses from 302 students in economics courses at four universities. They found students were willing to pay, on average, $62 for a web-based study guide, $45 for electronic class notes, and $18 for pod casts of lecture videos.

Methods and Procedures

The choice experiment (CE) approach to course-attribute valuation

Choice experiments have been used extensively in marketing, transportation, environmental, and agriculture literature to determine values people place on different goods (for examples of each see Hanley, Wright, and Adamowicz 1998; Hensher and Greene 2003; Louviere and Woodworth 1983; Lusk, Roosen, and Fox 2003). Similarly, CEs can be used to determine the value that students place on different attributes of college courses (both online and F2F). When college students enroll in classes, they make choices based on the provided information as well as their perceptions about different attributes of the course selections. Students' preferences for these attributes are based on the importance they place on courses given a particular sets of attributes and relative to other courses with different sets of attributes. The use of choice experiments in this context, allows the college course enrollment process to be simulated and the students' choice process captured. The results of the experiment can then be used to determine students' preferences and WTP for online and F2F course attributes.

Based on the student preferences and WTP results, a comparison can be made to other studies within the DE literature that have used course effectiveness measures, such as grades and satisfaction reports, to determine which interaction types are most important for online course effectiveness. In order to make these comparisons, online course attributes need to be translated in terms of one of the three student interaction types. Following the example of Anderson (2004), the design features (course attributes) of an institution's online course delivery platform [for this study Oklahoma State University's Desire-to-Learn (D2L) platform] that facilitate specific interactions can be identified and categorized as SC, SI, or SS. Based on this attribute categorization, students' preferences (and WTP) can then be compared to other research that has used effectiveness measures and conceptual student interaction definitions.

Predicting student preference based on the distance education literature

Based on the results of Bernard et al. (2009), students' preferences for SC type attributes (e.g. lecture video or online course notes) would be expected to be the highest, while preferences for SI and SS type attributes (e.g. student live chart or discussion board) would be expected to be the lowest. It is also reasonable to expect, based on the Bernard et al. results, that students would prefer attributes of a particular interaction type that allowed for higher quality or frequency of interaction compared to those of the same type that resulted in lower quality or frequency of interaction. For example, communication via live chat compared to email correspondence could allow for a student to perceive a higher frequency of an SI interaction since questions or concerns can be addressed more rapidly. Another example is the comparison between lecture videos and notes. Students may perceive a higher quality of an SC interaction to occur when watching a lecture video that explains a complicated topic compared to reading course lecture notes with the same information that was provided in the video.

Identifying the preferences for specific attributes will allow for students' broader preference for the online course to be determined. Bernard et al. demonstrated that the high variance of online course effectiveness resulted from interaction type variability across online courses. Given the level of each interaction type, an online course may be less, more, or as effective as its respective F2F counterpart. From the framework of students as consumers of college courses, students' preferences can be determined and used to estimate demand for college courses, given a specific set of course attributes (this methodology is similar to Lusk, Roosen, and Fox 2003). Using the work of Bernard et al. (2009) as a guide, estimations using different combinations of course attributes can demonstrate variations in preferences for particular courses and possibly explain variations in student performance.

Using this methodology and estimation results, predictions of online course enrollment can also be made based on the amount of information provided to students when selecting courses. It is well understood in the consumer economics literature that increasing the amount of attribute information provided to consumers can impact product selection (Arunachalam, Henneberry, Lusk, and Norwood 2009; Levin and Gaeth 1988). Therefore, it is reasonable to expect that students with more information about the available attribute bundles of online course will select online courses more frequently than F2F courses.

Experimental design and the conditional logit model

In this study, a conditional logit model was used to estimate students' preferences and WTP for college course attributes based on the data obtained from the CE. The estimated preferences were then used to: 1) determine students' for online courses compared to their F2F counterparts (the primary goal of this study); and 2) determine how course selection based on the amount of online course information available to students is impacted during enrollment (the secondary goal of this study). In the CE, students were presented with discrete choices between three alternatives: an online course, a F2F course, and an option to choose none. Each course was made up of a number of attributes that varied between the sets of choices while the “choose none” option (which was normalized to zero in the estimation procedure) provided that the model was fully identified. Within the framework of the CE, it was assumed that students made the selection which maximized their utility for each choice

Additionally, students were separated into two groups and presented with two different information sets regarding the attributes of online courses. This allowed for a comparison between students selecting online courses with minimal online course attribute information and students with additional online course attribute information. The first group was only given information about the online course topics and the number of other students enrolled in the course. At the time of enrollment, students would not really know what the final class size is but they would know, based on the provided information, what the maximum class size could reach. The assumption in this study is that students would make their class size decisions based on the maximum class size value. The second group was proved with the same information as the first, but they were also informed about the additional attributes available for each online course. The information given to students about the F2F courses was the same for each group (see Table 16(a) and Figures 5 and 6).

Estimating students' preferences for course attributes

A random utility function specifying a student's utility was defined as follows:

(1) $$U_{ij} = V_{ij} + \varepsilon_{ij}$$

where U_{ij} is the utility of student i making choice j, for $i = 1, \dots, N$ and $j = 1, \dots, J$; V_{ij} is the deterministic component of the utility function made up of the course attributes of option *j* and potential student-specific characteristics (V_{ij} is equal to zero when the choose none option is made); and ε_{ij} is the stochastic component consisting of unobserved qualities. McFadden (1973) demonstrated that if the stochastic component is independently and identically distributed across all *N* students and *J* options with Gumbel (type I extreme value) distribution, then the probability that a student selects option j is given by:

$$\text{(2)} \qquad \text{Prob}\{\text{choose option } j\} = \frac{\exp(\lambda V_{ij})}{\sum_{k=1}^{J} \exp(\lambda V_{ik})}$$

where λ is a scale parameter that is not separately determined from the parameters of attributes and is inversely related to the stochastic term in the utility function. In this study, the value of λ was assumed to be constant across the sub-groups of undergraduate students.

The deterministic component of the utility function (V_{ij}) that appears in equation (2) is specified based on the scenarios presented in the choice experiment. The scenario one model is:

$$\text{(3)} \qquad V_{ij} = \sum_{p=1}^{2} \alpha_{0p} D_{ijp} + \sum_{q=1}^{8} \alpha_{1q} FC_{ijq} + \sum_{r=1}^{8} \alpha_{2r} OC_{ijr} + \sum_{s=1}^{4} \alpha_{3s} FM_{ijs}$$
$$+ \sum_{t=1}^{4} \alpha_{4t} FT_{ijt} + \alpha_5 FZ_{ij} + \alpha_6 OZ_{ij} + \alpha_7 P_{ij}$$

where D_{ijp} is an indicator variable for the course delivery format (online or F2F); $FC_{ijq}$and OC_{ijr} are indicator variables for the undergraduate F2F and online course topics offered respectively; FM_{ijs} is an indicator variable for the number and days per week the F2F classes meet; FT_{ijt} is an indicator variable for the times of day the F2F classes meet,

FZ_{ij} and OZ_{ij} are the sizes of the F2F and online classes respectively (number of students enrolled); P_{ij} is the price for a three-hour college credit course; and α_{0p}, α_{1q}, α_{2r}, α_{3s}, α_{4t}, α_5, α_6, and α_7 are the parameters to be estimated. The model for scenario two is an expanded version of the scenario one model and includes additional online course attributed as follows:

$$(4) \qquad V_{ij} = \sum_{p=1}^{2} \beta_{0p} D_{ijp} + \sum_{q=1}^{8} \beta_{1q} FC_{ijq} + \sum_{r=1}^{8} \beta_{2r} OC_{ijr} + \sum_{s=1}^{4} \beta_{3s} FM_{ijs} + \sum_{t=1}^{4} \beta_{4t} FT_{ijt}$$
$$+ \sum_{u=1}^{4} \beta_{5t} OL_{iju} + \beta_{61} ON_{ij} + \beta_{62} OI_{ij} + \beta_{63} OE_{ij} + \beta_{64} OB_{ij} + \beta_{65} OD_{ij}$$
$$+ \beta_{66} OS_{ij} + \beta_7 FZ_{ij} + \beta_8 OZ_{ij} + \beta_9 P_{ij}$$

where OL_{iju}, ON_{ij}, OI_{ij}, OE_{ij}, OB_{ij}, OD_{ij}, and OS_{ij}, are indicator variables for the online course options of lecture videos, lecture notes, instructor live chat, take exams online, discussion board, and student live chat respectively; and β_{0p}, β_{1q}, β_{2r}, β_{3s}, β_{4t}, β_{5t}, β_{61}, β_{62}, β_{63}, β_{64}, β_{65}, β_{66}, β_7, β_8, and β_9 are parameters to be estimated. The MDC procedure in SAS was used to estimate both these models but it does not automatically assign an intercept. In both equations (3) and (4), the D_{ijp} indicator variable is included in the data set and the resulting estimated parameter is the intercept for each course format.

The objective function to be maximized is the log likelihood of equation (2) given the option choices of each student across the entire sample population:

$$(5) \qquad \max_{\boldsymbol{\theta}} \sum_{i}^{N} \sum_{j}^{J} C_{ij} \log\left(\frac{\exp(\lambda V_{ij})}{\sum_{k=1}^{J} \exp(\lambda V_{ik})}\right)$$

where C_{ij} is the choice of option j by student i and $\boldsymbol{\theta}$ is a vector of the parameters from equation (3) (estimates scenario one model) or equation (4) (estimates scenario two model). Students' WTP is for each course attributes (WTP_a) is given by:

$$(6) \qquad WTP_a = -\frac{\beta_a}{\beta_p}$$

where $\beta_a$is the parameter for course attribute a and β_p is the price parameter. Following Greene (2003), the variance of WTP is obtained using the delta method:

$$(7) \qquad \text{var}(WTP_a) = \left(\frac{-1}{\beta_p}\right)^2 \text{var}(\beta_a) + \left(\frac{\beta_a}{{\beta_p}^2}\right)^2 \text{var}(\beta_p) - 2\left(\frac{\beta_a}{{\beta_p}^3}\right)\text{cov}(\beta_a, \beta_p)$$

(Hole 2007 reported that the delta method out performs others procedures for estimating the variance of WTP). From equation (7), WTP confidence intervals can be calculated making testing hypotheses about students' preferences for specific design features of online courses straightforward and obvious from the results tables.

Determining the impact of additional information on course selection

The is secondary goal of this study is to determine, during the course selection process, how the amount of online course information available to students impacts the type of course, F2F or online, that is selected. In order to achieve this goal, a simulation was constructed allowing a comparison to be made between the group of students with limited online course information and those with additional online courses information. To make this comparison, two different hypothetical courses with specific course attributes were created. For each hypothetical course, an online version and F2F counterpart were created. In Table 16(a), the specific course attributes of the F2F and online versions of the two courses are shown.

The specific attributes for the two courses were selected in a semi-random process without replacement (so the same options could be selected twice) as follows. The course topics were selected from the nine available options. However, the F2F meeting times and days per week were selected from a pool of the three most common attributes for each category (8:30 AM, 11 AM, and 1:30 PM for the time and M, TR, MWF for the days per week). This restriction (as well as the one for the online course attributes described below) was included to provide a more realistic comparison of F2F and online courses. For example, a 6 PM weekend course would not be the most common type of F2F course. The options for the online course attributes were put into three categories: above average, average, and below average. The above average category included all of the online course attributes, including the most popular video category. The average category included attributes that are commonly used in many of the online courses offered at OSU, which includes the F2F lecture video (Hawkins 2011). The below average category only included the F2F lecture video and course lecture notes attributes. The bundles of attributes for each of the two courses course, based on these three categories, were randomly selected.

Using equation (2) and the parameter estimates for the specific course attributes, a set of probabilities were generated based on choosing: 1) an online course; 2) a F2F course; and 3) the "none" option (note that the sum of all three choices in a given set is equal to 1). The parameter estimates for the limited information group were generated from equation (3) while those for the additional information group were generated from equation (4). Based on the two different hypothetical courses and the two groups of students with different online course attribute information, the simulation generated four sets of probabilities for comparison.

Data

Data for this study are the undergraduate student responses from two parts of three-part survey of OSU-Stillwater Students conducted in November 2010. The surveys were distributed via email and included a link to SurveyMonkey where the survey had been constructed. That same semester, OSU implemented a new student email policy which greatly restricts researchers' access and frequency of contact to students via campus email. Contact was limited to a single email invitation with no opportunity for follow-up. For the two parts of the survey used in this study, emails were sent to the full student population (graduate and undergraduate students) over a six hour window. This included the approximately 10,900 undergraduate students (the value used to estimate the response rate, 10,827, was based on the student demographic information provided by the Department of Institutional Research and Information Management as OSU). The survey remained opened for approximately two weeks and in all, 1291 undergraduate students completed questionnaires (11.9% response rate). To maximize the response rate, given the limited student access, an Apple iPad was used an incentive for completing the survey and given away in a random drawing after the survey was closed. The basic demographic information of the undergraduates who completed the survey is presented in Table 16(b).

The online course design features of the OSU D2L platform were the basis for the specific online course attributes that allowed each of the three student interaction types (SC, SI, and SS) to occur. The other course attributes of F2F and online courses were based on the information provided to students at the time of enrollment. All registered

OSU students have access to the Student Self-Services (SIS) webpage which allows students to enroll in courses offered at OSU. This includes F2F as well as online courses. The information provided on the SIS webpage includes the basic course title, the meeting time and days per week the class meets, the number of available seats out of the total number of seats in the course, the meeting location and the name of the instructor teaching the course. For this study, the last two items in this list were not of significance and were not included in the survey questionnaires. It is also important to point out here that information about the specific design feature included in the online course can only be obtained by contacting the instructor of the course directly.

Although the goal was to capture as much real world attribute information as possible, a method to significantly reduce the large number of course titles available to undergraduate students was needed. Therefore, the course titles provided to students in the survey were based on the categories of general education requirements that the majority of OSU students must meet (nine in all). In the survey, the general education categories were referred to as the course topic.

Additionally, the design style of the choice questions including the type of information provided about online and F2F courses was based on the look of the SIS webpage (see Figures 5 and 6). For the second survey, the additional online course attribute information, based on the technological capabilities of the OSU D2L platform to provide SC, SI, and SS interactions, was presented to students in a way that was consistent with the SIS webpage design style.

To tests the hypotheses proposed in this study, students needed to be presented with a large number of course attributes. However, the number of choice questions combined with the additional student information questions needed to be low enough that students would actually complete the survey. This posed a significant survey design challenge. Using the FACTEX and OPTEX procedures in SAS (with the blocks structure feature), the choice questions were divided into blocks while maintaining an overall D-efficiency (see Kuhfeld, Tobias, and Garratt1994 for D-efficient experimental designs) of at least 90% (SAS Institute). For the first survey, six blocks of eight questions were generated and had a D-efficiency of 90%. For the second survey, six blocks of nine questions were generated with a D-efficiency of 92%.

One limitation of the delivery platform used (SurveyMonkey) was that it did not allow for a conjoint analysis type survey with the variety of courses attributes being presented to students in this study. To compensate for this limitation, images of the course choice questions were created that matched the factional factorial models of each survey with respect to the specific course attributes used. However, this also meant that students would not receive the choice questions in a randomly generated order.

Results and Discussion

Students Preferences and WTP for Courses and Course Attributes

Undergraduate students' preferences and WTP for course attributes are presented in Tables 17(a), 17(b), 17(c) and 17(d). The WTP values presented in these tables should be interpreted as the premiums students are willing to pay (when positive) or discounts needed (when negative) for college courses with these particular attributes relative to the base course (a scientific investigation course offered at 11 A.M. on Tuesdays and Thursdays). Since the individual attributes are part of the total course package, it is possible to see from the results tables how different combinations of course attributes will impact student demand for various courses.

There are a number of general trends regarding students' preferences for course attributes observable from these results. Regarding class time and the number of days per week for F2F courses, undergraduate students have the highest preference for those that meet late morning (11 AM) or early afternoon (1:30 PM) and meet two (Tuesday and Thursday) or three (Monday, Wednesday, and Friday) days per week. Regarding the subject of the courses, courses categorized as scientific investigation are most preferred in a F2F versus an online environment. Regarding course delivery methods, undergraduates also have the highest preference for short and medium videos (10-20 minutes and 20-30 minutes). Regarding WTP, on average, they are willing to pay about $120-$150 for videos depending on type. This differs from the results of the undergraduate F2F students' WTP values of $18 and $74 reported by Boyer, Briggeman, and Norwood (2009) and Flores and Savage (2007) respectively. The other difference is that undergraduate students' average WTP for course lecture notes in this study is about $90 while Boyer, Briggeman, and Norwood (2009) reported WTP values of about $45.

In the context of student interactions, the results in this study indicate that SC interactions (lecture videos and course notes) are the most preferred interaction type followed by SS (student live chat room and threaded discussion) and SI (instructor live chat) interactions. Within interactions types, all forms of videos are preferred over online course lecture notes, and the student live chat room attribute is preferred over the student-led threaded discussion attribute. For the most part, these results match up with the findings of Bernard et al. (2009) and the original conclusion of Moore 1989. However, Bernard et al. (2009) reported that SI interactions are more important than SS interactions from the course effectiveness framework, but the differences in this study between preferences for SS and SI interactions are small.

Impact of Information on Selecting Online Courses

The simulated demand for online courses based on specific courses attributes (see Table 18) and using the estimated preferences from Tables 17(c) and 17(d) are presented in Table 19. For each course, the simulation generated a limited-information set of probabilities and an expanded-information set of probabilities. Given a specific course (either course one or course two), comparisons can be made between delivery methods (F2F or Online) with in a probability set and between probability sets under the same delivery method.

Under the limited-information group for course one the probabilities are very close between students selecting the online and F2F courses. However, this particular comparison narrowly favors students selecting the online course. For this same course under the expanded-information group, the gap is much larger and still favors student selecting the online course over the F2F course. For course two and under the limited-information group, the gap between the online and F2F course is large and favors the F2F course. Under the expanded-information group for this same course, the gap is closer but still favors the F2F course.

The results of this simulation indicate that when students receive more information about specific course attributes during the course-selection process, their likelihood of choosing an online course compared to the F2F version increases. However, this result is also conditional on the presence of specific online course attributes that students value most. These results also suggests that depending on the specific course attributes present, including the course topic, students may actually prefer some courses in online versus F2F formats. The presence of specific course attributes may also shed some light on the causes of the amount of variation in effectiveness across online courses detected by Bernard et al. (2009). If students' preferences are any indication of course effectiveness, then the absence or presence of specific course attributes given students preferences for them, may be the cause of some of this variation.

Summary and Conclusions

The primary objective of this study was to determine students' preferences and WTP for online and F2F college-level course attributes. The secondary objective was to determine how the amount of information that students have about online course attributes during enrollment impact their selection of college-level courses. The motivation for the first objective was to present an alternative strategy, based on students' preferences, to determine how well online courses can substitute for F2F courses. The majority of DE studies have depended heavily on after-the-fact feedback, such as students' grades and satisfaction reports, to make this determination. Additionally, students have considerable experience with information and communication technology and, based on their experiences, can potentially make valuable contributions to the design process of online courses. The motivation for the secondary objective comes from the practical experiences that the researchers involved in this study have with regard to the amount online course attribute information available to students during enrollment.

To accomplish the objectives of this study, data consisting of undergraduate students responses to a survey that included a CE were used. Although OSU

Communication policy restricted the contact with students which limited the response rate to about 12%, nearly 1300 students completed the surveys. Additionally, the demographic make-up of respondent population was similar to that of the full undergraduate population.

Based on the results of this study, there are four trends with respect to students' preferences for college credit course that may provide insight to higher education faculty and administrators. First, there is an apparent premium time-period (between late morning and early afternoon) and number of days-per-week (two-three days during the week) that students prefer to take F2F courses. As demonstrated by the simulation, however, the probability that students would select an online version of a course increased as the number of technological attributes included in online course increased. This suggests that institutional efforts to use online courses to help meet on-site student demand would be more accepted by students when the online courses attributes students desire most are included.

Second, it appears that students prefer some courses in the F2F format and others in the online format. For example, the scientific investigation course topic was one of the most popular in the F2F format and the least popular in the online course format. On the other hand, humanities and natural sciences were two of the more popular course topics in the online format. For institutions wishing to develop and expand their online course offerings, increases the number of courses that students identified as most popular in the online format might be appropriate. Another consideration is the pricing strategy. For some universities, considering adjusting fees that reflect student demand for particular types of courses instead of being based on the college offering the course may be appropriate.

Third, students demonstrated the highest preferences for online course attributes that facilitated SC-type interaction. In fact, the online course attribute that was valued the most by students was shorter (10-20 minute) customized topic-videos. For many institutions wishing to differentiate their online courses and programs from other universities, customizing video as well as other online course attributes may be an important consideration.

Fourth, students selected online courses more frequently when additional information about online course attributes is available during courses selection, and when the attributes students value most are included. This last result also implies that, depending on the specific courses attributes included in the course, online courses may be more popular, considered about the same, or less popular than their F2F counterparts. This is an important consideration for institutions wishing to encourage enrollment in online courses.

In light of the fact that many higher education institutions have a strong incentive to develop and expand their online programs and offerings (Allen and Seaman 2010), using students input to help develop online course formats may be a necessary consideration. Although the students preferences determined in this study were based on design features of the OSU D2L platform, the model presented here has the flexibility to accommodate other kinds of online and F2F course attributes. Further, as the technology available to designers of online courses continues to change, re-evaluating students' preferences for college course attributes is a worthy endeavor.

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Table 16(a). Online and Face-to-Face Course Attribute Options in Choice Questions

Undergraduate course topic	*Additional online course attributes*
English Composition & Oral Communication	1-10 minute topic discussion video (SC)
American History & Government	10-20 minute topic discussion video (SC)
Analytical & Quantitative Thought	20-30 minute topic discussion video (SC)
Humanities	Recorded face-to-face lecture (SC)
Natural Sciences	Online course lecture notes (SC)
Social & Behavioral Sciences	Chat-room with instructor (SI)
Diversity	Chat-room with classmates (SS)
International Dimension	Threaded discussions with classmates (SS)
Scientific Investigation	Take exams and quizzes online
Time face-to-face course is offered	Online drop box for assignment
8:30 AM	*Other attributes of both courses*
11:00 AM	Number of students enrolled in course
1:30 PM	Price for a three hour course
4:00 PM	
6:30 PM	
Days per week face-to-face course meets	
M/150 minute class	
TR/75 minute classes	
MWF/50 minute classes	
MTWRF/30 minute classes	
Weekend class	

Table 16(b). Demographics of Students Completing the Surveys

Group	Survey	Actual[a]
Freshman	18.41%	20.51%
Sophomore	12.33%	17.69%
Junior	17.08%	19.71%
Senior	23.55%	22.51%
Female	56.22%	48.22%
Male	43.78%	51.78%
Resident[b]	70.81%	72.06%
Out-of-state	20.01%	19.99%
International	9.18%	7.95%

[a] From OSU student profile fall 2010.

[b] Based on all OSU campuses enrollment.

Table 17(a). Conditional Logit Parameter Estimates for College Course Attributes (Survey 1)

Parameter Name	Online		Face-to-face	
	Estimate	Standard Error	Estimate	Standard Error
Undergraduate course topic				
English Composition & Oral Communication	0.1045	(0.1319)	-0.1690	(0.1223)
American History & Government	0.5799***	(0.1302)	-0.1941	(0.1250)
Analytical & Quantitative Thought	0.0135	(0.1222)	-0.3182**	(0.1252)
Humanities	0.4099***	(0.1276)	-0.0145	(0.1255)
Natural Sciences	0.4519***	(0.1343)	-0.0768	(0.1287)
Social & Behavioral Sciences	0.3344**	(0.1321)	-0.2424***	(0.1294)
Diversity	0.4965***	(0.1273)	0.0219	(0.1346)
International Dimension	0.3331***	(0.1258)	-0.3386***	(0.1313)
Class size	-0.0010	(0.0015)	-0.0018	(0.0015)
Time face-to-face course is offered				
8:30 AM			-0.4824***	(0.0949)
1:30 PM			-0.1777*	(0.0964)
4:00 PM			-0.4013***	(0.0950)
6:30 PM			-0.6946***	(0.0950)
Days per week face-to-face course meets				
M/150 minute class			-0.4386***	(0.0909)
MWF/50 minute classes			-0.1495*	(0.0911)
MTWRF/30 minute classes			-0.5138*	(0.0926)
Weekend class			-1.2810*	(0.1024)
Price for a 3 credit hour class	-0.0032***	(0.0003)	-0.0032***	(0.0003)
Intercept	4.4544***	(0.2957)	5.3392***	(0.2962)
Log Likelihood	-4503			

Results are relative to: social and behavioral science (course topic), 11:00 AM (face-to-face time), Tuesday and Thursday (face-to-face days/week).

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 17(b). Estimated WTP and 95% CI for College Course Attributes (Survey 1)

Parameter Name	Online		Face-to-face	
	WTP	95% CI	WTP	95% CI
Undergraduate course topic				
English Composition & Oral Communication	$32.39	(-$47.67, $112.44)	-$52.35	(-$128.03, $23.33)
American History & Government	$179.65	($94.87, $264.44)	-$60.14	(-$137.05, $16.77)
Analytical & Quantitative Thought	$4.19	(-$69.97, $78.35)	-$98.58	(-$178.70, -$18.46)
Humanities	$127.01	($46.31, $207.72)	-$4.49	(-$80.72, $71.75)
Natural Sciences	$140.01	($54.77, $225.24)	-$23.79	(-$102.34, $54.77)
Social & Behavioral Sciences	$103.62	($22.36, $184.88)	-$75.09	(-$155.28, $5.09)
Diversity	$153.83	($71.60, $236.05)	$6.80	(-$74.91, $88.50)
International Dimension	$103.20	($24.10, $182.30)	-$104.90	(-$187.60, -$22.19)
Class size	-$0.32	(-$1.21, $0.58)	-$0.55	(-$1.50, $0.39)
Time face-to-face course is offered				
8:30 AM			-$149.46	(-$214.26, -$84.65)
1:30 PM			-$55.04	(-$115.06, $4.98)
4:00 PM			-$124.32	(-$187.11, -$61.53)
6:30 PM			-$215.21	(-$287.36, -$143.05)
Days per week face-to-face course meets				
M/150 minute class			-$135.89	(-$197.28, -$74.51)
MWF/50 minute classes			-$46.32	(-$102.58, $9.95)
MTWRF/30 minute classes			-$159.19	(-$224.92, -$93.46)
Weekend class			-$396.90	(-$499.22, -$294.57)

Results are relative to: social and behavioral science (course topic), 11:00 AM (face-to-face time), Tuesday and Thursday (face-to-face days/week).

Table 17(c). Conditional Logit Parameter Estimates for College Course Attributes (Survey 2)

Parameter Name	Online		Face-to-face	
	Estimate	Standard Error	Estimate	Standard Error
Undergraduate course topic				
English Composition & Oral Communication	0.1411	(0.1303)	0.0538	(0.1257)
American History & Government	0.0551	(0.1299)	0.1844	(0.1236)
Analytical & Quantitative Thought	0.1258	(0.1248)	0.1380	(0.1277)
Humanities	0.3280**	(0.1338)	-0.0385	(0.1255)
Natural Sciences	0.2193*	(0.1255)	0.0547	(0.1251)
Social & Behavioral Sciences	0.1730	(0.1256)	-0.0251	(0.1257)
Diversity	0.1149	(0.1291)	-0.0461	(0.1250)
International Dimension	0.1101	(0.1241)	-0.1157	(0.1263)
Class size	0.0008	(0.0015)	-0.0020	(0.0015)
Additional online course attributes				
1-10 minute topic discussion video (SC)	0.3889***	(0.0944)		
10-20 minute topic discussion video (SC)	0.4481***	(0.0939)		
20-30 minute topic discussion video (SC)	0.4087***	(0.0936)		
Recorded face-to-face lecture (SC)	0.3549***	(0.0954)		
Online course lecture notes (SC)	0.2638***	(0.0587)		
Chat-room with instructor (SI)	0.2021***	(0.0571)		
Chat-room with classmates (SS)	0.1423**	(0.0589)		
Threaded discussions with classmates (SS)	0.1871***	(0.0581)		
Take exams and quizzes online	0.1423**	(0.0596)		
Online drop box for assignment	0.2035***	(0.0577)		
Time face-to-face course is offered				
8:30 AM			-0.3255***	(0.0934)
1:30 PM			-0.0035	(0.0906)
4:00 PM			-0.2940***	(0.0891)
6:30 PM			-0.5162***	(0.0924)
Days per week face-to-face course meets				
M/150 minute class			-0.3142***	(0.0900)
MWF/50 minute classes			-0.1052	(0.0941)
MTWRF/30 minute classes			-0.3616***	(0.0951)
Weekend class			-1.1692***	(0.0953)
Price for a 3 credit hour class	-0.0029***	(0.0003)	-0.0029***	(0.0003)
Intercept	3.2332***	(0.2946)	4.8091***	(0.3040)
Log Likelihood	-4813			

Results are relative to: social and behavioral science (course topic), 11:00 AM (face-to-face time), Tuesday and Thursday (face-to-face days/week), and absence of any additional online course attributes.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 17(d). Estimated WTP and 95% CI for College Course Attributes (Survey 2)

Parameter Name	Online		Face-to-face	
	WTP	95% CI	WTP	95% CI
Undergraduate course topic				
English Composition & Oral Communication	\$48.02	(-\$38.56, \$134.59)	\$18.29	(-\$65.56, \$102.14)
American History & Government	\$18.75	(-\$68.00, \$105.49)	\$62.72	(-\$19.85, \$145.29)
Analytical & Quantitative Thought	\$42.80	(-\$40.90, \$126.49)	\$46.94	(-\$39.08, \$132.96)
Humanities	\$111.58	(\$20.10, \$203.06)	-\$13.11	(-\$96.83, \$70.61)
Natural Sciences	\$74.61	(-\$10.35, \$159.57)	\$18.62	(-\$65.00, \$102.23)
Social & Behavioral Sciences	\$58.85	(-\$25.74, \$143.43)	-\$8.54	(-\$92.32, \$75.25)
Diversity	\$39.08	(-\$47.33, \$125.50)	-\$15.67	(-\$99.03, \$67.69)
International Dimension	\$37.47	(-\$45.91, \$120.85)	-\$39.35	(-\$124.42, \$45.72)
Class size	\$0.26	(-\$0.72, \$1.24)	-\$0.68	(-\$1.67, \$0.31)
Additional online course attributes				
1-10 minute topic discussion video (SC)	\$132.32	(\$65.53, \$199.11)		
10-20 minute topic discussion video (SC)	\$152.45	(\$83.99, \$220.91)		
20-30 minute topic discussion video (SC)	\$139.05	(\$69.28, \$208.82)		
Recorded face-to-face lecture (SC)	\$120.74	(\$53.64, \$187.85)		
Online course lecture notes (SC)	\$89.75	(\$46.67, \$132.84)		
Chat-room with instructor (SI)	\$68.77	(\$27.76, \$109.78)		
Chat-room with classmates (SS)	\$48.42	(\$7.65, \$89.18)		
Threaded discussions with classmates (SS)	\$63.65	(\$22.68, \$104.62)		
Take exams and quizzes online	\$48.42	(\$6.66, \$90.18)		
Online drop box for assignment	\$69.22	(\$27.84, \$110.61)		
Time face-to-face course is offered				
8:30 AM			-\$110.75	(-\$175.69, -\$45.81)
1:30 PM			-\$1.20	(-\$61.58, \$59.19)
4:00 PM			-\$100.01	(-\$160.25, -\$39.78)
6:30 PM			-\$175.63	(-\$244.66, -\$106.60)
Days per week face-to-face course meets				
M/150 minute class			-\$106.90	(-\$171.57, -\$42.23)
MWF/50 minute classes			-\$35.80	(-\$99.55, \$27.95)
MTWRF/30 minute classes			-\$123.03	(-\$192.34, -\$53.72)
Weekend class			-\$397.78	(-\$503.15, -\$292.41)

Results are relative to: social and behavioral science (course topic), 11:00 AM (face-to-face time), Tuesday and Thursday (face-to-face days/week).

Table 18. Course Attributes Used to Simulate Online and F2F Course Demand

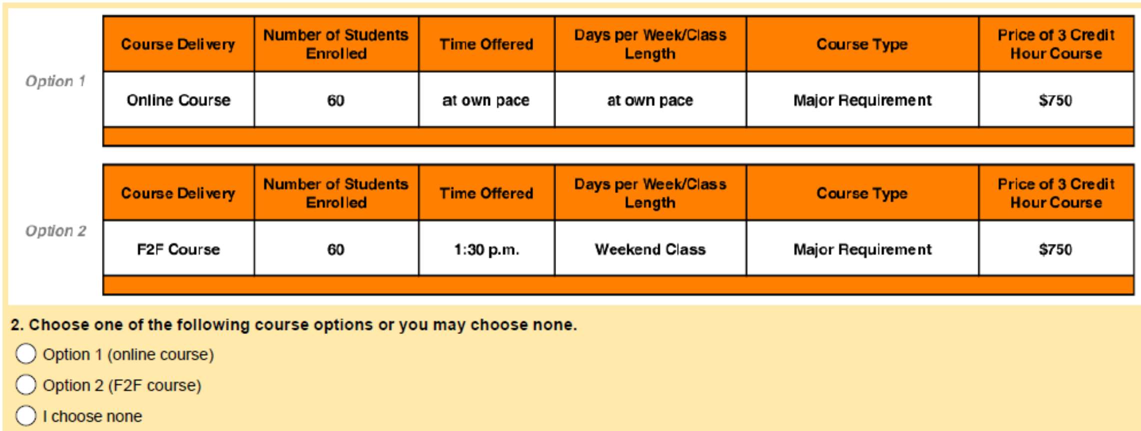
Course Attributes	Course 1	Course 2
Basic Attributes		
Topic	English composition & oral communication	Scientific investigation
Class Size	70	35
Price	$1,000	$1,000
Face-to-face time	8:30 AM	11:00 AM
Face-to-face days per week	MWF	TR
Expanded Online Attributes		
20-30 minute topic videos	Yes	No
Face-to-Face Lecture videos	No	Yes
Course notes	Yes	Yes
Online exams	Yes	Yes
Chat-room with Instructor	Yes	No
Drop box	Yes	No
Threaded Discussion	Yes	Yes
Chat-room with Student	Yes	No

Table 19. Simulation of Impact of Additional Attribute Information on Student Demand

	Online	F2F	None
	No information about additional online course attributes		
Course 1[a]	45.19%	41.99%	12.83%
Course 2	27.30%	64.40%	8.30%
	Specific information about additional online course attributes		
Course 1	61.20%	30.83%	7.97%
Course 2	33.87%	56.74%	9.38%

Based on parameters estimates from Tables 17(a) and 17(c).

[a] See Table 5 for course attributes information.



Option 1	Course Delivery	Number of Students Enrolled	Time Offered	Days per Week/Class Length	Course Type	Price of 3 Credit Hour Course
	Online Course	60	at own pace	at own pace	Major Requirement	$750

Option 2	Course Delivery	Number of Students Enrolled	Time Offered	Days per Week/Class Length	Course Type	Price of 3 Credit Hour Course
	F2F Course	60	1:30 p.m.	Weekend Class	Major Requirement	$750

2. Choose one of the following course options or you may choose none.

- Option 1 (online course)
- Option 2 (F2F course)
- I choose none

Figure 5. Example of Course Choice Questions in Survey 1

Option 1

Course Delivery	Number of Students Enrolled	Time Offered	Days per Week/Class Length	General Course Topic	Price of 3 Credit Hour Course
Online	20	at own pace	at own pace	Major Requirement	$750

Additional Online Course Information	Availability
Video lecture type	1-10 minute topic discussion
Course lecture notes	Available
Taking exams and quizzes	Take at prearranged time/location
Drop box for assignments	Not available
Chat-room with instructor	Not available
Threaded discussion with classmates	Not available
Chat-room with classmates	Not available

Option 2

Course Delivery	Number of Students Enrolled	Time Offered	Days per Week/Class Length	General Course Topic	Price of 3 Credit Hour Course
F2F	60	4:00 p.m.	MWF/50 minute classes	Major Elective	$875

2. Choose one of the following course options or you may choose none.

- ◯ Option 1 (online course)
- ◯ Option 2 (F2F course)
- ◯ I choose none

Figure 6. Example of Course Choice Questions in Survey 2

CHAPTER IV

CHARACTERISTICS OF STUDENTS SELECTING ONLINE COURSES

Introduction

Higher education is experiencing a potential paradigm shift in the way in which college-level courses are delivered [face-to-face (F2F), online, or hybrid] to students (Allen and Seaman 2010; Bejerano 2008; Haythornthwaite and Andrews 2011; Jenkins et al. 2011; Oblinger, Barone, and Hawkins 2001). Over that past several years, greater proportions of students are selecting online courses instead of F2F courses. Between 2002 and 2008, public and private universities in the U.S. experienced a 260% increase in the proportion of students enrolling in online courses relative to F2F courses (Allen and Seaman 2010). One reason for this increase is because many institutions of higher education have adopted strategies that use online courses and programs to keep up with the overall demand for college level courses (Allen and Seaman 2010). The increased enrollment in online courses may also be related students' level of acceptance towards online courses compared to F2F courses, as well as their familiarity with the technology used to deliver online courses (Allen and Seaman 2010; Bejerano 2008; Haythornthwaite and Andrews 2011; Jenkins et al. 2011; Oblinger, Barone, and Hawkins 2001; Russell 1999). Additional evidence supporting a potential paradigm shift in college-course delivery can be seen on college and university campuses where many on-site, college-age (18-24 years of age) students are now substituting online courses for their F2F counterparts (Bejerano 2008).

At their onset, online learning environments were believed to be appropriate for non-traditional students (students 25 years and older, and with careers or family obligations) for two reasons (Howell, Williams, and Lindsay 2003). First, the maturity and experience of non-traditional students allowed them to achieve learning objectives with a minimal amount of technology and direction. Second, the flexibility of online courses and programs made it possible for non-traditional students to complete degree requirements while maintaining work, family, and social obligations. Most of the generalizations in the distance education (DE) literature regarding the characteristics of non-traditional students taking online courses have reflected these ideas (Allen and Seaman 2010; Bejerano 2008; Haythornthwaite and Andrews 2011; Howell, Williams, and Lindsay 2003; Jenkins et al. 2011; Oblinger, Barone, and Hawkins 2001).

While non-traditional students have shown a continued and strong interest in online courses and programs (Howell, Williams, and Lindsay 2003; Oblinger, Barone, and Hawkins 2001), under many circumstances on-site, college-age students may also desire the online formats over F2F courses (Haythornthwaite and Andrews 2011; Jenkins et al. 2011). The interest that college-age students have for online courses may be related, in part, to the effect that web 2.0 technologies, such as web-based social networks, blogs, and streaming video, have had on communication and learning. For example, online social networking, texting, instant messaging, and emailing have become the primary means of communication for many college-aged students (Haythornthwaite and Andrews

2011; Jenkins et al. 2011). Many of these web 2.0 technologies are very similar to the design features used to create online learning environments.

Although non-traditional student enrollment has accounted for a large portion of total college-course enrollment and online college-course enrollment is growing much faster than total college-course enrollment, it is unclear what the proportion of non-traditional versus on-site, college-aged students make up enrollment in the online courses (Allen and Seaman 2010; Howell, Williams, and Lindsay 2003; Oblinger, Barone, and Hawkins 2001). As the popularity and acceptance of online courses have risen across most institutions of higher education, it may be that the characteristics of students enrolling in online courses are also changing (Allen and Seaman 2010; Haythornthwaite and Andrews 2011; Howell, Williams, and Lindsay 2003; Jenkins et al. 2011; Oblinger, Barone, and Hawkins 2001). Do non-traditional students account for the majority of online course enrollment, or are greater numbers of on-site, college age students beginning to flock to online courses? This question is at the heart of the potential paradigm shift in the way that college-level courses are delivered (Allen and Seaman 2010; Bejerano 2008; Haythornthwaite and Andrews 2011; Jenkins et al. 2011; Oblinger, Barone, and Hawkins 2001). The objective of this study is to answer this question by determining the characteristics of students who choose online courses and compare the results to previous depictions of online students in the DE literature.

This study is organized as follows. In the background section, the discussion about the potential paradigm shift in the way in which college-levels course are delivered is expanded. The key feature of this discussion is the potential effect from intuitional strategies to meet student demand combined with advances in technology has had on the demand for online courses among students. The model (an ordered logit model) used to determine which student characteristics impact their course selection is developed in the methods and procedures section. A description and explanation of the specific inputs used in this model are given in the data section. In the results and discussion section, the key finding are presented and compared to previous DE studies. Finally, an overview of this study is given and the relevant policy implications are discussed in the summary and conclusion section.

Background

Potential factors contributing to the rise in online course demand

There are three factors that are highlighted here that have potentially interacted and contributed to the significant rise in the demand for online courses: 1) the shift in strategy by higher education institutions to meet total student demand by increasing online course and program offerings (Allen and Seaman 2010); 2) the demand by non-traditional students for higher education which has been driven by the labor market and changes in technology (Howell, Williams, and Lindsay 2003; Oblinger, Barone, and Hawkins 2001); and 3) the potential impact of web 2.0 technologies on the communication and learning preferences of college-age students (Haythornthwaite and Andrews 2011; Jenkins et al. 2011). Oblinger, Barone, and Hawkins (2001) recognized that the growth trend of total student enrollment driven by both non-traditional and college-age students would eventually overwhelm the infrastructure at many higher education institutions. Therefore, they believed that developing and expanding online courses and programs by these institutions was inevitable to meet the demand of both groups of students. In 2008, one-in-four undergraduate students had taken at least one online course, and many colleges and universities reported that online courses and programs are an essential part of their long-term institutional strategy to compete with other institutions and to meet student demand (Allen and Seaman 2010).

According to Howell, Williams, and Lindsay (2003), the demand for higher education by non-traditional students has continued to increase over several decades and has been primarily related to increased demand by employers for college graduates and updated skills. However, the increased availability and affordability of personal computers and the internet has also allowed more non-traditional students to gain access to online courses and programs. Until recently, the market for online courses and programs has been primarily geared toward older, self-directed students with work, family, and social constraints, but this trend is potentially changing (Bejerano 2008; Howell, Williams, and Lindsay 2003; Oblinger, Barone, and Hawkins 2001).

Although demand for higher education is generally understood to be driven by the demands of the labor market (Campbell and Siegel 1967), the demand for online courses by college-age students potentially has two additional drivers (Bejerano 2008; Haythornthwaite and Andrews 2011; Jenkins et al. 2011). First, online courses are being used as alternatives to F2F courses when scheduling conflicts or competition to enroll in the most demanded F2F courses occurs (Bejerano 2008). This opportunity for on-site, college-age students to use online courses as substitutes for F2F courses is the result of the strategies adopted by higher education institutions to mitigate infrastructure concerns as well as compete with other institutions offering online courses and programs (Allen and Seaman 2010; Bejerano 2008).

Second, Millennials' have demonstrated preference for the technology used to deliver online courses (Haythornthwaite and Andrews 2011; Jenkins et al. 2011). Over the past decade, the effect of web 2.0 technologies has potentially altered the way many Millennials, now of college-age, prefer to communicate and learn. According to Haythornthwaite and Andrews (2011) and Jenkins et al. (2011), not only have Millennials become familiar with web 2.0 technologies, they have also made significant contributions to the application and development of the technologies. Additionally, these technologies can allow participants to maintain moderate to high levels of anonymity when making contributions to a variety of online forums. Since many design features of online courses are similar to web 2.0 technologies, college-age students may perceive that online courses can also provide a lower risk environment with respect to course participation compared to their F2F counterparts (Haythornthwaite and Andrews 2011; Jenkins et al. 2011). For this reason, Haythornthwaite and Andrews (2011) and Jenkins et al. (2011) argue that some online course formats may actually result in increased student participation relative to the F2F version of the course.

Distinguishing between non-traditional and college-age students

Since the rise in demand for online college-level courses is a recent phenomena, within the DE literature the characteristics contributing to non-traditional and college-age students' preferences for online courses have not been well established (Allen and Seaman 2010; Bejerano 2008; Haythornthwaite and Andrews 2011; Howell, Williams, and Lindsay 2003; Jenkins et al. 2011; Oblinger, Barone, and Hawkins 2001). However, using the some of the general characteristics of non-traditional students provided by the DE literature, college-age students can be distinguished from non-traditional students using basic demographic information. For example, Howell, Williams, and Lindsay (2003) have identified non-traditional students as being older, 25 years of age or older, while college age students are between the ages of 18-24. On the other hand, it may be more difficult to use employment information to distinguish between college-age and non-traditional student as some college-age students may be employed while some non-traditional students may be unemployed.

Another set of characteristics that may distinguish between students selecting online versus F2F courses are preferences for information and communication technologies. For example, Haythornthwaite and Andrews (2011), Jenkins et al. (2011), and Oblinger, Barone, and Hawkins (2001) have suggested that exposure to web 2.0 technologies has resulted in an increased interest in online formatted courses, especially by Millennials. Based on this logic, college-age students' who frequently use web 2.0 technologies, such as social networking and streaming video sites, should also be more likely to take online courses compared to students who infrequently visit these sites. Additionally, Haythornthwaite and Andrews (2011) have implied that students who prefer communicating via text and instant messaging, which potentially allows for the perception of some level of anonymity, may also have higher preferences for online courses compared to students using more direct forms of communications (such as F2F conversation or phone calls).

Finally, there may be other student characteristics or aspects of online courses not previously discussed in the DE literature which impacts students' preferences for online courses. For example, language barriers and limited selection of relevant courses may deter students from selecting online courses. Additionally, students enrolled in majors that require considerable laboratory work or other hands-on-training may believe online courses are not practical. One the other hand, students' learning styles and previous experiences with online courses may positively or negatively influence their preferences for online courses.

Methods and Procedures

In order to identify which student characteristics potentially impacted students' choice of online course selection, a list of potential student characteristics was first generated. A range of different student characterizes, based on students' college major, course load, employment, basic demographic information, preferences for learning and communicating, use of different computer technology, and experience and knowledge about online courses were drawn from the DE literature (Bejerano 2008; Bernard et al. 2009; Haythornthwaite and Andrews 2011; Howell, Williams, and Lindsay 2003; Jenkins et al. 2011; Oblinger, Barone, and Hawkins 2001; Russell 1999), as well as the researchers' experience with college-level students (summary statistics of the characteristics questions are provided in Table 20). A survey was developed that included questions about these student characteristics (which comprised the independent variables in the model) and students were also asked to identify, on a five-level Likert item format, their likelihood of taking another online course (the dependent variable in the model). A further explanation of the survey format, implementation, and response rate is provided in the proceeding data section.

In order to determine the relative impact that each of the student characteristics had on students' likelihood of selecting an online course, an ordered logit model was constructed based on student responses to survey questions using the PROC LOGISTIC procedure in SAS (SAS Institute). The ordered logit model is as follows:

$$L_i^* = \boldsymbol{X_i^T \Upsilon} + \epsilon_i \tag{1}$$

$$L_{i,j} = \left\{\begin{array}{l} 0 \text{ if } L_i^* \leq 0, \text{very likely} \\ 1 \text{ if } 0 \ < L_i^* \leq \mu_1, \text{likely} \\ 2 \text{ if } \mu_1 < L_i^* \leq \mu_2, \text{neither likely nor unlikley} \\ 3 \text{ if } \mu_2 < \ L_i^* \leq \mu_3, \text{unlikely} \\ 4 \text{ if } \mu_3 \leq L_i^*, \text{very unlikley} \end{array}\right\} \tag{2}$$

$$\begin{aligned} \text{Prob}\{L_{i,j} = 0|\boldsymbol{X_i}\} &= \Phi(-\boldsymbol{X_i^T \Upsilon}) \\ \text{Prob}\{L_{i,j} = 1|\boldsymbol{X_i}\} &= \Phi(\mu_1 - \boldsymbol{X_i^T \Upsilon}) - \Phi(-\boldsymbol{X_i^T \Upsilon}) \\ \text{Prob}\{L_{i,j} = 2|\boldsymbol{X_i}\} &= \Phi(\mu_2 - \boldsymbol{X_i^T \Upsilon}) - \Phi(\mu_1 - \boldsymbol{X_i^T \Upsilon}) \\ \text{Prob}\{L_{i,j} = 3|\boldsymbol{X_i}\} &= \Phi(\mu_3 - \boldsymbol{X_i^T \Upsilon}) - \Phi(\mu_2 - \boldsymbol{X_i^T \Upsilon}) \\ \text{Prob}\{L_{i,j} = 4|\boldsymbol{X_i}\} &= 1 - \Phi(\mu_3 - \boldsymbol{X_i^T \Upsilon}) \end{aligned} \tag{3}$$

$$s.t. \ \ 0 < \mu_1 < \mu_2 < \mu_3,$$

where L_i^* is the latent attitude of the student and not directly observable, $\boldsymbol{X_i}$ is a vector of student information (student characteristics) proved, $\boldsymbol{\Upsilon}$ is a vector of the parameters to be estimated, ϵ_i is the error term, $L_{i,j}$ is the Likert item selected by student i that belongs to category j and maps L_i^*, $\Phi(\cdot)$ is the logistic distribution, $i = 1, \dots, N,\ j = 0, \dots, 4$, and μ_1, μ_2, and μ_3 are additional parameters that are estimated (see Greene 2005). For the objective function, the log likelihood function is maximized by changing the parameters as follows:

$$\max_{\boldsymbol{\lambda}} \Lambda = \sum_{i=1}^{N} \sum_{\text{j}=0}^{4} L_{i,j} \log\left[\Phi(\mu_j - \boldsymbol{X_i^T \Upsilon}) - \Phi(\mu_{j-1} - \boldsymbol{X_i^T \Upsilon})\right] \tag{4}$$

where $\boldsymbol{\lambda}$ is a vector of the parameters (μ_j and $\boldsymbol{\Upsilon}$), $L_{i,j} = 1$ if student i belongs to category j and 0 otherwise (see Fok and Frances 2002). The estimated parameters from the ordered logit model are interpreted as the marginal effect on the log of the odds ratio given each characteristic and not the marginal effects of the of the student characteristics themselves ($\boldsymbol{X}_i$). The log odds ratio is given by:

$$\log\left(\frac{\text{Prob}\{L_i = l|\boldsymbol{X_i}\}}{\text{Prob}\{L_i = l + 1|\boldsymbol{X_i}\}\}}\right) \qquad (5)$$

$$\text{for } l \in \{1,2,3,4\},$$

For the sake of analysis in this study, only the parameters sign ($+/-$ means that the student characteristic increases/decreases the probability that a student will select "very likely" when asked about taking an online class), relative magnitude (compared to other characteristics considered in the model), and the significance level ($\alpha \ \leq 10\%$) will be considered.

Data

Data for this study are from an email survey (via SurveyMonkey) of Oklahoma State University (OSU-Stillwater) students that was conducted in the fall 2010 semester. At the beginning of the fall 2010 semester (and prior to the launch of this survey), OSU Communications Department implemented a new policy that restricts researchers access and frequency of contact to students via email. However, the authors of this study were given special permission to sample the full OSU-Stillwater student population (graduate and undergraduate students), but the contact was limited. Only a single email invitation to participate in the survey was allowed (there was no opportunity for follow-up emails). For this study, nearly 22,000 emails were sent over a six hour window to OSU-Stillwater email addresses. In order to maximize the response rate, an incentive (Apple iPad) was given away in a random drawing of participants that completed the survey. In all, 2691 students completed the questionnaires during the two weeks the survey was open which resulted in a response rate of about 12.6%. The basic student demographic information based on the participants who completed the survey as well as that of the total OSU-Stillwater population is presented in Table 21.

Twenty-seven questions were asked about students' college major, course load, employment, basic demographic information, preferences for learning and communicating, use of different computer technology, and experience and knowledge about online courses. Much of the characteristic information obtained from students was in the form of rating responses (on a 1-10 scale, where 10 was the highest and 1 was the lowest) or Likert items responses (1-5 or 1-6 scales). To save degrees of freedom during model estimation, the data consisting of ratings and Likert items responses were reduced to binary responses as follows. Ratings responses were categorized as "lower preference" if the question was rated from 1 to 5 and "higher preference" if rated from 6 to10. Likert items with a 1-5 scale (where responses ranged from "very good" to "very poor") were categorized as "good" if the Likert item response was 1 or 2, and "poor" if the Likert item response was 3 to 5. The reason the Likert items response of 3 was categorized as "poor" is because there were not enough observations to allow the SAS procedure to generate a "neither good nor poor" parameter estimate. Finally, Likert items with a 1-6 scale (where responses ranged from a time value of "4 hours or more" to a time value of "none") were classified the "highest frequency of use" if the Likert item response was 1 and as "lower frequencies of use" if the Likert item response was 2 to 6. The dependent variable, students' responses to the question asking about their likelihood of taking an online course, was not reduced to a binary response.

Results and Discussion

The numbers and proportions of students who have and who have not taken online courses based on survey responses are shown in Table 22. This tabled is divided into two groups: 1) college-age students who are undergraduates and are not enrolled in an online degree programs, 2) graduate and non-traditional students who are or are not enrolled in online programs. Over half (55.9%) of the collage-age students and two-thirds graduate and non-traditional students (70.8%) have taken at least one online course. With respect to college-age students, this number, based on 2010 data, is twice the size of the 2008 value reported by Allen and Seaman (2010).

The results of the ordered logistic model parameter estimates for the student characteristics based on students selecting online courses are presented in Table 23. As discussed in the data section, many of student characteristics were reduces to binary values. Where the characteristics were reduced, the parameter estimates shown in Table 23 are based on the indicator variables for "higher preference," "good" and "highest frequency of use."

There are three sets of results, based on a pooled model (combined undergraduate and graduate students' responses), model for undergraduate students' responses only, and a model for graduate students' responses only. The results of the log-likelihood test used to determine if the pooled model was the appropriate model indicate that the parameters estimates of undergraduate and graduate student differ (tests statistic is $\chi_1^2 = 70$). However, there are a number of consistencies across the three models even though the significance level of parameters varies and the results for all three models are discussed below.

Although the results presented here are not intended to suggest a causal relationship between student characteristics and taking online courses, there are a number of significant parameters estimates which support much of the DE literature and these findings point to some interesting trends. There are three trends related to the historical view of non-traditional students as the primary group of students taking online college-level courses. First, the age parameter is positive in all three models and significant in two of the three. However, freshman and sophomore students were more likely than junior and senior students to select “very likely” with respect to take an online course, and undergraduate students were more likely than graduate students to select “very likely” respect to take an online course. The first part of this finding may be the case since freshman and sophomores would potentially have a wider selection of online courses compared to juniors and seniors. Second, as the number of hours employed per week students reported increased from “none” to “more than 30 hours per week” (the later value was used as the base of comparison), the likelihood hood of selecting “very likely” to take an online course increased. Third, as the number of college-credit hours taken increases the likelihood of selecting “very likely” to take an online course decreased.

The results also highlight, to an extent, the potential impact of information and communication technology on students’ likelihood to select online courses. The parameters for “high frequency of social networking,” “high preference for communicating via social networks,” “high preference for communicating via instant messaging,” and “high preference for communicating via live streaming video” are positive across all models and significant. However, the significance is only intermittently across the three models. Additionally, the parameter for “high preference for communicating F2F” is negative and significant in two of the three models. Theses finding support the ideas of Haythornthwaite and Andrews (2011), Jenkins et al. (2011), and Oblinger, Barone, and Hawkins (2001) who believe that student’s familiarity and use of web 2.0 technologies positively influences students’ selection of online courses.

There are additional student characteristics that are potentially related to students selecting online courses that were revealed in this study and that have not previously been discussed the DE literature. The first is how students’ collage major preferences may affect online course selection. In this study, college majors were simplified into eight Biglan categories that are based on student learning preferences (see Schommer-Aikins, Duell, and Barker 2003; Sinclair and Muffo 2002; Stoecker 1994). The results presented are relative to soft-applied non-life majors which includes business (e.g. accounting, marketing, finance, and management majors) and economics majors (but does not include agricultural and applied economics which are classified as hard applied life majors). In general, this study found that students in soft-applied non-life majors are the most likely group of students to select “very likely” to take an online course. At the undergraduate level, students in majors that are hard-applied non-life (e.g. different engineering majors) and soft-applied life (e.g. communications, English, history, philosophy, and art majors) are the most unlikely groups of students select “very likely” to take an online course, while graduate students in hard-pure life (e.g. anatomy, biochemistry, biology, and botany majors) and hard-pure non-life e.g. (mathematics, physics and chemistry majors) are the most unlikely groups of students to select “very likely” to take an online course.

The second set of findings not previously discussed in the literature relates to undergraduates preferences for learning difficult topics. The two results that were significant were also positive, and they include “meeting with the course instructor” and “searching the web.” The third set of findings, also at the undergraduate level, was that international students are the least likely student group of students to select “very likely” to take an online course, while students classified as out-of-state residents were the most likely group of students to select “very likely” to take an online course. Finally, there is a positive relationship between students experience with and knowledge about online courses and their likelihood to select “very likely” to take an online course.

Summary and Conclusions

The primary goal of this study was to determine the characteristics of students who are selecting online courses and in doing so answer the broader question: do non-traditional students account for the majority of online course enrollment, or are greater numbers of on-site, college-age students selecting online courses? This question is at the core of the potential paradigm shift occurring across colleges and universities in the manner in which courses are being delivered, i.e. via F2F, online, or hybrid. Online courses have been primarily taken by non-traditional students; however, due to total student demand for higher education, many institutions of higher education have developed policies that have opened the door for college-age students to take online courses to fulfill degree requirements. At the same time, developments in technology resulting in increased access to personal computers and the internet, as well as the effect of web 2.0 technologies on the exchange of information and communication are reshaping the way in which learning is occurring.

Based on the survey responses in this study, graduate and non-traditional students make up a large portion of students taking online courses. However, the number of college-age students who have taken at least one online course is much greater than the number of graduate and non-traditional students who have done so. These findings indicate there are two distinct populations of students enrolling in online courses, non-traditional students and on-site, college-age students. This presents a potential opportunity for institutions wishing to differentiate themselves from other colleges and universities by the types of online courses that are offered, i.e. online courses specifically designed for online programs taken by non-traditional students, and those intended to fulfill the specific degree requirements of on-site college-age students.

Additionally, this study found that undergraduate students earlier in their college careers, freshman and sophomores compared to juniors and seniors, are much more likely to want to take online courses. Therefore, institutions interested in expanding online courses offerings could focus some of their efforts on increasing online courses relating to general education requirements. For institutions with large class sizes and where students are not able to receive very much personalized attention from the instructors or teaching assistants, this recommendation would be especially relevant. This result also implies that there may be fewer upper-division online-course options. This presents another potential area to investigate for institutions wishing to expand online course offerings.

There are a two consideration identified in this study that deserve more attention and research. First, the relationship between students' majors and their preferences for online courses needs to be explored further. This includes determining what specific kinds of courses students believe are well suited for the online format. There are a number of courses where hands-on activities (e.g. science labs) are a considerable part of the course. However, as technology continues to develop many of theses of courses may become practical in the online format.

Second, much more empirical work is needed that investigates the impact of web 2.0 technologies on students desire to take online courses. This study found significant and positive relationships between many web 2.0 technologies and students likelihood of selecting online courses; however, a causal relationship was not established. There are two questions to consider. Do students who frequently use web 2.0 technologies to communication want to take online courses because it is a more familiar or safer environment? Or, are there other benefits that web 2.0 technologies can provide in the learning environment?

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Table 20. Summary Statistics of Student Characteristics Questions

Likelihood of taking online course [a]		*Other student demographics*	
Very Likely	32.17%	Female	54.95%
Likely	25.80%	Male	45.05%
Neither likely nor unlikely	16.42%	Mean age (years)	24.09
Unlikely	16.05%	"In-state" resident student	71.15%
Very unlikely	9.57%	"Out of state" resident student	19.25%
Student status		International student	9.61%
Freshman	17.76%	Enrolled in online degree program	10.42%
Sophomore	12.40%	Never taken Online Course	37.23%
Junior	16.57%	Taken at least one online course	62.77%
Senior	24.72%	*Preference to learn difficult topics* [b]	
Masters	18.50%	Discuss with students	8.61
Doctorate	10.05%	Use visual aids	8.25
Major by Biglan category		Other books	6.89
Hard pure life	4.50%	Hands-on activities	4.72
Hard pure non-life	3.72%	Meet with instructor	6.68
Hard applied life	14.30%	Course text	5.36
Hard applied non-life	15.71%	Attend class	8.01
Soft pure life	7.56%	Homework	7.88
Soft pure non-life	8.60%	Search the web	6.72
Soft applied life	12.92%	Resource center	7.23
Soft applied non-life	28.78%	*Communication preference*	
Undecided	3.91%	Face-to-face	9.00
Number of hours taken - fall 2010		Phone	6.59
Less than 6 hours	6.44%	Texting	6.24
6-8 hours	13.81%	Email	7.35
9-11 hours	11.99%	Social network	5.82
12-15 hours	52.49%	Instant messaging	4.83
16 or more hours	15.26%	Live internet video	5.61
Number of hours working - fall 2010		*Computer/internet use* [c]	
Not working at a job	35.63%	Time social networking sites (hours)	1.79
Work less than 10 hours	8.49%	Time browsing web (hours)	1.59
Work 10-20 hours/week	24.42%	Time playing video games (hours)	1.15
Work 20-30 hours/week	15.00%	*Online Course Experience*	
Working more than 30 hours/week	16.46%	Good online course experience	3.63
		Good knowledge of multimedia	2.57
		Good online course knowledge	2.82

a. Percentages are based on total sample population.

b. Scores are averages based on a 10 point rating scale, 10 = the highest and 1 = the lowest

c. Times reported are per day averages

d. Scores are the average based on a 5 Likert item scale, 1 = very good, 2 = good, 3 = neither good nor poor, 4 = poor, and 5 = very poor

Table 21. Comparison of Student Demographics

Group	Survey	Actual[a]
Freshman	17.76%	20.51%
Sophomore	12.40%	17.69%
Junior	16.57%	19.71%
Senior	24.72%	22.51%
Masters	18.50%	12.72%
Doctoral	10.05%	7.00%
Female	54.95%	48.22%
Male	45.05%	51.78%
Resident[b]	71.15%	72.06%
Out-of-state	19.25%	19.99%
International	9.61%	7.95%

a. From Fall 2010 Student Profile, Institutional Research and Information Management
b. Based on all OSU campuses enrollment

Table 22. Frequency of Students Taking Online Courses by Age

Frequency of taking online courses	Age < 25 years old[a]		Age ≥ 25 years old	
	Number	Percent	Number	Percent
Never taken an online course	703	44.10%	286	29.21%
Taken 1 online course	326	20.45%	167	17.06%
Taken 2 online courses	182	11.42%	137	13.99%
Taken 3 onli9ne courses	169	10.60%	100	10.21%
Taken 4 online courses	105	6.59%	91	9.30%
Taken 5 or more online courses	109	6.84%	198	20.22%

Note: Data are based on student responses to survey questions.

a. Only Includes undergraduate students who not enrolled in an online degree programs.

b. Includes all graduate students and students 25 years or older.

Table 23. Ordered logit Parameter Estimates of Student Characteristics in Likelihood to Take Online Course Model

Parameter	Pooled		Undergraduate		Graduate	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Likelihood of taking online course						
Intercept	-3.2719***	0.3885	-2.9057***	0.4958	-3.1186***	0.7030
Intercept	-1.5782***	0.3842	-1.1360*	0.4917	-1.5666**	0.6945
Intercept	-0.5240	0.3828	-0.0574	0.4907	-0.5291	0.6913
Intercept	0.8940**	0.3838	1.3338***	0.4923	1.0430	0.6931
Student status						
Freshman[a]	1.4336***	0.2326	0.5985***	0.1472	-	-
Sophomore	1.3598***	0.2274	0.5180***	0.1399	-	-
Junior	1.0138***	0.2135	0.1768	0.1224	-	-
Senior	0.8697***	0.2004	-	-	-	-
Masters	0.4521***	0.1575	-	-	0.4115**	0.1801
Major by Biglan category						
Hard pure life (relative to soft applied non-life)	-0.2420	0.1836	-0.0499	0.2063	-1.1575**	0.4506
Hard pure non-life	-0.3530*	0.2027	-0.1659	0.2615	-0.7085**	0.3541
Hard applied life	-0.1289	0.1200	-0.0712	0.1437	-0.2726	0.2403
Hard applied non-life	-0.3190***	0.1192	-0.4160***	0.1397	-0.1582	0.2453
Soft pure life	-0.1492	0.1545	-0.0776	0.1777	-0.2910	0.3276
Soft pure non-life	-0.2301	0.1439	-0.2589	0.1640	-0.1136	0.3150
Soft applied life	-0.3006**	0.1260	-0.3917***	0.1440	0.1090	0.2761
Preference to learn difficult topics						
Discuss with students (relative to low preference)	-0.0847	0.1543	-0.2510	0.1762	0.3697	0.3488
Use visual aids	0.1752	0.1349	0.3161**	0.1596	-0.0819	0.2630
Other books	-0.0786	0.0935	-0.00868	0.1081	-0.3685*	0.2006
Hands-on activities	0.1349	0.0854	0.0756	0.0998	0.3835**	0.1757
Meet with instructor	0.1743*	0.0890	0.1711*	0.0996	0.1636	0.2113
Course text	0.0675	0.0852	0.0198	0.0984	0.2145	0.1807
Attend class	-0.1229	0.1219	-0.1024	0.1394	-0.2909	0.2657
Homework	-0.0393	0.1108	-0.0734	0.1292	-0.0356	0.2294
Search the web	0.2363***	0.0867	0.2388**	0.0995	0.1762	0.1882
Resource center	0.0022	0.0987	0.0385	0.1142	-0.2622	0.2094
Other student demographics						
Gender (relative to male)	0.0134	0.0405	0.0187	0.0478	-0.0224	0.0799
Age	0.0161**	0.0079	0.0190*	0.0113	0.0062	0.0118

a. student status is relative to doctoral students in pooled model and seniors in undergraduate model.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

Table 23. Ordered logit Parameter Estimates of Student Characteristics in Likelihood to Take Online Course Model (Continued)

Parameter	Pooled		Undergraduate		Graduate	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
"In-state" resident (relative to international)	0.0595	0.1556	0.5496**	0.2686	-0.0963	0.2322
"Out of state" resident	0.0669	0.1656	0.6848**	0.2833	-0.2189	0.2534
Number of hours taken - fall 2010						
Less than 6 hours (relative to work > 30 hours/week)	0.2575	0.1599	-0.00954	0.3185	0.03900	0.2815
6-8 hours	0.0449	0.1124	0.5789**	0.2765	-0.2275	0.2440
9-11 hours	0.0465	0.1055	-0.0581	0.2017	-0.1069	0.2425
12-15 hours	-0.1589	0.0981	-0.2307*	0.1263	-0.1817	0.3046
Number of hours working - fall 2010						
No job	-0.2547***	0.0722	-0.1908**	0.0805	-0.3848*	0.2064
Work less than 10 hours	-0.3785***	0.1084	-0.3384***	0.1185	-0.4190	0.3342
Work 10-20 hours/week	-0.0713	0.0739	-0.0225	0.0913	-0.0508	0.1529
Work 20-30 hours/week	0.1302	0.0873	0.2807**	0.1128	0.0776	0.1656
Online degree program (relative to not online deg. Program)	0.3760***	0.0801	0.2974***	0.0985	0.4876***	0.1486
Number of online courses taken						
Never taken Online Course (relative to taken 5 or more)	-0.0830	0.0894	-0.1567	0.1067	0.0765	0.1742
Taken 1 online course	-0.6322***	0.0826	-0.7311***	0.0973	-0.3907**	0.1654
Taken 2 online courses	-0.3356***	0.0964	-0.2300**	0.1174	-0.5810***	0.1787
Taken 3 online courses	-0.0404	0.1078	-0.0256	0.1256	-0.1369	0.2211
Taken 4 online courses	0.3132**	0.1272	0.3020*	0.1552	0.3868	0.2366
Online Course Experience						
Good online course experience (relative to poor experience)	2.3473***	0.1098	2.3103***	0.1310	2.5528***	0.2136
Good knowledge of multimedia (relative to poor knowledge)	0.3458***	0.0834	0.3511***	0.0995	0.2191	0.1617
Good online course knowledge (relative to poor knowledge)	0.4126***	0.0848	0.4536	0.0997	0.4189**	0.1685
Communication preference						
Face-to-face (relative to low preference)	-0.4638**	0.1878	-0.6400	0.2072	0.4649	0.5087
Phone	0.0310	0.0867	0.0591	0.1007	-0.0219	0.1772
Texting	0.1314	0.0893	0.1155	0.1082	0.2203	0.1666
Email	-0.0115	0.1038	0.0113	0.1188	-0.1670	0.2310
Social network	0.2021*	0.1076	0.2487**	0.1237	0.0641	0.2345
Instant messaging	0.1014	0.1507	0.3123*	0.1857	-0.1416	0.2743
Live internet video	0.2081**	0.0817	0.1343	0.0957	0.3314**	0.1653
Web-interaction term	-0.2081	0.1788	-0.4448**	0.2142	0.1783	0.3582
Computer/internet use						
Frequency of social networking (relative to low frequency)	0.3298*	0.1875	0.2548	0.2044	0.8042	0.5161
Frequency of browsing web	0.1482	0.2222	0.2406	0.2435	-0.3578	0.5781
Frequency playing video games	-0.2490	0.2092	-0.2435	0.2470	-0.2074	0.4179
R-square	0.4208		0.3978		0.5045	
Log likelihood	-6748		-4896		-1782	

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

CHAPTER V

DEVELOPING A MEASURE OF SCHUMPETERIAN ACTIVITY

Introduction

There has been a growing concern about the manner in which entrepreneurship has been characterized with regard to government policy analysis within the economic literature (Ahmad and Hoffman 2008; Ahmad and Seymour 2008; Avanzini 2009; Goetz et al. 2010; Goetz and Freshwater 2001; Shane 2008; Wennekers and Thurik 1999). This concern has developed as the emphasis of firm size on economic growth has shifted from large firms to small and medium sized start-ups (Wennekers and Thurik 1999; Shane 2008). As a result of this shift, government policies have been devised to encourage entrepreneurship in hopes they may also increase the odds of long-term economic prosperity. Within the analysis framework of many of these policies, however, entrepreneurship has been characterized as a "one size fits all" concept. This has led to some confusion about the impact that governmental policies can have on the creation of entrepreneurship, as well as the uncertainty around what exactly it is that some believe U.S. policies should be trying to encourage.

One part of the problem with relying on a general characterization of entrepreneurship is its multidimensional nature (Ahmad and Hoffman 2008; Ahmad and Seymour 2008; Avanzini 2009; Davis 2007; Miller 1983; Wennekers and Thurik 1999). More specifically, popular proxies of entrepreneurship, such as new firm formation or sole proprietorships, can include multiple types of entrepreneurship and the environments that encourage particular entrepreneurship types can vary dramatically (Ahmad and Hoffman 2008; Avanzini 2009; Goetz et al. 2010). Depending on the intent of the policy considered, analysis that utilizes proxies with aggregated forms of entrepreneurship could be misleading.

For example, Schumpeterian activity[2] is one form of entrepreneurship that is closely associated with innovation, high technology use, and a strong entrepreneurial climate (Cunningham and Lischeron 1991; Das and Ting 1998; Goetz et al. 2010; Goetz and Freshwater 2001; Shane 1996; Van Stel, Carree, and Thurik 2005). Additionally, Schumpeterian activity is believed to drive long-term job growth by creating additional opportunities for all types of entrepreneurs, including future Schumpeterian-type entrepreneurs (Aghion and Howitt 1990; Goetz et al. 2010; Shane 1996; Wennekers and Thurik 1999). On the other hand, necessity entrepreneurship is believed to result from high levels of unemployment, and the jobs created by necessity entrepreneurs are potentially short-lived since they may disappear when better opportunities arise (Acs and Varga 2005; Goetz et al. 2010; Wennekers et al. 2005). If proxies including these two types of entrepreneurship (as well as other entrepreneurship types) were used to analyze policies designed to increase long-term job growth, misleading results will potentially

[2]In this paper, the term Schumpeterian activity is used to describe the economic growth resulting from the process of creative destruction as described by Aghion and Howitt (1990).

occur. This may be especially true if the economic environment is such that the entrepreneurship types making up a particular proxy not only differs from what was intended, but also dominates the measure.

Another part of the problem with the "one size fits all" characterization of entrepreneurship is the inability to discern the impact of potential policies due to proxy selection. Some researchers argue that as a developed nation, policies in the U.S. should be focused on specifically encouraging Schumpeterian activity (Goetz et al. 2010; Shane 2009; Wennekers and Thurik 1999). This is the case because many believe that Schumpeterian activity is the only way to ensure long-term sustainable growth (Goetz and Freshwater 2001; Goetz et al. 2010; Shane 1996; Wennekers and Thurik 1999). This belief appears to be embraced by much of the literature which relies heavily on Schumpeterian-type definitions of entrepreneurship (Acs and Varga 2005; Armington and Acs 2002; Goetz 2008; Goetz et al. 2010; Goetz and Freshwater 2001; Lee, Florida, Acs 2004; Shane 1996; Shane 2009; Sutaria and Hicks 2004; Wennekers and Thurik 1999). However, many of these empirical works use proxies of entrepreneurship that include multiple forms of entrepreneurship and are not necessarily consistent with their Schumpeterian-type definitions. As a result the intent of a policy can be somewhat blurred by the mischaracterization of the entrepreneurship type in the analysis.

The chief contributor to both aspects of the entrepreneurship characterization problem is that measures of specific entrepreneurship types, in particular Schumpeterian activity, are difficult to construct. This leads to the main concern addressed in this study: developing a suitable measure of Schumpeterian activity. The main challenge of isolating a measure of any specific entrepreneurship type is that disaggregating new or existing firm data into their respective types of entrepreneurship is very difficult. As a result, many settle for measures based on particular firm sizes or industry types. However, the main concern with this type of disaggregation is that Schumpeterian type entrepreneurship can occur in any industry type and within firms of any size.

In place of disaggregating firm data into particular industry types or firm sizes which still contains different types of entrepreneurship, another approach to developing a measure of Schumpeterian activity is to incorporate a wide range of its characteristics into a single model. Recently, one school of thought has emerged that is focused on generating measures of entrepreneurship that include a broader range of inputs (Ahmad and Hoffman 2008; Ahmad and Seymour 2008; Avanzini 2009). It is proposed in this study that this idea can be utilized to estimate different types of entrepreneurship, specifically Schumpeterian activity, by refining the inputs used to generate them.

The overall objective of this study is to add to the growing body of literature focused on developing better measures of entrepreneurship. In particular, a measure is constructed that captures the amount of Schumpeterian activity among U.S. States. In this study, the methodology laid out by Avanzini (2009) is used to construct a composite entrepreneurship indicator (CEI) from a wide number of measures, variables, and indices believed to be related to Schumpeterian activity. The CEI is intended to reflect the relative amount of Schumpeterian activity between states, and the inputs of the CEI are selected such that different facets of Schumpeterian activity are incorporated into the measure. This methodology employs a scoreboard approach to constructing a measure of Schumpeterian activity which allows each input to be examined in the context of their respective contributions. One advantage of this approach is that the use of a scoreboard helps to ensure that the essence of Schumpeterian activity is what is actually being captured in the measure.

What follows is: 1) additional background about developing a measure of Schumpeterian activity; 2) the methods and procedures employed in this study; 3) the empirical results; and 4) a discussion of policy recommendations and future research. The background section includes a further discussion of the role that Schumpeterian activity plays in economic development policy. This is followed by a brief discussion of popular entrepreneurship proxies used in the literature. This section is concluded with an overview of the development of composite indicators and their applications to describe different aspects of economic activity. In the methods and procedures section, Avanzini's (2009) methodology is applied to construct a CEI model intended to measure Schumpeterian activity for U.S. states. This section incorporates the discussion about the inputs used to generate the CEI models including summary statistics, input sources, and Pearson correlation maps. In the results section, the constructed CEIs are examined with regard to their component parts and then compared to popular entrepreneurship proxies. They are also compared to the Kauffman Index of Entrepreneurial Activity (KIEA; Fairlie 2011) and average wage per job data, the latter of which is used as an indicator of economic growth. Next, the entrepreneurial culture results of Goetz and Freshwater (2001) are compared to these same measures (popular proxies, KIEA, and average wages) to provide further support for using the CEI as a measure of Schumpeterian activity. Additionally, a plot of new firm formation and the CEI is examined in the context of entrepreneurship and economic development. This article concludes with a discussion about the implications of the results with respect to state level policy and avenues for further study.

Background

Why Schumpeterian Activity?

Many researchers believe that the presence of Schumpeterian activity is necessary for long-term economic growth (Aghion and Howitt 1990; Goetz et al. 2010; Shane 1996; Wennekers and Thurik 1999). Aghion and Howitt (1990) explained that the process of Schumpeterian activity begins when competition among firms drives innovation and leads to technological progress. Within a group of industries, creative destruction results when old ideas or practices give way to new, more innovative ideas and technologies. Mature economies such as the U.S. are particularly suited to capitalize on the growth from this technical progress which leads to more Schumpeterian activity (Goetz et al. 2010; Wennekers and Thurik 1999). Further, growth from Schumpeterian activity can also lead to growth from other forms of entrepreneurship.

A number of studies have demonstrated that a U-shape trend exists between levels of early stage entrepreneurship (the proportion of 18-64 year olds actively starting a business) and economic development (Bosma et al. 2008; Goetz et al. 2010; Wennekers and Thurik 1999). In earlier phases of development, these levels are high. As economies mature the levels decline. In the most advanced economies such as the U.S., however, these levels begin to rise again and are believed to be closely related to the impact of Schumpeterian activity (Goetz et al. 2010). The general belief is that, in the most evolved agglomeration economies, shifts are occurring from manufacturing-based to knowledge-based economies. As a result, more opportunities are available for firms of multiple sizes and across different industries. For these reasons, Goetz et al. (2010) and Shane (2009) argue that state and local government policies should be more focused on encouraging Schumpeterian activity than any other type of entrepreneurship.

Popular Proxies of Entrepreneurship

Several studies have examined the impact of state and local government policies on the creation of Schumpeterian-type activity (Armington and Acs 2002; Lee, Florida, Acs 2004; Shane 1996; Sutaria and Hicks 2004). In each study, a derivative of new or existing firms was used as a measure of Schumpeterian activity (Shane 1996) or Schumpeterian-type entrepreneurship (Armington and Acs 2002; Lee, Florida, Acs 2004; Sutaria and Hicks 2004). In the later cases, concepts associated with Schumpeterian activity, such as innovation, high levels of technology use, and strong entrepreneurial culture (or climate), were used to describe the characteristics of entrepreneurship without explicitly referring to it as Schumpeterian activity. As a result, the use of entrepreneurship within these later studies has been framed as synonymous with Schumpeterian activity. On the other hand, the proxies of entrepreneurship used in each of these studies (Armington and Acs 2002; Lee, Florida, Acs 2004; Shane 1996; Sutaria and Hicks 2004) may have also captured a lot more information than their definitions implied.

For example, Armington and Acs (2002), Lee, Florida, Acs (2004), and Sutaria and Hicks (2004) used new firm formations as proxies for their Schumpeterian-type definitions of entrepreneurship. As Goetz et al. (2010), Julien (2007), and Wennekers and Thurik (1999) point out, not all entrepreneurship is Schumpeterian-type. In fact, much of the entrepreneurship captured by new firm formations is not necessarily consistent with many concepts associated with Schumpeterian activity.

According to Goetz et al. (2010), there are three general types of entrepreneurship: factor-based (dominated by sectors relying on natural resources), Efficiency-based (dominated by manufacturing), and Innovation-based (dominated by service sectors and is separated into Schumpeterian-type entrepreneurship and necessity type entrepreneurship). Firm births data includes a wide range of industry types and firm sizes, and potentially all of entrepreneurship types. Since non-Schumpeterian-type entrepreneurship accounts for the highest proportion of total entrepreneurship (Hamilton-Pennell 2011), firm birth data would potentially include a lot more information about other forms of entrepreneurship relative to what the Schumpeterian-type definitions suggest.

This same argument can be made for sole proprietorships, another popular Schumpeterian-type proxy. Most new start-ups are sole proprietorships and they are believed to account for the majority of small manufacturers and service firms (Acs and Szerb 2009; Lundström and Stevenson 2005). However, many sole proprietors, especially those in service related industries (such as attorneys, accountants, or lawn care professionals) are not necessarily innovative in nature nor do they employ high levels of technology.

Another popular indicator of entrepreneurship is the Kauffman Index of Entrepreneurial Activity (KIEA) which measures the adult (age 20-64) non-business owner population who start a new business (Fairlie 2011). By definition, the KIEA is a broad measure incorporating all entrepreneurship types (Goetz 2008; Goetz et al. 2010), and it captures start-ups that are employer and well as non-employer firms (Fairlie 2008). Although the use of the KIEA is not intended to singularly capture Schumpeterian activity, use of the KIEA as an analytical tool to compare other entrepreneurship proxies, including potential measures of Schumpeterian activity, could produce valuable insight.

Developing Composite Indicators

The problems associated with using simple proxies to capture particular types of entrepreneurship led to the emergence of a new school of thought within the economic literature: the development of measures that include a broad array of inputs and allow for more focused policy analysis (Ahmad and Hoffman 2008; Ahmad and Seymour 2008; Avanzini 2009; Davis 2007; Leitão 2007). The main challenge of developing these measures is the process of incorporating a wide range of inputs in a way that a single overall value is generated. One way to think about a particular type of entrepreneurship is to break it down into smaller, identifiable parts. A strategy that has recently become popular in the literature uses the scoreboard approach to examine different dimensions of entrepreneurship (Avanzini 2009; Davis 2007; Leitão 2007). These scoreboards (composite indicators) are made up of a number of conceptual categories, which contain sub-indicators that can be measured directly, and can be compressed into a single, manageable value. However, the relative contribution made by each sub-indicator is not lost in the aggregation process. This characteristic of the scoreboard approach assures that the level of contribution by a particular sub-indicator is consistent with what the literature specifies. Figure 7 is a conceptual design of a composite indicator of entrepreneurship (CEI) based on Avanzini (2009). Each of the categories (red and blue colored ellipses) feeding into the CEI are made up of sets of inputs that are consistent with the category definition.

The framework for constructing composite indicators from a large number of single indicators was established by Freudenberg (2003) and Nardo et al. (2005). The main benefit of using composite indicators is that they can summarize complex and multi-dimensional factors that cannot normally be captured by single observable measures. Although composite indicators can be sensitive to inputs, especially when outliers are present, composite measures of entrepreneurship, specifically those that capture Schumpeterian activity, can be constructed with carefully selected data.

Following the work of Freudenberg (2003) and Nardo et al. (2005), Avanzini (2009) applied the composite indicator framework to measuring entrepreneurship. He established a set of criteria for categorizing different determinants and indicators of entrepreneurship. He distinguished between seven dimensions (referred to as categories in this paper) of entrepreneurship that included: 1) entrepreneurial activity; 2) employment; 3) economic activity; 4) entrepreneurial spirit, culture, and initiative; 5) barriers to entry; 6) knowledge procurement; and 7) innovation. Each category was comprised of individual and measurable determinants and indicators (referred to as sub-indicators in this study) that matched the dimension definition.

Avanzini's empirical work was confined to identifying how different principle component analysis (PCA) techniques weighted the categories and sub-indicators of his CEIs. At one extreme, he constructed an overall entrepreneurship index (OEI) which was generated from the weights of sub-indicators without the consideration of their respective categories. At the other extreme, both the category weights and the weights of the sub-indicator within a category were used to create the multi-dimensional entrepreneurship index (MEI).

The OEI and MEI constructed by Avanzini (2009) were intended to capture the broader characteristics of multiple entrepreneurship types across the 69 nations that he considered in his study. The measures also reflected where each nation stood in their economic development success relative to the whole group. Based on the results, it is clear that both the OEI and MEI placed more developed nations (where Schumpeterian activity was expected to be highest) towards the top of the list. This implies that the OEI and MEI could potentially be used as an indicator of Schumpeterian activity.

Methods and Procedures

Defining the CEI Inputs

In this study, Avanzini's methodology is used to construct an OEI and MEI for U.S. states and for two different years, 2002 and 2007. Using state level data, 45 sub-indicators of entrepreneurship were obtained and categorized based on Avanzini's definitions (see Table 24). The data comprising the sub-indicators for the 2002 and 2007 CEIs are for U.S. states in years 2000-2002 and 2005- 2007 respectively to avoid endogeneity issues in the data. The inputs used to construct the CEI were obtained from the American Banking Institute (ABI), US Census Bureau (including the Survey of Business Owners for 2002 and 2007), US Department of Labor, Kauffman Foundation, Bureau of Economic Analysis (BEA), Federal Deposit Insurance Corporation (FDIC), Tax Foundation, and US Patent and Trademark Office (USPTO). Where scaling was appropriate, inputs were scaled to per capita (or per 1,000 population), per total firms, or per GDP (in thousands of dollars).

The selection criterion for sub-indicators was determined by data appropriateness and availability at the state level framework. The framework of Avanzini's (2009) seven categories of entrepreneurship characteristics were modified to the following:

1) Entrepreneurial activity which considers firm dynamics, survival and public ownership;
2) Employment based on firm size, entry, and exit;
3) Economic activity based on receipts, firms size and value of exports;
4) Entrepreneurial culture which are reflected by the diversity of non-public firm ownership;
5) Barriers to entry consider the availability of resources such as capital, labor force education levels, and state tax rates;
6) Knowledge procurement is based on the amount and type of human capital present; and
7) Innovation captures the research and development input as well as human capital output.

The summary statistics of the inputs are presented in Tables 25 and 26, and Pearson correlation maps are shown in Figures 8 and 9.

The correlation maps provide a method to determine how well sub-indicators are related to others within a respective category. This is particularly relevant for the second CEI method (constructing the MEI) described in the next subsection. Ultimately, sub-indicators within each category should be highly correlated ($\geq 0.5/\leq -0.5$). In Figures 8 and 9, it does appear that, for the most part, sub-indicators with each category are highly correlated with one another (as seen in the shaded diagonal section of each figure). It also appears that sub-indicators in the first three categories are highly correlated with one another, as are sub-indicators in the last three categories. This suggests that some spill over between categories is occurring.

It is also important to note that the relationships between Schumpeterian activity and four of the sub-indicator categories (entrepreneurial activity, employment, economic activity, and barriers to entry) are not well established in the entrepreneurship literature. However, these four categories are important considerations for entrepreneurship as a whole (i.e., all categories of entrepreneurship). On the other hand, the entrepreneurial culture, knowledge procurement, and innovation are believed to be strongly associated with Schumpeterian activity (Cunningham and Lischeron 1991; Das and Ting 1998; Goetz et al. 2010; Goetz and Freshwater 2001; Shane 1996; Van Stel, Carree, and Thurik 2005).

The entrepreneurial activity category includes sub-indicators that capture the amount of new and young firm activity, the impact on employment from new and exiting firms, firm survivability, and general firm ownership (public versus private). At its core, the amount entrepreneurial activity should measure new and young firm activity (Goetz et al. 2010; Fairlie 2011; Van Stel, Carree, and Thurik 2005; Wennekers et al. 2005; Wennekers and Thurik 1999). Some researchers attribute the amount of entrepreneurial activity with innovation (Van Stel, Carree, and Thurik 2005). Avanzini (2009) expanded the earlier concepts of entrepreneurial activity to include elements of firm dynamics and survivability. That strategy is adopted in this study as well.

The employment category captures the relationship between the aggregated types of entrepreneurship (measured as new firm formation) and employment (see Avanzini

2009). This category includes both self-employment rates and employee firm rates. There is a common belief that Schumpeterian-type entrepreneurship frequently occurs in small or micro sized firms. Where agglomeration economies exit (i.e., higher average number of workers per firm), spillover opportunities may also exist for Schumpeterian-type entrepreneurs (Acs and Varga 2005; Armington and Acs 2002; Fritsch and Mueller 2007; Goetz et al. 2010). On the other hand, self-employment rates are typically associated with factor-based or necessity entrepreneurship and potentially account for the majority of new firm formations (Acs and Szerb 2009; Goetz et al. 2010; Lundström and Stevenson 2005). Interestingly, the correlations in Figures 8 and 9 demonstrate that a significant negative relationship exists between self-employment rates and average firm size (and in 2002 average firm size in entry). Therefore, each sub-indicator with in this category could potentially be related to the amount of Schumpeterian activity present; however, the impact by each may be negative or positive in nature.

Economic activity is driven by all forms of entrepreneurship (Bosma et al. 2008; Goetz et al. 2010). One of the primary measures of economic activity is productivity (Wennekers et al. 2005), which is measured in this study by the average value exports and receipts for all firms. Following Avanzini (2009), this category also includes sub-indicators that capture relative proportion of small, medium and micro sized firms in each state.

The definition of entrepreneurial culture is somewhat ambiguous in the entrepreneurship literature, but has been broadly described as the level of acceptance or support that a state has for entrepreneurial endeavors (Armington and Acs 2002; Florida 2002; Goetz and Freshwater 2001; Lee, Florida, and Acs 2004) A number of measures for the entrepreneurial culture have been proposed, such as the amount of sole proprietorships (Armington and Acs 2002), the Creativity Index (Florida 2002), or the diversity index (Lee, Florida, and Acs 2004). On the other hand, Avanzini (2009) used a range of entrepreneurship types (e.g. female business ownership and necessity entrepreneurs) to describe the entrepreneurial culture. Although measures of different entrepreneurship types were not available at the state level, the sub-indicators included in the entrepreneurial culture category in this study combine the available data that matches Avanzini (2009) with the spirit of the other measures described above.

The barriers-to-entry category includes measures of available financial, physical, and human capital, and is intended to reflect how well states can support the different capital requirement of businesses. It is general recognized that restrictions on financial, physical, and human capital will greatly impair new firm formation (Armington and Acs 2002; Avanzini 2009; Porter et al. 2004; Sutaria and Hicks 2004). Also, the human and financial capital sub-indicators in this category are highly correlated with inputs within the knowledge procurement and innovation categories.

Following Avanzini (2009), knowledge procurement is defined as the human capital resources needed to generate the output associated with innovation. Innovation is defined both by the financial capital needed to generate innovation output as well as the output in the form of patents. Both of these categories are highly correlated with one another, but not highly correlated with the entrepreneurial culture category.

Aggregating Inputs with Principle Component Analysis

In order to construct an aggregated measure of Schumpeterian activity similar to Avanzini's (2009) results, the overall dimension of the data set in this study (50 X 45) had to be reduced to a single dimension (50 X 1). PCA is one technique that can be used to accomplish this goal. The main goal of PCA is to retain the largest amount of variation between the observations of the original data as possible while reducing the overall dimension of sub-indicators (Jolliffe 2002).

Using the PRINCOMP procedure in SAS (SAS institute), the sub-indicators are transformed into a matrix of orthogonal vectors which are the principle components (or Eigenvectors). Each eigenvector accounts for a proportion of the total variation within the dataset. Give that seven categories of sub-indicators were identified it is assumed that the majority of the variation within the data set would be accounted for by the first seven principle components. In this case, the first seven Eigenvectors accounted for 75.04% and 73.80% of the variation for 2002 and 2007 respectively. In order to obtain the 50 X 1 dimension of the CEI (i.e. the CEI which is represented by a single value for each state), however, only the first Eigenvector is used. As a result, some of the sub-indicators (and conceptually the most significant category) will contribute more to CEI than others.

Following Avanzini (2009), the individual elements of the first Eigenvector were squared (the first Eigenvector accounted for 22.02 % and 23.34% of the variation for the 2002 and 2007 data set respectively). This created a vector of sub-indicator weights that were then multiplied by a standardized version of original data set (the original data is standardized based on the mean and variance of each column of sub-indicators). This process generates one form of the CEI (the OEI) as follows:

$$1(a) \qquad \boldsymbol{OEI}_t = \boldsymbol{\lambda_t^T \xi_t}$$

where $\boldsymbol{OEI}_t$ is the OEI version of the CEI in year *t*, $\boldsymbol{\lambda_t}$ is the weight vector of the sub-indicators (the individual squared elements of the Eigenvector), and $\boldsymbol{\xi_t}$ is a matrix of the standardized set of categories and sub-indicators. In essence, the $\boldsymbol{OEI_t}$ is a vector of estimated and standardized observations that reflect the relative amount of Schumpeterian activity between states for a given year.

A second form of the CEI (MEI) was constructed using Consensus PCA (Avanzini 2009). Each category of sub-indicators were weighted within the category (the individual squared elements of the Eigenvector of the sub-indicators within each category), and each category was weighted (the squared elements of the categorical Eigenvector). When these two sets of weights are multiplied together, an overall weight of the sub-indicator is determined (the average amount of variation accounted for by this techniques was 19,72% and 20.21% for 2002 and 2007 respectively, which is lower than the OEI method). This second form of the CEI was generated as follows:

$$1(b) \qquad \boldsymbol{MEI_t = [\Upsilon_t \gamma_t]^T \xi_t}$$

where $\boldsymbol{MEI_t}$ is the MEI version of the CEI, $\boldsymbol{\Upsilon_t}$ is a diagonal matrix of the category weights, and $\boldsymbol{\gamma_t}$ is the within category weight vector of the sub-indicators.

Results and Discussion

The main purpose of this study was to create an estimate of Schumpeterian activity for U.S. states in the form of CEIs that incorporates a wide range of inputs. What follows is a discussion of the results, which is divided into two parts. In the first part, the composition of the CEI is examined in detail. In Tables 27 and 28, the CEIs (OEI and MEI) are presented side-by-side with new firm formation, sole proprietors, and the KIEA. In Tables 29 and 30, the sub-indicators and categories weights that were used to construct the CEIs are shown.In the second part of this section, the CEI is established as a measure of Schumpeterian activity. To distinguish between the CEIs and the other entrepreneurship measures considered in this study, Pearson Correlation coefficients were generated for the CEIs, new firm formation, sole proprietors, the KIEA, and average wage per job data (see Tables 31 and 32). Average wage per job data was included in the analysis since it has been used as an indicator at the state and local levels for the quality of jobs created (Porter et al. 2004). Table 33 provides more support for the CEI as a measure of Schumpeterian activity. Goetz and Freshwater's (2001) measure of entrepreneurial culture, believed to be strongly associated with higher levels of Schumpeterian activity, was compared to firm births, sole proprietorships, the KIEA, and average wages 1996 (the data year for the entrepreneurial culture measure generated; data needed to construct a CEI for 1996 is not available). Finally, the OEIs for 2002 and 2007 were plotted against new firm births to demonstrate the trend associated with these two measures (see Figures 10 and 11).

Composition of the CEI

The rankings presented in Tables 27 and 28 are based on the OEI version of the CEIs. Many of the top ranked states in these two tables have historically had large industrial complexes (e.g. states around the Great Lakes region), are adjacent to Washington D.C., or have major research institutions within their borders. This observation is consistent with the belief that agglomeration economies allow for potential spillovers that positively impact the levels of Schumpeterian activity as well as other types of entrepreneurship (Acs and Varga 2005; Armington and Acs 2002; Fritsch and Mueller 2007; Goetz et al. 2010). These spillover opportunities can occur from a broad range industry types. Additionally, states with large and established industry sectors that can provide spillover opportunities for Schumpeterian type entrepreneurs typically have larger urban centers.

However, the CEI ranking results also suggest that presence of a large population (or urban center) does not necessarily guarantee the presence of spillover opportunities and higher levels of Schumpeterian activity. For example, three of the states located near the bottom of the 2002 CEI rankings (lowest 15 states) have above average population densities (Florida, Hawaii, and New Hampshire), and two of these states have metropolitan populations greater than 800,000 (the population density values used here are based on U.S. Census data for 2001 and 2006). In 2007, there were five states in the lowest 15 rankings that had above average population densities (Florida, Hawaii, New Hampshire, Rhode Island, and Tennessee) and three of the five have large urban centers (metropolitan area greater than 800,000).

States with low population densities (or the absence of large urban centers and agglomeration economies), typically performed the worse in the CEI rankings. In fact, four out of the five states in 2002 with the lowest U.S. population densities appeared in the lowest 15 rankings (Alaska, Montana, North Dakota, and Wyoming). In 2007, however, only one out of the five states with the lowest population densities appeared in the lower 15 rankings (Montana). Although these results suggest that agglomeration economies are an important factor for proving opportunities for Schumpeterian activity, there may be other avenues for states that do not have this particular attribute. A more detailed investigation into the specific components of the CEI leading to these results is investigated in a follow up project that is currently underway.

The contributions made to the CEIs by some of the sub-indicators and categories are consistent with what was expected for a measure of Schumpeterian activity (see Table 29 and 30). More specifically, it was expected that innovation and high technology use (knowledge procurement) would make up a large part of the CEIs (the weight for the knowledge procurement category was between 41-56% of CEI depending on the CEI model and year). Additionally, between 62-80% (depending on the CEI and year) of the CEI was accounted for when specific sub-indicators under the barriers to entry category (college degrees, venture capital and SBRI funding) were included with innovation and knowledge procurement. Once again, this result is consistent with the expected impact of agglomeration economies on Schumpeterian activity discussed above.

The proportion of the CEIs made up by the entrepreneurial culture, spirit and initiative category, however, was much lower than expected (0.2-6%). For comparison, Avanzini's (2009) results for the entrepreneurial culture, spirit, and initiative category contribution ranged from 4 to 18%. In this present study, it may be the case that the entrepreneurial culture was potentially not well represented at the state level by the variables included in the model. On the other hand, it may be that the entrepreneurial culture is a more complex concept and is comprised of aspects of other variables under different categories. For example, Florida (2002) identified a positive correlation between cities with high technology firms and cultural diversity. Similarly there is a strong and positive correlation between two sub-indicators under the entrepreneurial culture, spirit, and initiative category (foreigners per capita and artisans per total firms) and all of the sub-indicators under the knowledge procurement and innovation categories (see Figures 8 and 9).

One final noteworthy characteristic to point out about the sub-indicator and category contributions is the difference between the OEI and MEI contributions from the employment and economic activity categories. For the OEI, the weights from the employment and economic activity categories ranged between 2.5-3.7% and 2.5-3.3% respectively (depending on the year), while the same MEI category weight ranges were 4.4-10.4% and 10.6-13.5% respectively. Other contributions from sub-indicators and categories were more similar across the two CEI methods. The main reason to point this feature out is that, even with these differences, the two CEI methods produced very similar results. This is an important consideration, since it was noted earlier in this article that PCA can be very sensitive to inputs.

The CEI as a Measure of Schumpeterian Activity

To establish the CEIs as a measure of Schumpeterian activity, it was necessary to distinguish the CEIs from other measures of entrepreneurship. The Pearson Correlation coefficients of the two CEI measures (OEI and MEI) differ only slightly (see Tables 31 and 32). However, the CEI's are negatively correlated with new firm formations, sole proprietors, and the KIEA (all results are significant). A similar relationship is seen in Table 33 between the Goetz and Freshwater (2001) entrepreneurial culture measure and new firm formations, sole proprietors, and the KIEA[3]. However, only the sole proprietorships coefficient is significant. This indicates that the CEIs are capturing entrepreneurship aspects very different from the more general measures (i.e. new firm

[3] Data for 1996 was not available to construct a CEI for a direct comparison with the Goetz and Freshwater entrepreneurial culture. Therefore, an indirect comparison of the CEI and their entrepreneurial culture value was made by using the same measures for comparison but in different data years.

formations, sole proprietors, and the KIEA), but similar to the Goetz and Freshwater (2001) measure.

In short, the CEIs appear to have a positive relationship with entrepreneurial culture generated by Goetz and Freshwater (2001). Although a state's entrepreneurial culture and Schumpeterian activity do not measure the same phenomenon, the presence of strong entrepreneurial culture is crucial for Schumpeterian activity to thrive (Goetz and Freshwater 2001). In other words, one would expect to find higher levels of Schumpeterian activity where the entrepreneurial culture is strong.

These particular results also imply that aggregated measures of entrepreneurship are made up of growth that includes more than just the Schumpeterian activity, and this additional growth dominates the measures (the cause of the negative correlation). This finding is supported by the general belief that, at any level of measurement, the proportion of non-Schumpeterian type entrepreneurship is always much higher relative to that of Schumpeterian activity (Hamilton-Pennell 2011). Further, it also makes the point that using general measures of entrepreneurship in policy analysis to capture Schumpeterian activity or Schumpeterian-type definitions of entrepreneurship will lead to potentially misleading results.

Another important feature to point out is that the CEIs have a significant and positive correlation with average wage per job data. However, new firm formations, sole proprietors, and the KIEA are negatively correlated to the wage data but these correlations are not significant. This suggests that the CEIs also have a positive relationship with economic growth, which is similar to the effect one would expect between a measure of Schumpeterian activity and economic growth. With respect to the other three general entrepreneurship measures, the negative correlation with the average wage per job data implies that some states with higher new firm formations were potentially dominated by growth due to entrepreneurship types associated with lower wages.

Additional support for the CEIs capturing Schumpeterian activity is presented in Figures 10 (2002) and 11 (2007) where it appears that the OEI has a negative or an inverse relationship with new firm births[4]. The effect is similar to what has been reported across countries as economies mature (Acs, Audretsch, and Evans 1994; Bosma et al. 2008; Carree et al. 1999; Goetz et al. 2010; Wennekers and Thurik 1999). It is important to point out that it is not suggested in this study that states to the left in the plot are developing economies, as is the case at the country-level framework. Instead, the purpose of the plot was to demonstrate that a similar trend (negative or inverse in nature) was occurring at the U.S. state level between the Schumpeterian activity measure and firm births. It is suggested, based on these plots, that states that are more to the right have a greater amount of economic development occurring relative to states that are more to the left. This idea is supported by the correlation between average wage per job data, the OEIs, and firm births.

Additionally, the plotted data can be divided into two parts. Approximately half to two-thirds of the data contribute to the downward movement of the slope (to the left in the plot), while the reaming half to one-third (to the right in the plot) appears to level off. Based on this observation, a rough transition point, where the leveling off point begins can be identified. Based on these two plots (Figures 10 and 11), many of the states to the right of these approximate transitions points have agglomeration economies. According

[4] Delaware appears as a potential outlier in the data.

to Goetz et al. (2010), these states should also have a greater mix of small and large firms (this idea will be further investigated in a follow up project). Additionally, these states to the right of the approximate transition points in Figures 10 and 11 would also be expected to have more knowledge-based firms that have transitioned from manufacturing-based economies. The best evidence for this case is to consider that many of the states to the right of the transition points in 2002 and 2007 have historically had strong manufacturing-based economies, and that two of the three categories with the highest weights were knowledge procurement and innovation.

Conclusion and Recommendations

In this study, an argument was constructed to point out the need for more accurate measures of Schumpeterian activity. To demonstrate the concerns of using general measures of entrepreneurship in policy analysis when the true intentions of the measures were to capture the amount of Schumpeterian activity, two important points were made. First, entrepreneurship is a multidimensional concept and not well represented by simple proxies. In fact, it was pointed out that general measures capture multiple types of entrepreneurship and that these different types may have conflicting qualities. Where this has been the case, misleading results regarding policy analysis may have occurred.

Second, Goetz et al. (2010) argue that Schumpeterian activity in developed nations should be the specific focus of state and local policy. More specifically, the analysis of U.S. policies should be such that Schumpeterian activity is clearly defined and well measured. Most of the research focusing on entrepreneurship and policy analysis at the state and local levels embrace this idea with their Schumpeterian-type definitions.

However, suitable measures of Schumpeterian activity have not been readily available. As a result, the use of simple proxies may have led to some confusion about policy intent.

To address these issues in this study, a CEI intended to specifically measure the relative amount of Schumpeterian activity among U.S. states was constructed from a wide range of inputs. This approach was presented as an alternative to efforts that use measures of new or existing firm data that include aggregated entrepreneurship types. One feature of the CEI methodology (the scoreboard approach) is that each component (the sub-indicators) can be examined in the context of their individual contributions to the overall measure. Although a detailed examination of the impact from specific inputs was beyond the scope of this study, a number of interesting features were noted for further investigation as well as for potential policy implications.

To begin, although the placement of the top states in the CEI supports beliefs about agglomeration economies, the shift from 2002 to 2007 of the placement of states in the lower third of the CEI suggest an opportunity for some states without well developed agglomeration economies. One avenue for further study would be to identify the relationship between inputs that most greatly impacted this shift and state level policies. This shift also implies that the states with less evolved agglomeration economies may have other comparative advantages that can potentially be capitalized upon by policy makers. Therefore, states with these comparative advantages should specifically develop policy that can support and exploit these recourses instead of reproducing policies of states with more evolved agglomeration economies.

Another consideration for further examination is the relationship between states' entrepreneurial culture and the CEI implied by the similarities between the Goetz and

Freshwater (2001) measures and the CEI. However, this relationship can be better established. Also, there was not a significant relationship between the Goetz and Freshwater (2001) entrepreneurial culture measure and the general entrepreneurship measures considered. One suggestion is to develop a more detailed entrepreneurship culture measure and compare it to the CEI as well as the general entrepreneurship measures. The logic behind this idea is that since entrepreneurship is multidimensional, the entrepreneurial culture supporting it may be similar in nature. Therefore, an aggregated measure of entrepreneurship may be more similar to an aggregated measure of the entrepreneurial culture; whereas, the CEI may be more similar to a disaggregated measure of the entrepreneurial culture.

One area of future study that could provide support for the use of the CEI would be to use different sets of inputs (sub-indicators) or to change up the categories entirely. By doing so, the result presented above may represent a dramatic reshuffling the placement of states within the CEI. In this study, there were two observations that provide support for making this future inquiry. First, there were only subtle differences between the contributions of inputs of the CEI methodologies and years with two exceptions, the employment and economic activity. The two methodologies, however, produced similar overall results. Second, it was also noted that the entrepreneurial culture category that makes up each CEI did not contribute as much to the measure as expected. As proposed in the results section, this may have resulted because the entrepreneurial culture sub-indicators were not a good representation of the entrepreneurial culture itself. Another possibility is that the other sub-indicators from different categories could have been unobserved characteristics that are indirectly contributing to the entrepreneurial culture. In any case, by significantly altering the categories and sub-indicators it can potentially be determined how stable the CEI results presented here are.

One final and important consideration is the availability of data used to develop the measures of Schumpeterian activity in this study. The CEIs were constructed using a wide range of inputs from a number of sources (see Table 1). Currently, many of these data are only available in five year intervals or not available at all at the local level of government. For states committed to the development of policies that encourage entrepreneurship, regardless of the type of entrepreneurship considered, the collection of relevant data is paramount. This is especially true at the local government level, where many of the important inputs to appropriately examine policies do not exist.

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Table 24. Identification and Source of Sub-indicators Used to Generate CEI

Category Name	Sub-indicator Name	Sub-indicator Source
Entrepreneurial Activity	Business bankruptcies per total firms	ABI/U.S. Census
	New firm entry relative to total firms	U.S. Census
	Firm exit relative to total firms	U.S. Census
	Business bankruptcies per firm exit	ABI/U.S. Census
	Young firm entrepreneurship index (firm age 0-3 years)	U.S. Census/Dept. Labor
	Young firm entrepreneurship index (firm age 0-5 years)	U.S. Census/Dept. Labor
	Kauffman index of entrepreneurial activity	Kauffman Foundation
	Publicly held firms per total firms	U.S. Census SBO
	Established business activity index (firms greater than age 5 years)	U.S. Census/Dept. Labor
Employment	Average size of firm entry	U.S. Census
	Share of firm entry in employment	U.S. Census
	Share of firm exit in employment	U.S. Census
	Average number of workers for all firms	U.S. Census
	Self-employment rate	BEA
Economic Activity	Average value of receipts for all firms ($1000)	U.S. Census SBO
	Medium, small, and micro firms per total firms	U.S. Census
	Medium, small, and micro firms per capita	U.S. Census
	Average value of exports per total firms (in thousands $)	U.S. Census
Entrepreneurial Culture	Percentage of female owned firms per total firms	U.S. Census SBO
	Percentage of Asian owned firms per total firms	U.S. Census SBO
	Percentage of Hispanic owned firms per total firms	U.S. Census SBO
	Percentage of Native American owned firms per total firms	U.S. Census SBO
	Percentage of African American owned firms per total firms	U.S. Census SBO
	Percentage of foreigner per capita	U.S. Census SBO
	Percentage of artisan firms per total firms	U.S. Census SBO
Barriers to Entry	Net loans & leases per GDP (in thousands $)	FDIC/BEA
	States tax burden	Tax Foundation
	Percentage of high school graduates per capita	U.S. Census
	Percentage of persons with bachelor degrees per capita	U.S. Census
	Percentage of persons with advanced degrees per capita	U.S. Census
	Average SBRI funding per capita	U.S. Census
	Venture capital dispersed per capita	U.S. Census
	Highest individual tax rate	Tax Foundation
	Highest corporate tax rate	Tax Foundation
Knowledge Procurement	Academic articles per capita	U.S. Census
	Science and engineering doctorates conferred per capita	U.S. Census
	Physicians per capita	U.S. Census
	Percentage of computer and mathematical occupations per total labor force	Dept. Labor
	Percentage of architecture and engineering occupations per total labor force	Dept. Labor
	Percentage of life, physical, and social science occupations per total labor force	Dept. Labor
	S&E Doc Holders	U.S. Census
Innovation	Academic research and development spending per capita ($)	U.S. Census
	Industry performed research and development per capita ($)	U.S. Census
	Patents issued to academic institutions per capita	U.S. Census
	Total patents issued per capita	USPTO

Table 25. Summary Statistics of 2002 CEI Inputs

Sub-Indicator Name	Mean	Std. Error	Minimum	Maximum
Business bankruptcies/total firm	0.6542%	0.4819%	0.1914%	2.9703%
Entry rate	12.1960%	1.6744%	9.7000%	17.7000%
Exit rate	-11.5000%	1.0721%	-14.4000%	-9.5000%
Business bankruptcies/firm exit	5.6940%	4.0787%	1.7480%	25.9082%
Young firm entrepreneurship Index (3 yr)	0.0108	0.0019	0.0077	0.0162
Young firm entrepreneurship index (5 yr)	0.0145	0.0025	0.0106	0.0215
KIEA	0.2772%	0.0796%	0.1277%	0.4802%
Publicly held firms/total firms	2.8911%	0.7413%	2.0544%	6.9341%
Established business activity index	0.5037	0.0428	0.3945	0.6144
Average size firm entry	9.2830	1.5240	5.6881	13.1748
Share firm entry in employment	6.5800	1.0719	5.0000	10.8000
Share firm exit in employment	5.8040	0.7946	4.3000	7.7000
Average # workers all firms	4.6811	0.6935	2.9220	5.9375
Self-employment rates	9.7211%	1.6338%	7.0958%	13.7009%
Average receipts all firms ($1000)	909.8030	232.6067	445.0807	1831.4800
Med, small, micro firms /total firms	84.3760%	2.7218%	79.6469%	91.5470%
Med, small, micro firms/1000 population	19.8891	3.2112	15.3915	28.5655
Exports/total firms ($ 1000s)	23.9442	13.6841	3.8474	74.3447
Female owned/total firms	27.0269%	2.1176%	22.3956%	30.9803%
Asian owned/total firms	3.4685%	6.4708%	0.4314%	45.2753%
Hispanic owned/total firms	3.5476%	4.8283%	0.4051%	21.7305%
Native Am owned/total firms	1.1252%	1.4417%	0.2706%	8.2887%
African Am owned/total firms	3.9930%	3.9079%	0.1374%	15.6491%
Foreigner per capita	7.5762%	5.9545%	1.0953%	26.9422%
Artisan firms/total firms	0.0816%	0.0441%	0.0288%	0.2856%
Net loans & leases/GDP	6.2011	8.4804	0.6921	40.7806
State tax burden	9.0506%	1.2450%	4.7002%	11.7531%
High school/ some college	85.5580	4.0061	78.1000	92.2000
Bachelor's degree	25.9980	4.5196	15.9000	37.6000
Advanced degree	3.9902	1.5419	1.3447	10.3028
Average SBRI funding per capita	0.1119%	0.1333%	0.0142%	0.7975%
Venture capital dispersed per capita	2.4935%	3.9344%	0.0000%	23.1497%
Individual tax rate	5.5768%	3.1858%	0.0000%	12.0000%
Corporate tax rate	6.4956%	2.9173%	0.0000%	12.0000%
Academic article output per capita	0.0484%	0.0227%	0.0172%	0.1490%
S&E doctorates conferred per capita	0.0082%	0.0037%	0.0023%	0.0226%
Physicians/1000 population	0.2435%	0.0586%	0.1608%	0.4252%
Comp. & math jobs/total labor force	0.8699%	0.3694%	0.2956%	1.9202%
Arch. & eng. jobs/total labor force	0.8107%	0.2280%	0.4248%	1.4370%
Life, phys. & soc. Sci. jobs/total labor force	0.4071%	0.1450%	0.2240%	0.9087%
Sci. & eng. PhD holders per capita	0.2264%	0.0992%	0.1071%	0.5434%
Academic R&D per capita ($)	0.03046	0.01128	0.01147	0.07199
Industry Performed R&D per capita ($)	0.00016	0.00013	0.00001	0.00051
Patents to academic institutions per capita	0.0009%	0.0007%	0.0000%	0.0034%
Total patents per capita	0.0303%	0.0236%	0.0063%	0.1399%

Table 26. Summary Statistics of 2007 CEI Inputs

Sub-Indicator Name	Mean	Std. Error	Minimum	Maximum
Business bankruptcies/total firm	0.4091%	0.1926%	0.1469%	1.3300%
Entry rate	13.1400%	1.9593%	10.4000%	18.5000%
Exit rate	-10.7540%	0.9792%	-13.8000%	-9.0000%
Business bankruptcies/firm exit	3.8861%	1.7145%	1.4366%	11.5734%
Young firm entrepreneurship Index (3 yr)	0.0108	0.0024	0.0071	0.0183
Young firm entrepreneurship index (5 yr)	0.0141	0.0030	0.0096	0.0237
KIEA	0.2951%	0.0884%	0.0817%	0.4626%
Publicly held firms/total firms	3.6902%	0.7395%	2.4764%	6.9354%
Established business activity index	0.5034	0.0463	0.3863	0.6086
Average size firm entry	8.1819	1.5254	5.0837	13.8191
Share firm entry in employment	6.3200	1.2102	4.5000	10.6000
Share firm exit in employment	5.0560	0.6351	3.9000	6.7000
Average # workers all firms	4.3732	0.6077	3.0182	5.6902
Self-employment rates	11.7411%	1.7542%	8.1291%	16.1973%
Average receipts all firms ($1000)	1074.6700	246.0610	597.0982	2001.5000
Med, small, micro firms /total firms	82.2955%	2.9785%	76.7116%	89.0786%
Med, small, micro firms/1000 population	20.1323	3.5341	15.1278	29.8788
Exports/total firms ($ 1000s)	35.7457	18.1676	4.6491	94.4019
Female owned/total firms	27.4518%	2.2467%	22.1472%	32.5932%
Asian owned/total firms	4.0847%	6.8133%	0.5642%	47.2092%
Hispanic owned/total firms	4.4224%	5.4844%	0.4663%	23.6294%
Native Am owned/total firms	1.1678%	1.6791%	0.2323%	9.9690%
African Am owned/total firms	5.5931%	5.2465%	0.2019%	20.4009%
Foreigner per capita	8.3693%	6.1445%	1.2950%	27.6716%
Artisan firms/total firms	0.0791%	0.0472%	0.0279%	0.3041%
Net loans & leases/GDP	11.5528	25.8945	0.6637	128.7441
State tax burden	9.3362%	1.1703%	5.8823%	11.8343%
High school/ some college	86.0060	3.6629	78.5000	91.2000
Bachelor's degree	26.7400	4.6871	17.3000	37.9000
Advanced degree	4.5555	1.8061	1.4879	11.7752
Average SBRI funding per capita	0.1469%	0.1661%	0.0179%	1.0303%
Venture capital dispersed per capita	1.1202%	2.0171%	0.0000%	11.6630%
Individual tax rate	5.4813%	3.1362%	0.0000%	12.0000%
Corporate tax rate	6.7454%	2.6463%	0.0000%	12.0000%
Academic article output per capita	0.0530%	0.0246%	0.0207%	0.1646%
S&E doctorates conferred per capita	0.0086%	0.0038%	0.0018%	0.0251%
Physicians/1000 population	0.2599%	0.0642%	0.1685%	0.4667%
Comp. & math jobs/total labor force	0.9604%	0.4103%	0.3238%	2.3081%
Arch. & eng. jobs/total labor force	0.8091%	0.2034%	0.5028%	1.3390%
Life, phys. & soc. Sci. jobs/total labor force	0.4482%	0.1824%	0.2171%	0.9219%
Sci. & eng. PhD holders per capita	0.2349%	0.1016%	0.1144%	0.5453%
Academic R&D per capita ($)	0.03691	0.01374	0.01754	0.08438
Industry Performed R&D per capita ($)	0.00015	0.00013	0.00001	0.00054
Patents to academic institutions per capita	0.0007%	0.0005%	0.0000%	0.0033%
Total patents per capita	0.0273%	0.0207%	0.0035%	0.0926%

Table 27. Comparison of Different Measures of Entrepreneurship (2002)

State	Rank (OEI)	OEI	MEI	Firm Births	Proprietors	KIEA
Delaware	1	3.9410	3.9427	2.75	86.98	0.13%
Connecticut	2	1.6685	1.6718	2.08	109.51	0.18%
New Jersey	3	1.2575	1.2556	2.50	85.23	0.24%
Illinois	4	1.2484	1.2376	2.03	90.73	0.24%
Massachusetts	5	1.1541	1.1498	2.27	99.59	0.19%
Indiana	6	0.8311	0.8456	2.05	89.62	0.24%
Wisconsin	7	0.8111	0.8277	2.12	100.33	0.28%
Ohio	8	0.7694	0.7781	1.82	89.50	0.18%
Pennsylvania	9	0.7595	0.7412	1.86	86.93	0.14%
Georgia	10	0.7593	0.7336	2.51	93.80	0.22%
Virginia	11	0.6960	0.6573	2.31	90.54	0.25%
Michigan	12	0.6948	0.7359	1.99	86.57	0.25%
Kansas	13	0.6191	0.6196	2.48	122.66	0.33%
Minnesota	14	0.5811	0.5824	2.52	117.23	0.35%
Texas	15	0.5729	0.6088	2.22	110.64	0.36%
Missouri	16	0.4833	0.4610	2.49	109.31	0.27%
New York	17	0.4742	0.4572	2.38	87.57	0.31%
Louisiana	18	0.3013	0.3510	2.04	90.41	0.26%
Iowa	19	0.2865	0.3008	2.15	126.63	0.20%
California	20	0.2434	0.2355	2.47	107.12	0.40%
Washington	21	0.2358	0.3325	2.78	101.52	0.23%
Nebraska	22	0.1892	0.1965	2.47	128.17	0.34%
Tennessee	23	0.1533	0.1431	2.04	114.44	0.29%
North Carolina	24	0.0909	0.0788	2.34	94.70	0.37%
Kentucky	25	0.0808	0.0928	1.88	99.08	0.29%
Maryland	26	-0.1456	-0.2153	2.24	97.34	0.35%
Nevada	27	-0.2147	-0.2525	3.00	97.52	0.27%
South Dakota	28	-0.2173	-0.2204	2.97	150.64	0.34%
Arizona	29	-0.2213	-0.2347	2.41	89.26	0.30%
Colorado	30	-0.2216	-0.2504	3.41	134.68	0.39%
South Carolina	31	-0.2271	-0.2179	2.30	93.07	0.26%
Alabama	32	-0.2312	-0.2458	2.02	88.83	0.19%
Oregon	33	-0.2795	-0.2469	2.85	116.45	0.28%
Rhode Island	34	-0.5614	-0.5948	2.26	80.91	0.13%
Arkansas	35	-0.6239	-0.6423	2.32	101.64	0.18%
Utah	36	-0.6260	-0.6516	3.02	113.34	0.30%
New Hampshire	37	-0.6530	-0.6520	2.52	118.53	0.25%
Alaska	38	-0.7086	-0.6723	3.10	133.84	0.48%
North Dakota	39	-0.7137	-0.6795	2.51	153.01	0.25%
Mississippi	40	-0.7510	-0.7806	1.97	88.00	0.21%
West Virginia	41	-0.7871	-0.7919	1.85	82.08	0.15%
Florida	42	-0.9053	-0.9256	3.08	92.63	0.30%
Hawaii	43	-0.9999	-1.0378	2.28	103.95	0.32%
Oklahoma	44	-1.0295	-1.0583	2.36	121.68	0.37%
New Mexico	45	-1.1723	-1.2183	2.32	96.95	0.36%
Wyoming	46	-1.2407	-1.1953	4.06	148.03	0.34%
Idaho	47	-1.3776	-1.3700	3.17	132.52	0.31%
Vermont	48	-1.4451	-1.3679	2.73	147.63	0.28%
Maine	49	-1.5600	-1.5431	2.85	126.19	0.25%
Montana	50	-1.9892	-1.9716	3.49	165.52	0.45%

Table 28. Comparison of Different Measures of Entrepreneurship (2007)

State	Rank (OEI)	OEI	MEI	Firm Births	Proprietors	KIEA
Delaware	1	3.7538	3.7806	2.68	112.14	0.14%
Connecticut	2	2.2354	2.0585	2.20	136.78	0.21%
New Jersey	3	1.5806	1.4510	2.75	112.83	0.26%
Massachusetts	4	1.3851	0.9963	2.32	121.62	0.24%
Illinois	5	1.1094	1.0362	2.34	108.80	0.24%
Louisiana	6	0.9358	1.2733	2.72	117.51	0.44%
Kansas	7	0.8711	0.8487	2.54	135.24	0.25%
Indiana	8	0.8015	0.9810	2.15	100.89	0.24%
Wisconsin	9	0.7925	0.8819	2.21	115.34	0.29%
Minnesota	10	0.6608	0.5805	2.67	133.65	0.31%
Ohio	11	0.5619	0.6617	1.90	105.23	0.19%
New York	12	0.5286	0.3761	2.63	108.39	0.35%
Nebraska	13	0.4759	0.4440	2.56	138.11	0.31%
Virginia	14	0.4638	0.2571	2.55	111.03	0.22%
Pennsylvania	15	0.4603	0.4451	1.98	101.96	0.15%
Texas	16	0.4528	0.6645	2.34	132.80	0.29%
Iowa	17	0.3825	0.4683	2.33	136.93	0.26%
Washington	18	0.3632	0.5251	3.25	119.09	0.22%
South Dakota	19	0.2058	0.1454	3.16	158.77	0.29%
California	20	0.1950	0.1354	2.73	129.09	0.40%
Missouri	21	0.0772	0.0656	2.58	124.02	0.24%
Kentucky	22	0.0580	0.3403	1.97	108.80	0.32%
North Dakota	23	-0.0485	0.0228	2.91	166.52	0.25%
Alaska	24	-0.0961	-0.0092	3.11	138.78	0.37%
Maryland	25	-0.1242	-0.4843	2.37	125.64	0.32%
Michigan	26	-0.1332	-0.0521	2.06	107.82	0.29%
Georgia	28	-0.2265	-0.2617	2.74	122.52	0.40%
Alabama	29	-0.2310	-0.1050	2.24	114.54	0.10%
North Carolina	30	-0.2410	-0.2246	2.61	115.50	0.32%
Utah	31	-0.2663	-0.3963	3.63	136.88	0.34%
Nevada	32	-0.3099	-0.2424	3.26	123.61	0.30%
Colorado	33	-0.3563	-0.6954	3.76	156.94	0.34%
Arizona	34	-0.3621	-0.3219	2.71	107.87	0.46%
Oregon	35	-0.4744	-0.4500	3.34	132.49	0.35%
Tennessee	36	-0.4902	-0.3094	2.19	132.40	0.44%
Oklahoma	37	-0.5695	-0.5839	2.53	136.96	0.34%
Rhode Island	38	-0.5734	-0.7088	2.54	100.62	0.21%
New Hampshire	39	-0.6784	-0.8293	2.69	142.26	0.28%
Arkansas	40	-0.7039	-0.5208	2.32	112.53	0.34%
South Carolina	41	-0.8331	-0.6670	2.53	120.53	0.26%
West Virginia	42	-0.8841	-0.6473	1.95	93.25	0.08%
Hawaii	43	-0.9592	-1.1354	2.42	131.18	0.21%
New Mexico	44	-0.9946	-1.0401	2.49	112.96	0.25%
Idaho	45	-1.0734	-1.0189	4.04	154.11	0.46%
Mississippi	46	-1.1076	-0.9295	2.22	106.79	0.30%
Florida	47	-1.4016	-1.4106	3.51	119.06	0.36%
Vermont	48	-1.5004	-1.6481	3.25	172.14	0.42%
Montana	49	-1.7312	-1.8174	4.42	180.63	0.40%
Maine	50	-1.8439	-1.8202	3.05	146.16	0.27%
Wyoming	27	-0.1371	-0.1097	4.43	174.16	0.43%

Table 29. Weights of Sub-indicators Contribution to OEI

Category Name	Sub-Indicator Name	2002	2007
Entrepreneurial Activity	Business bankruptcies/total firm	0.04%	0.04%
	Entry rate	0.75%	1.74%
	Exit rate	0.02%	0.17%
	Business bankruptcies/firm exit	0.05%	0.04%
	Young firm entrepreneurship Index (3 yr)	0.45%	0.53%
	Young firm entrepreneurship index (5 yr)	0.42%	0.44%
	KIEA	0.64%	0.59%
	Publicly held firms/total firms	0.21%	0.06%
	Established business activity index	0.29%	1.37%
Employment	Average size firm entry	1.57%	0.05%
	Share firm entry in employment	0.12%	1.08%
	Share firm exit in employment	0.35%	0.55%
	Average # workers all firms	1.62%	0.76%
	Self-employment rates	0.08%	0.08%
Economic Activity	Average receipts all firms ($1000)	2.58%	0.72%
	Med, small, micro firms /total firms	0.40%	1.42%
	Med, small, micro firms/1000 population	0.04%	0.30%
	Exports/total firms ($ 1000s)	0.24%	0.03%
Entrepreneurial Culture	Female owned/total firms	1.92%	1.38%
	Asian owned/total firms	0.21%	0.22%
	Hispanic owned/total firms	0.04%	0.00%
	Native Am owned/total firms	0.76%	0.54%
	African Am owned/total firms	0.08%	0.01%
	Foreigner per capita	1.61%	0.98%
	Artisan firms/total firms	0.57%	0.31%
Barriers to Entry	Net loans & leases/GDP	0.42%	0.27%
	State tax burden	2.33%	2.82%
	High school/ some college	0.30%	1.19%
	Bachelor's degree	6.14%	6.08%
	Advanced degree	6.01%	6.48%
	Average SBRI funding per capita	5.09%	5.78%
	Venture capital dispersed per capita	6.04%	5.14%
	Individual tax rate	1.11%	1.63%
	Corporate tax rate	1.20%	1.45%
Knowledge Procurement	Academic article output per capita	8.42%	7.91%
	S&E doctorates conferred per capita	8.01%	6.97%
	Physicians/1000 population	6.44%	6.80%
	Comp. & math jobs/total labor force	5.62%	4.74%
	Arch. & eng. jobs/total labor force	1.78%	2.37%
	Life, phys. & soc. Sci. jobs/total labor force	1.42%	1.53%
	Sci. & eng. PhD holders per capita	5.92%	5.98%
Innovation	Academic R&D per capita	5.19%	4.91%
	Industry Performed R&D per capita	6.09%	5.66%
	Patents to academic institutions per capita	5.45%	6.12%
	Total patents per capita	1.97%	2.76%

Table 30. Weights of Categories, within Category Sub-indicator, and Overall Sub-indicator Contribution to MEI

Category Name	Sub-Indicator Name	2002 Cat. %	2002 Within Cat. %	2002 Overall %	2007 Cat. %	2007 Within Cat. %	2007 Overall %
Entrepreneurial Activity	Business bankruptcies/total firm	3.45%	3.27%	0.11%	9.96%	0.87%	0.09%
	Entry rate		23.17%	0.80%		21.87%	2.18%
	Exit rate		20.48%	0.71%		13.54%	1.35%
	Business bankruptcies/firm exit		1.68%	0.06%		2.55%	0.25%
	Young firm entrepreneurship Index (3 yr)		15.79%	0.54%		19.47%	1.94%
	Young firm entrepreneurship index (5 yr)		13.96%	0.48%		18.28%	1.82%
	KIEA		6.60%	0.23%		10.44%	1.04%
	Publicly held firms/total firms		0.02%	0.00%		0.06%	0.01%
	Established business activity index		15.03%	0.52%		12.93%	1.29%
Employment	Average size firm entry	10.37%	32.94%	3.42%	4.38%	38.44%	1.68%
	Share firm entry in employment		0.53%	0.05%		8.10%	0.35%
	Share firm exit in employment		0.41%	0.04%		5.04%	0.22%
	Average # workers all firms		36.79%	3.82%		26.16%	1.15%
	Self-employment rates		29.33%	3.04%		22.26%	0.97%
Economic Activity	Average receipts all firms ($1000)	13.46%	19.04%	2.56%	10.64%	16.74%	1.78%
	Med, small, micro firms /total firms		34.56%	4.65%		31.56%	3.36%
	Med, small, micro firms/1000 population		35.63%	4.80%		33.79%	3.59%
	Exports/total firms ($ 1000s)		10.76%	1.45%		17.92%	1.91%
Entrepreneurial Culture	Female owned/total firms	5.82%	19.40%	1.13%	0.17%	20.48%	0.03%
	Asian owned/total firms		12.76%	0.74%		14.12%	0.02%
	Hispanic owned/total firms		18.91%	1.10%		18.75%	0.03%
	Native Am owned/total firms		0.02%	0.00%		0.00%	0.00%
	African Am owned/total firms		0.53%	0.03%		0.99%	0.00%
	Foreigner per capita		30.47%	1.77%		30.08%	0.05%
	Artisan firms/total firms		17.91%	1.04%		15.57%	0.03%
Barriers to Entry	Net loans & leases/GDP	25.75%	0.46%	0.12%	26.81%	2.05%	0.55%
	State tax burden		6.17%	1.59%		10.05%	2.70%
	High school/ some college		1.44%	0.37%		2.82%	0.76%
	Bachelor's degree		18.79%	4.84%		18.35%	4.92%
	Advanced degree		18.94%	4.88%		16.34%	4.38%
	Average SBRI funding per capita		21.72%	5.59%		18.11%	4.86%
	Venture capital dispersed per capita		20.51%	5.28%		16.30%	4.37%
	Individual tax rate		6.79%	1.75%		9.33%	2.50%
	Corporate tax rate		5.19%	1.34%		6.64%	1.78%
Knowledge Procurement	Academic article output per capita	25.30%	19.32%	4.89%	30.12%	18.63%	5.61%
	S&E doctorates conferred per capita		18.27%	4.62%		17.22%	5.19%
	Physicians/1000 population		14.05%	3.55%		14.73%	4.43%
	Comp. & math jobs/total labor force		14.59%	3.69%		13.75%	4.14%
	Arch. & eng. jobs/total labor force		6.35%	1.61%		9.29%	2.80%
	Life, phys. & soc. Sci. jobs/total labor force		8.68%	2.20%		7.36%	2.22%
	Sci. & eng. PhD holders per capita		18.74%	4.74%		19.03%	5.73%
Innovation	Academic R&D per capita	15.86%	27.04%	4.29%	17.93%	21.07%	3.78%
	Industry Performed R&D per capita		29.10%	4.61%		29.94%	5.37%
	Patents to academic institutions per capita		29.32%	4.65%		30.02%	5.38%
	Total patents per capita		14.54%	2.31%		18.97%	3.40%

Table 31. Pearson Correlation of Different Measures of Entrepreneurship (2002)

Measure	OEI	MEI	Firm Births	Proprietors	KIEA	Ave. Wage
OEI	1.0000	0.9995	-0.3867	-0.4776	-0.4112	0.6589
	-	*0.0001*	*0.0055*	*0.0005*	*0.003*	*0.0001*
MEI	-	1.0000	-0.3811	-0.4665	-0.4106	0.6572
	-	-	*0.0063*	*0.0006*	*0.0031*	*0.0001*
Firm Births	-	-	1.0000	0.6505	0.4961	-0.0178
	-	-	-	*0.0001*	*0.0002*	*0.9024*
Proprietors	-	-	-	1.0000	0.539	-0.2066
	-	-	-	-	*0.0001*	*0.1499*
KIEA	-	-	-	-	1.0000	-0.0748
	-	-	-	-	-	*0.6056*
Ave. Wage	-	-	-	-	-	1.0000

Note: the p-value is in italics and below the correlation coefficient

Table 32. Pearson Correlation of Different Measures of Entrepreneurship (2007)

Measure	OEI	MEI	Firm Births	Proprietors	KIEA	Ave. Wage
OEI	1.0000	0.9877	-0.3288	-0.2855	-0.3505	0.6177
	-	*0.0001*	*0.0197*	*0.0444*	*0.0126*	*0.0001*
MEI	-	1.0000	-0.3627	-0.3268	-0.3482	0.5208
	-	-	*0.0096*	*0.0205*	*0.0132*	*0.0001*
Firm Births	-	-	1.0000	0.7196	0.5288	-0.0060
	-	-	-	*0.0001*	*0.0001*	*0.9670*
Proprietors	-	-	-	1.0000	0.4552	-0.0119
	-	-	-	-	*0.0009*	*0.9348*
KIEA	-	-	-	-	1.0000	-0.1204
	-	-	-	-	-	*0.4048*
Ave. Wage	-	-	-	-	-	1.0000

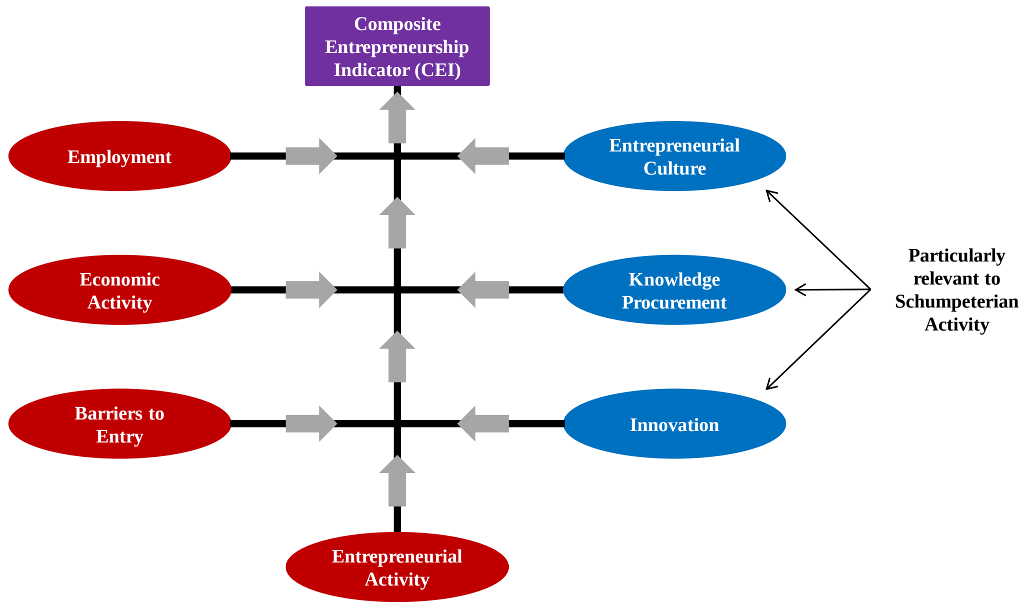
Note: the p-value is in italics and below the correlation coefficient

Table 33. Pearson Correlation of Entrepreneurial Culture and Other Entrepreneurship Measures (1996)

Measure	Entrepreneurial Culture[a]	Firm Births	Proprietors	KIEA	Ave. Wage
Entrepreneurial Culture[a]	1.0000	-0.0868	-0.2895	-0.1338	0.0805
	-	*0.5491*	*0.0414*	*0.3542*	*0.5780*
Firm Births	-	1.0000	0.7337	0.4917	-0.0427
	-	-	*0.0001*	*0.0003*	*0.7686*
Proprietors	-	-	1.0000	0.5866	-0.0641
	-	-	-	*0.0001*	*0.6582*
KIEA	-	-	-	1.0000	-0.1178
	-	-	-	-	*0.2170*
Average Wage	-	-	-	-	1.0000

Note: the p-value is in italics and below the correlation coefficient

a. Based on the Goetz and Freshwater (2001) measure of entrepreneurial culture



Source: This figure is a modification of the conceptual design of Avanzini (2009) as applied to developing a measure of Schumpeterian Activity.

Figure 7. Conceptual Design the Scoreboard Approach for Developing a Composite Entrepreneurship Indicator

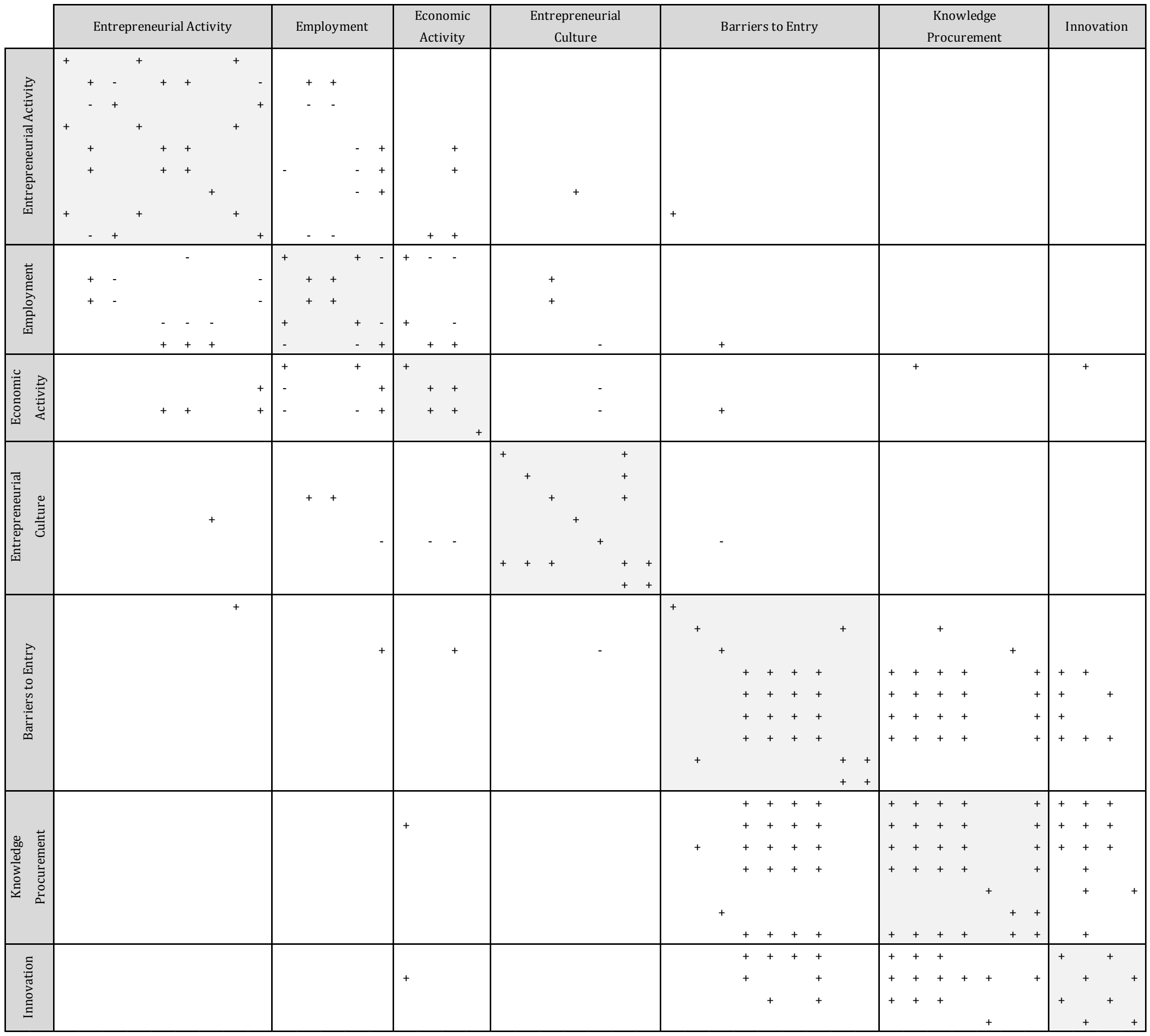


Figure 8. Pearson Correlation Map of the 2002 CEI Model Inputs and Categories of Inputs

The “+” indicates a positive correlation ≥ 0.5, and the “-” indicates a negative correlation ≤ -0.5.

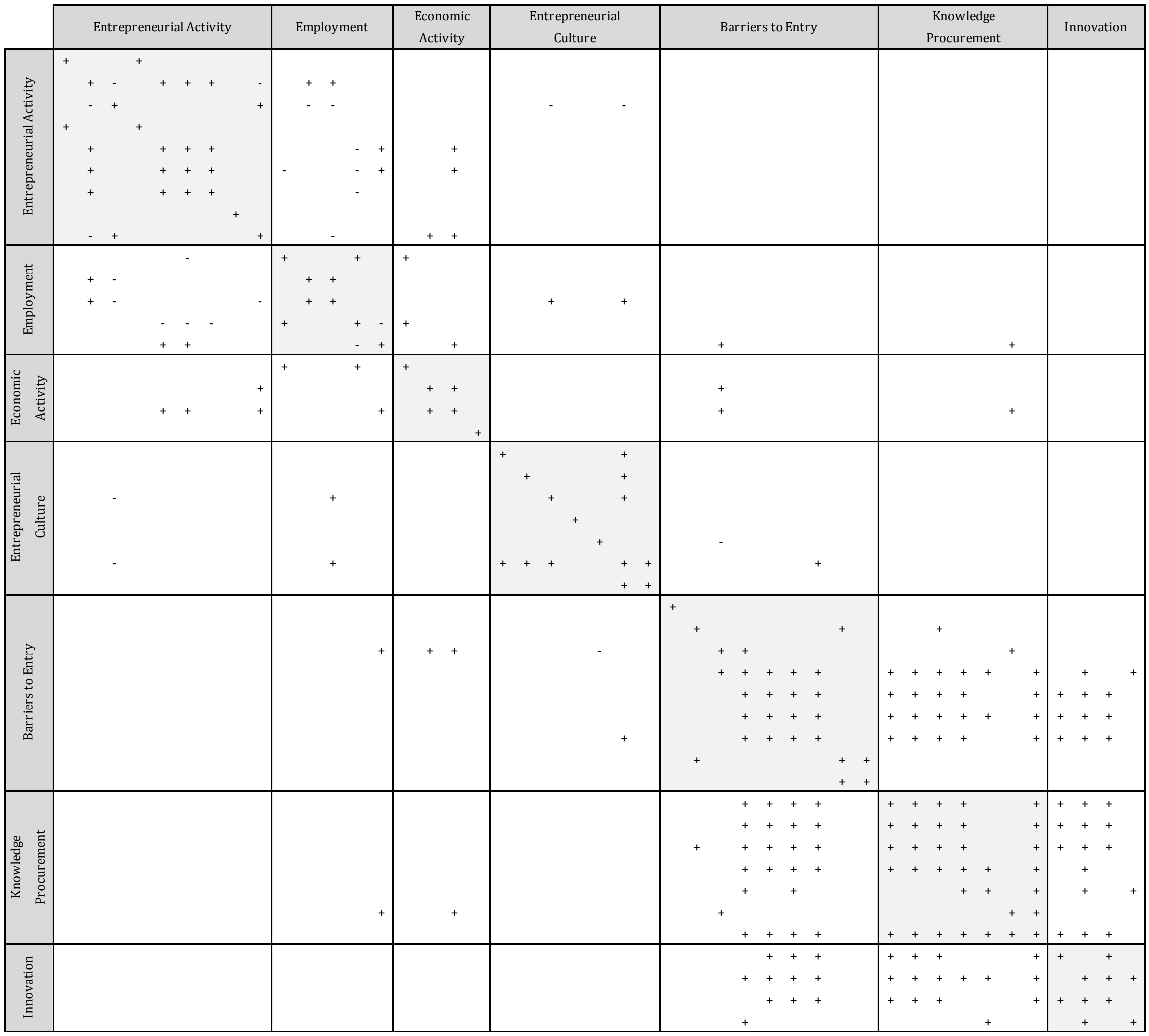


Figure 9. Pearson Correlation Map of the 2007 CEI Model Inputs and Categories of Inputs

The “+” indicates a positive correlation ≥ 0.5, and the “-” indicates a negative correlation ≤ -0.5.

Figure 10. Negative Trend - Firm Births vs. Schumpeterian Activity (2002)

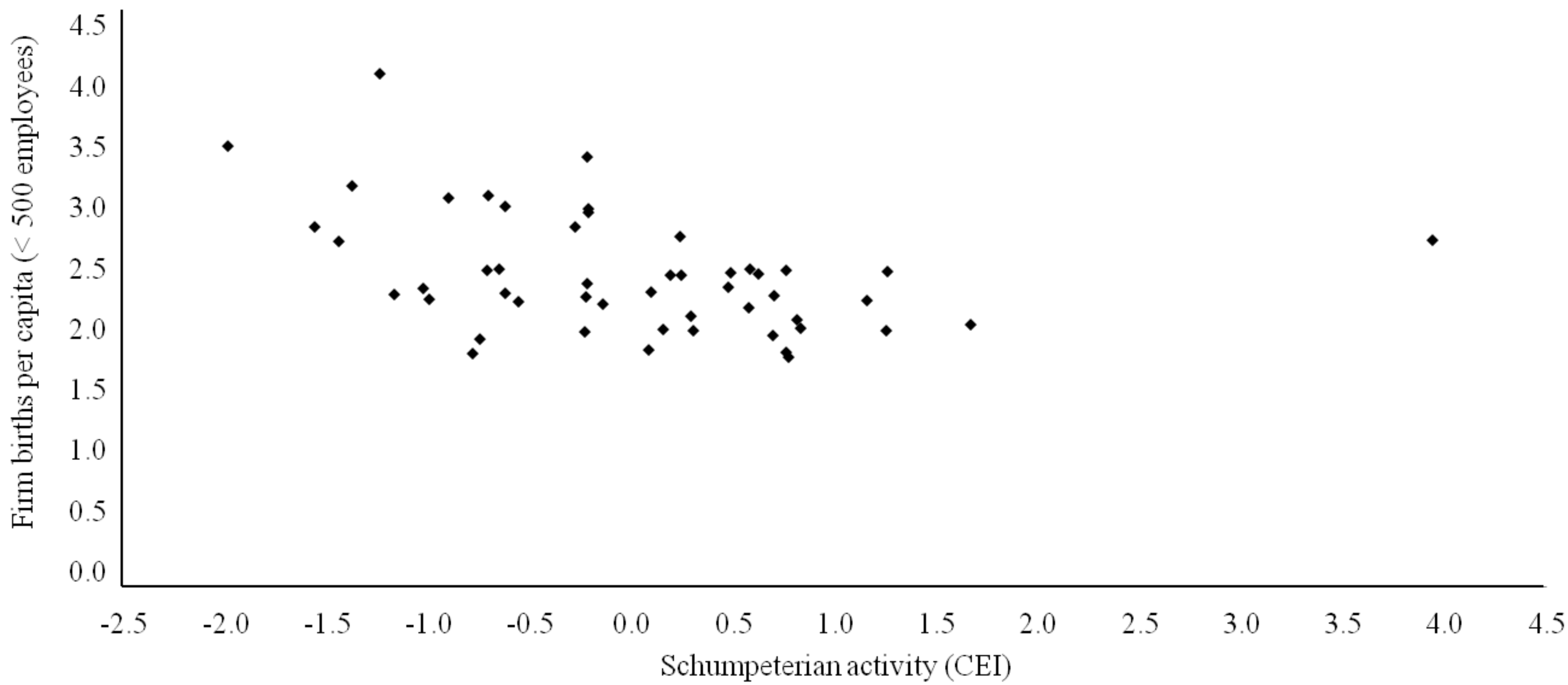
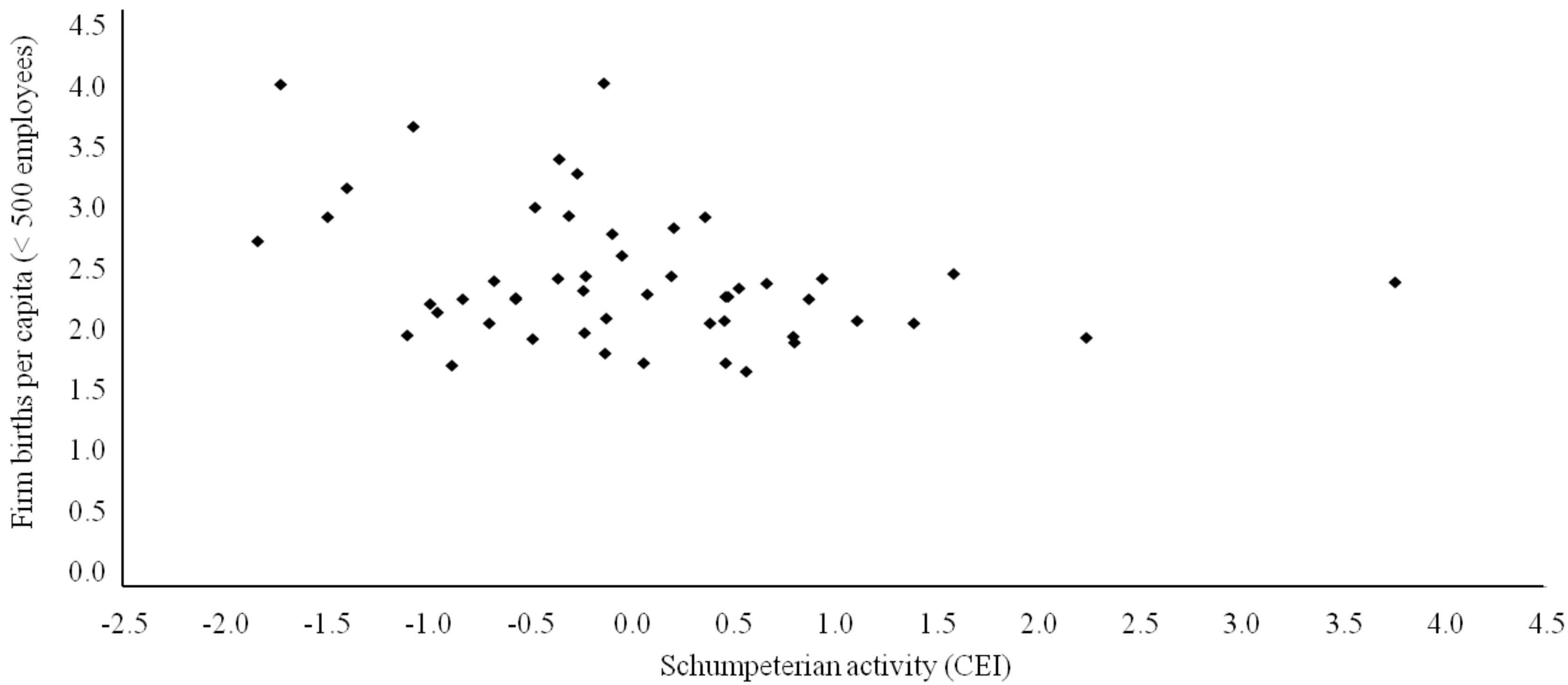


Figure 11. Negative Trend - Firm Births vs. Schumpeterian Activity (2007)



CHAPTER VI

CONCLUSION

The discipline of agricultural economics evolved during the 20th century from being primarily focused on agriculture related production to include a much broader range of fields (Penson, Capps, and Rosson 2002). While the unifying theme of this work is innovation within the discipline of agricultural economics, the underlying motivation of this work has been to demonstrate a wide array of modeling techniques and data-type usage within different the fields. In particular this work examined: 1) the cost of insect resistance to pesticide in stored grain; 2) the demand for college level courses and course attributes; 3) the characteristics of students selecting online for college level courses; and 4) the development of a measure of Schumpeterian (entrepreneurial) activity.

As demonstrated in chapter 2, *Resistant Pests and Stored Grain Costs*, there was a considerable amount of uncertainty regarding many of the inputs that were needed to model changes in cost associated with pest resistance. As a result, much of the necessary data needed to be simulated. Since potential outcomes were dependent on the choices made over time, mathematical programming techniques developed in engineering disciplines were used to construct the dynamic models. Additionally, the chapter was interdisciplinary because modeling had entomological and economic specifications.

In chapter 3, *Students' Preferences for College Credit Courses*, an approach used in the transportation and marketing literature of the 1980s and 1990s was applied to the field of education economics. Further, the online teaching pedagogy and changes in computer technology impacted the economic outcomes in this study. Similarly, in chapter 4, *Characteristics of Students Selecting Online Courses*, students' exposure to information and communication technology as well as their individual learning preferences impacted results.

The quantitative procedure used to estimate the composite entrepreneurship indicators in chapter 5, *Developing a Measure of Schumpeterian Activity*, was developed in the discipline of applied mathematics. Similar applications have been used in a number of other disciplines, such as chemistry, geology, and meteorology (Jolliffe 2002). Additionally, the study of entrepreneurship has traditionally appeared in the business and economics literature; however, it also has strong roots in sociology and psychology (Thornton 1999).

Boland and Crespi (2010) point out that the discipline of agriculture economics is in another era of transition. As the discipline of agriculture economics continues to evolve in the 21st century, there will be more potential opportunities to incorporate ideas from other academic disciplines into research activities. Albert Einstein has been credited with asking, "if we knew what is was we were doing, it would not be called research, would it?" (Oliver 2010). In the spirit of Einstein's question, future research in agricultural economics will be challenged with similar uncertainty as new ideas from other academic disciplines are adopted. In this way, the discipline of agricultural economics will continue to be innovative.

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APPPENDICES

In compliance with the Oklahoma State University (OSU) Institutional Research Board (IRB), a request was submitted to the IRB to conduct a university wide survey of OSU students. This request was with respect to the data collected for chapters 3, *Students' Preferences for College Credit Courses*, and 4, *Characteristics of Students Selecting Online Courses*, of this document. The request was approved on November 2, 2010 and the research was concluded prior to the end of the IRB approved protocol. The approval letter is shown on the following page of this appendix.

Oklahoma State University Institutional Review Board

Date: Friday, October 29, 2010

IRB Application No AG1041

Proposal Title: What do we Really Know About the Online Course Market?

Reviewed and Processed as: Exempt

Status Recommended by Reviewer(s): Approved Protocol Expires: 10/28/2011

Principal Investigator(s):

John Thomas Mann	Shida R. Henneberry	Brian Adam
555 Ag Hall	424 Ag Hall	413 Ag Hall
Stillwater, OK 74078	Stillwater, OK 74078	Stillwater, OK 74078

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in section 45 CFR 46.

X The final versions of any printed recruitment, consent and assent documents bearing the IRB approval stamp are attached to this letter. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be submitted with the appropriate signatures for IRB approval.
2. Submit a request for continuation if the study extends beyond the approval period of one calendar year. This continuation must receive IRB review and approval before the research can continue.
3. Report any adverse events to the IRB Chair promptly. Adverse events are those which are unanticipated and impact the subjects during the course of this research; and
4. Notify the IRB office in writing when your research project is complete.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact Beth McTernan in 219 Cordell North (phone: 405-744-5700, beth.mcternan@okstate.edu).

Sincerely,

Shelia M. Kennison

Shelia Kennison, Chair
Institutional Review Board

VITA

John Thomas Mann II

Candidate for the Degree of

Doctor of Philosophy

Thesis: INNOVATION ACROSS SUB-DISCIPLINES OF AGRICULTURAL ECONOMICS: THE COST OF INSECT RESISTANCE TO PESTICIDE IN STORED GRAIN, THE DEMAND FOR COLLEGE COURSES, AND MEASURES OF SCHUMPETERIAN ACTIVITY

Major Field: Agricultural Economics

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in Agricultural Economics at Oklahoma State University, Stillwater, Oklahoma in May 2012.

Completed the requirements for the Master of Business Administration at Oklahoma Christian University, Edmond, Oklahoma in 2008.

Completed the requirements for the Bachelor of Science in Organizational Leadership at Southern Nazarene University, Bethany, Oklahoma in 2006.

Experience:
Teaching and Research Assistant
Oklahoma State University
August 2008-May 2012

Researcher
Economic Impact Group
June 2008-December 2008

Assignment Desk Manager
Griffin Communications
November 1991-August 2008

Professional Memberships:
American Agricultural Economics Association
American Economic Association
Southern Regional Science Association

Name: John Thomas Mann II Date of Degree: May, 2012

Institution: Oklahoma State University Location: Stillwater, Oklahoma

Title of Study: INNOVATION ACROSS SUB-DISCIPLINES OF AGRICULTURAL ECONOMICS: THE COST OF INSECT RESISTANCE TO PESTICIDE IN STORED GRAIN, THE DEMAND FOR COLLEGE COURSES, AND MEASURES OF SCHUMPETERIAN ACTIVITY

Pages in Study: 178 Candidate for the Degree of Doctor of Philosophy

Major Field: Agricultural Economics

Scope and Method of Study:
This work is composed of four individual articles. The first uses mathematical programming and recent discoveries in entomology genetics to determine the cost of insect resistance to phosphine fumigants in stored grain. The second uses a conditional logit model based on a choice experience to determine students' preferences for online and face-to-face college courses and course attributes. The third uses an ordered logit model based on survey responses to identify the characteristics of students selecting online courses. The fourth uses principle component analysis to develop composite entrepreneurship indicator as a measure of Schumpeterian activity for states.

Findings and Conclusions:
The major findings of each article are as follows. 1) Costs associated with fumigant-resistant insects make integrated pest management more attractive than calendar-based fumigation in cooler climates. There may also be an externality due to higher fumigation effectiveness. Since high proportions of strong resistant pests only begin to appear after a long time-horizon when fumigation effectiveness is high, managers may be unaware of pest resistance levels until strong resistant insects are in high proportions. 2) Student's preferences for online or face-to-face (F2F) courses depend on specific attributes of the courses. Students reported having the highest preferences for customized online courses. Additionally, the frequency with which students selected online courses increased as more online course information was available. 3) Based on survey responses, half of college-age undergraduate students reported taking at least one online course. Freshman and sophomores were more likely to select online courses than juniors and seniors. Additionally, there are indications that use of web 2.0 technologies was positively related to the likelihood of students selecting online courses. 4) The composite entrepreneurship indicator (CEI) was negatively correlated with firm births, sole-proprietorships, and the Kauffman Index of Entrepreneurial Activity, and was positively correlated with average wage per job data. This suggests that states with higher levels of firm births have lower levels of Schumpeterian activity. These results also suggest that firm births are not good measures of Schumpeterian-type entrepreneurship.

ADVISER'S APPROVAL: Dr. Brian Adam