University of Neavada, Reno

Essays in Regional Economics and Natural Resource Management

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy in Resource Economics

by

Yiheng Li

Dr. Klaus Moeltner/Dissertation Advisor

December, 2010

University of Nevada, Reno
Statewide • Worldwide

THE GRADUATE SCHOOL

We recommend that the dissertation
prepared under our supervision by

YIHENG LI

entitled

Essays In Regional Economics And Natural Resource Management

be accepted in partial fulfillment of the
requirements for the degree of

DOCTOR OF PHILOSOPHY

Klaus Moetlner, Ph.D., Advisor

Thomas R. Harris, Ph.D., Committee Member

Tigran Melkonyan, Ph.D., Committee Member

Michael K. Price, Ph.D., Committee Member

Thomas Quint, Ph.D.., Graduate School Representative

Marsha H. Read, Ph. D., Associate Dean, Graduate School

December, 2010

ABSTRACT

Essays in Regional Economics and Natural Resource Management

by

Yiheng Li

My dissertation consists of three essays that examine the empirical issues in Regional Economics and Natural Resource management. The first essay proposes a solution to the problem of using small datasets to predict regional fiscal conditions. I formulate a "Model-Averaging" framework via Bayesian methods and test it on a Vector Autoregressive Model (VAR) using a fiscal dataset for Nevada counties. I show that informative priors from neighboring counties are effective in lowering the variance of the posterior distributions of the individual counties. Furthermore, I show that the "Model-averaged" predictive posteriors via the marginal likelihoods of each individual model enhance the prediction accuracy. I find that region-pairs with similar revenue and expenditure levels generate better predictions than region-pairs with fiscal gaps.

The second essay investigates the "Jump bidding" behavior in the National Wild Horse and Burro Internet Adoptions in response to the problem of unsatisfactory adoption rate and climbing maintenance costs that the Bureau of Land Management

(BLM) is facing. A Poisson model based on the number of aggressive bids each adopter submits reveal that “Jump-bidding” is related to the bidding quota assigned by the Bureau of Land Management (BLM). Adopters of higher allowance tend to bid more aggressively than others. The results also indicate that only certain types of animals are receiving aggressive bids, and that the level of competition is intensified by aggressive bidders. This eliminates the possibility that aggressive bidding discourages competition and concludes the auction early as previous literature suggest. I also show that “Jump-bidding” is a major booster of the animal selling price, this contradicts the previous findings that jump bidders have negative impacts on auction revenue.

The third essay explores “Late bidding” behavior in the National Wild Horse and Burro Internet Adoptions. I examine the relationship between late bidding and its impact on the level of competition and adoption price. I show that the number of bids each bidder submits drives the late bidding occurrence, this indicates animals receive higher levels of bidding competition attract more “Snipers”. I find that bidders of larger bidding quota are less motivated to be “Snipers”, and the colors that draw the interest of “Snipers” are similar to colors that draw the attention of “Jump bidders”. I also show that the final selling price is inversely related to the submission time of the winning bid. Animals that are adopted at a later time are sold at higher prices. This implies a symmetric distribution of the valuations for the wild horses and burros that are adopted via the Internet.

Dedicated to my parents

ACKNOWLEDGEMENTS

First, I am deeply indebted to my advisers Dr. Klaus Moeltner and Dr. Thomas Harris for their continuous guidance and support. I would also like to thank Dr. Michael Price, Dr. Tigran Melkonyan and Dr. Thomas Quint for their valuable advice and suggestions. The projects I have worked on with Dr. Thomas Harris and Dr. Michael price are also beneficial to my research, so I am thankful for their directions and experience. I would like to thank Karen Malloy from the Bureau of Land Management for providing high-quality data and her insightful comments. Finally, I would like to thank my parents and friends for their encouragement and support along this journey.

TABLE OF CONTENTS

ABSTRACT i

DEDICATION iii

ACKNOWLEDGEMENTS iv

LIST OF TABLES vii

LIST OF FIGURES x

CHAPTER

1. Introduction 1

2. Regional Economics Analysis With Small Samples: Combining Local Data with Information from Spatial Neighbors in a Bayesian Model-Averaging Framework 4

2.1 Introduction 4
2.2 A Bayesian Model-Averaging Framework 7
2.2.1 Bayesian Vector Autoregression (BVAR) 8
2.2.2 Gibbs Sampling 10
2.2.3 Derivation of Marginal Likelihood - “Model Probability” 11
2.2.4 Posterior Predictive Distribution and Measurement of “Model-fit” 13
2.3 Empirical Analysis 15
2.3.1 Data and Model Specification 15
2.3.2 BVAR Estimation 16
2.4 Summary and Conclusions 30

3. Estimating “Jump-bidding” Impact in National Wild Horse and Burro Internet Adoptions 34

3.1 Introduction 34
3.2 Theoretical Review of Auction and “Jump-bidding” 38
3.2.1 Auction - What is it? 38
3.2.2 Prior Theory on Signaling and “Jump-bidding” in Ascending Auctions 39
3.3 Field Data 45
3.4 Empirical Analysis 51
3.4.1 “Jump-bidding” and Level of Competition with Animal Features 52
3.4.2 ”Jump-bidding” and bidding allowance 54
3.4.3 ”Jump-bidding” and Auction Revenue 55
3.5 Discussion and Conclusions 57

4. Estimating “Sniping” Impact in National Wild Horse and Burro Internet Adoptions 60

4.1 Introduction 60
4.2 Theoretical Review of “Late Bidding” - Motivation and Strategic Moves 63
4.2.1 A general model of bidding in Internet Auctions with a fixed end time 63
4.2.2 Prior theory on “Late bidding” in Internet Auctions with Private Values 64
4.2.3 Late Bidding in Wild Horse and Burro Adoptions . 65
4.3 Field Data 67
4.4 Empirical Analysis 69
4.4.1 Late bidding and bidding allowance 73
4.4.2 Late bidding and level of Competition with Animal Features 75
4.4.3 Late Bidding and Auction Revenue 77
4.5 Discussion and Conclusions 79

5. Conclusion 81

APPENDICES 84

BIBLIOGRAPHY 85

LIST OF TABLES

Table

2.1 Posterior Model Probability - All county combinations 21

3.1 A two-stage auction game with Jump-Bidding (Avery, 1998) 41

3.2 Summary of Number of bids and jump-bids in all 15 sessions 47

3.3 Group of Colors 51

3.4 Animal Types 51

3.5 Poisson Regression of "Jump-Bidding" impact on level of competition with animal groups 53

3.6 Animal counts by Type and Color 53

3.7 Poisson regression of bidding allowance impact on Jump bidding . . 55

3.8 Ordinary Least Square Regression - "Jump bidding effect on Auction Revenue" 56

4.1 Group of Colors 71

4.2 Animal Types 72

4.3 Animal counts by Type and Color 72

4.4 Late bidding and Bidding Allowance - Last 30 Minutes 74

4.5 Late bidding and Bidding Allowance - Last 5 Minutes 74

4.6 Late bidding and Animal Features - Last 30 minutes 76

4.7 Late bidding and Animal Features - Last 5 minutes 76

4.8 Late bidding and Auction Revenue - Last 30 minutes 78

4.9 Late bidding and Auction Revenue - Last 5 minutes 78

A.1 Carson City - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 86

A.2 Churchill County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 87

A.3 Clark County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 88

A.4 Douglas County - Revenue and Expenditure Per Capita Prediction with PPP Values Comparison 89

A.5 Elko County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 90

A.6 Esmeralda County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 91

A.7 Eureka - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 92

A.8 Humboldt County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 93

A.9 Lander County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 94

A.10 Lincoln County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 95

A.11 Lyon County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 96

A.12 Mineral County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison 97

A.13 Nye County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison . . . 98

A.14 Pershing County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison . . . 99

A.15 Storey County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison . . . 100

A.16 Washoe County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison . . . 101

A.17 Whitepine County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison . . . 102

LIST OF FIGURES

Figure

2.1 Marginal Effect Posterior Distribution - Lagged Revenue in VAR equations . . . 17

2.2 Marginal Effect Posterior Distribution - Lagged Expenditure in VAR equations . . . 18

2.3 Posterior Predictive Distribution - Carson (Diffuse Prior) . . . 23

2.4 Posterior Predictive Distribution - Carson (Weighted Average Prediction) . . . 24

2.5 Posterior Predictive Distribution - Lander (Diffuse Prior) . . . 24

2.6 Posterior Predictive Distribution - Lander (Weighted Average Prediction) . . . 25

2.7 Posterior Predictive Distribution - Pershing (Diffuse Prior) . . . 25

2.8 Posterior Predictive Distribution - Pershing (Weighted Average Prediction) . . . 26

2.9 Posterior Predictive Distribution - Pershing (Diffuse Prior) . . . 26

2.10 Posterior Predictive Distribution - Pershing (Weighted Average Prediction) . . . 27

2.11 Posterior Predictive Distribution - Storey (Diffuse Prior) . . . 27

2.12 Posterior Predictive Distribution - Storey (Weighted Average Prediction) . . . 28

2.13 Posterior Predictive Distribution - White Pine (Diffuse Prior) 28

2.14 Posterior Predictive Distribution - White Pine (Weighted Average Prediction) 29

2.15 Revenue-Expenditure comparison by county (1995-2007) - Pershing 30

2.16 Revenue-Expenditure comparison by county (1995-2007) - White Pine 31

3.1 Jump bid Increments Distribution 47

3.2 Number of Bids and Jump-bids of 15 sessions 48

3.3 Total Revenue of 15 sessions 49

3.4 Jump bids percentage distribution per animal 50

4.1 Cumulative Distribution over time of Bidder's Last Bids 68

4.2 Cumulative Distribution over time of Each Animal's Last Bids . . . 69

4.3 Distribution of Late Bids by Bidder 70

4.4 Distribution of Late Bids by Animal 71

CHAPTER 1

Introduction

My dissertation consists of three essays that examine the empirical issues in Regional Economics and Natural Resource management. The first essay proposes a Bayesian Model Averaging framework to mitigate the problem of data shortage that often occurs in Regional Fiscal Forecasting. The second and third essays investigate adopter behavior in the National Wild Horse and Burro Internet Adoptions. The results are used to make recommendations of the adoption rules and policies in response to the unsatisfactory adoption rate and rising maintenance costs of wild animals that the Bureau of Land Management (BLM) is facing.

In the first essay entitled "Combining Local Data with Information from Spatial Neighbors in a Bayesian Model-Averaging Framework", I propose a weighted average approach to the problem of data shortage in regional fiscal planning. This framework combines information from all relevant regions within an area to generate improved predictions of the future budget fluctuation, particularly when using small time-series data. First I estimate a Bayesian Vector Autoregressive (BVAR) model on the county level fiscal dataset of Nevada. I show that the posterior distributions variance of the marginal effects are reduced if including the informative priors from other counties in the BVAR estimation compare to the models use only the diffuse prior. Then I derive the marginal likelihood of each county model that uses the informative priors from neighbor counties and transform them into "Model Weights". These weights are used to generate the Model-Averaging predictive posterior for each county. The results show better predictions than using diffuse priors in 5 counties. I find that the model weights in some counties are not evenly distributed, i.e., 90% of the weighted average predictive posteriors of county A come from county B or *vice versa.* By comparing the fiscal structures of counties in terms of revenue and expenditure distribution, I find that among the counties with improved predictions, the regions with similar revenue and expenditure level to these counties are better predictors than counties with different fiscal conditions.

In the second essay entitled "Estimating Jump Bidding Impact in National Wild Horse and Burro Internet Adoptions", I examine the adopter behavior in the auctions and their bidding preference using the Poisson model and Ordinary Least Square (OLS) regression based on the biding records of 15 auction sessions during three years' period. The results are used to review the current Internet adoption rules and policies. The Poisson model results indicate that jump bidding directs the competitions among certain groups of animals. I find that in Internet auctions, where adopters view animals on-line, colors are more important in driving the competition than other characteristics. For example, brown or similar color animals are preferred to white or grey animals in the auctions. In addition, adopters' bidding allowance that is assigned by the Bureau of Land Management (BLM) prior to each auction session determines their aggressiveness in the bidding process. Higher allowance bidders tend to submit more jump bids than others. The OLS results show that jump bidding in the wild horse and burro auctions encourages competition and has a positive impact on the selling price of each adopted animal.

In the Wild Horse and Burro Adoptions, late bidding or "Sniping" is another issue related to auction efficiency. This type of bidding only occurs in fixed time auctions, which allow bidders to bid on the target item towards the closing of the auction to avoid a bidding war and maximize payoffs. However, previous literature claims this behavior is negatively related to auction revenue and the level of competition in ascending auctions.

In the third essay entitled "Estimating Sniping Impact in National Wild Horse and Burro Internet Adoptions", I investigate the relationship between late bidding and the level of competition associated with bidding allowances. I show that preassigned bidding quota discourages late bidding: bidders with higher allowance are less likely to be "Snipers". Late bidders are attracted by similar colors as the Jump bidders. Furthermore, OLS results indicate the later a winning bid occurs, the higher the final adoption price. The results imply that the valuation of animals are symmetrically distributed among the bidders and competition, and stays constant for certain animal groups.

CHAPTER 2

Regional Economics Analysis With Small Samples: Combining Local Data with Information from Spatial Neighbors in a Bayesian Model-Averaging Framework

2.1 Introduction

Fiscal forecasting in regional economics is always accompanied with uncertainty. The basic idea is to use past information to generate the probability distributions of future events at the regional level. One of the main difficulties in practice is data shortage. In some cases, researchers can only get access to a few years' datasets. Therefore, classic statistical modeling is not a preferred option to accomplish the prediction tasks. As an alternative, Bayesian methods have been numerously used in forecasting models at both National and Regional level to overcome this problem. For example, Litterman(1986) summarizes the gain in forecasting efficiency by using a Bayesian Vector Autoregression (BVAR) model based on 1971-1975 National

Macroeconomic Data; Lesage and Mugura (1990) use a Bayesian shrinkage approach in their payroll model of 7 metropolitan areas of Ohio. The paper imposes stochastic restrictions that shrink the parameters of the individual metropolitan-area models toward the estimates arising from a pooled model of all areas and find better results from the shrinkage than the pooled-data.

In the past decade, scholars also demonstrate various types of techniques in tackling the problem of small samples via Bayesian estimation. In the field of resource optimization, Moeltner and Woodward (2009) show how to capture additional information via refined priors by Bayesian estimation in their wetland benefit transfer paper; In the area of epidemiology, Branscuma et al. (2008) develop a flexible non-parametric Bayesian model for regional disease-prevalence estimation based on cross-sectional data that are obtained from several subpopulations or clusters such as villages, cities or herds. In the field of regional economics, Adkins et al. (2003) use “Gibbs Sampling” in their studies of Oklahoma manufacturing sector to simulate the posterior distribution of a Trans-log production function under both empirically based informative and minimally informative priors. Lesage and Pan (1995) propose a “Spatial Contiguity Prior” technique in an agricultural output forecasting model among 15 corn-producing states. The main feature of this paper is the incorporation of a normally ignored issue - “Spatial Contiguity’ in the modeling of cross-sections among metropolitan areas, counties, states, or even countries. The inclusion of the informative priors from neighboring regions is shown to be an effective way to enhance forecasting accuracy. In an ensuing study of “Price-deflator” time series of 48 continental states, Lesage and Dowd (1997) use the same technique to emphasize the importance of geographical location in the price-level determination. In general, all of these papers indicate the benefits of Bayesian estimation by incorporating prior information in the analysis scenarios of small sample size.

Given the existing literature in applying Bayesian methods to the economic analysis with small samples, the main goal of this chapter is to design a "Model-Averaging" framework that can be used to improve the accuracy of prediction models in regional economics forecasting. More specifically, a Model Averaging approach using cross-region informative priors is integrated into a Bayesian Vector Autoregressive (BVAR) model and tested to see if it provides better predictions for the regional fiscal forecasting. The empirical implementation is based on the revenue and expenditure data of Nevada at the county-level. The impetus of this case selection stems from the persisting concerns on the inter-temporal linkage between government revenue and expenditures in regional economic planning.

In the late 1980's. Holtz et al. (1989) start the investigation of "Revenue-Expenditure" inter-temporal linkage by analyzing the fiscal data from 171 municipal governments over the period 1972-1980 via a Vector Auto Regressive (VAR) model. They find that past revenues help to predict current expenditures, but past expenditures do not alter the future path of revenues. This last finding is contrary to results that have emerged from their previous analysis of federal fiscal data. More importantly, Hotlz et al. (1989) recognize the problem of using stacked time series cross-section observations in the VAR model, which is the possibility that each unit has an "individual effect". This individual effect summarizes the influence of unobserved variables that has a persistent effect on the dependent variable.

To overcome this issue, this chapter uses a Bayesian Vector Autoregressive Regression (BVAR) model to examine the inter-temporal linkage between the revenue and expenditure per capita using only 13 year's observations from all counties in Nevada. Instead of imposing instrumental variables under General Linear Modeling (GLM) like Holtze et al. (1989), the BVAR model of this chapter employs both diffuse and informative priors from neighboring counties to mitigate the problem of small samples. Moreover, the results of all counties from the BVAR models that use the informative priors of neighboring counties is assimilated into a "Model-Averaging" structure based on each model's marginal likelihood. The predictions from these results are compared with the results of each county's BVAR estimation that uses only the diffuse priors. The purpose of this approach is twofold. First, it measures the effectiveness of the Bayesian Autoregressive Regression model in a small sample size scenario; Second, it testifies in what context do informative priors from contiguous areas help improve the prediction accuracy in a regional economic setting.

In pursuance of these objectives, the rest of this chapter is structured as follows: section 2 provides a review of the Bayesian Auto-Regression Model (BVAR) and the methodologies use in the development of the "Model-Averaging" framework; section 3 presents the summary of the data and the specification of the BVAR model used in the empirical implementation; section 4 shows the estimation process of the BVAR model and the steps of building the "Model-Averaging" framework, with results comparisons of the predictions accuracy among selected counties; section 5 concludes with findings and recommendations for future research.

2.2 A Bayesian Model-Averaging Framework

This section provides background information of the three components in the proposed Bayesian Model-Averaging framework: the Bayesian Vector Autogregressivon Model, the marginal likelihoods and the Predictive Posteriors distribution.

2.2.1 Bayesian Vector Autoregression (BVAR)

The Bayesian vector autoregression (BVAR) was first introduced by Litterman (1980). It uses prior information regarding the mean and variance of model coefficients to solve the problem of collinearity and degree of freedom in the classic vector autoregression. Another feature of using a BVAR model is the simplicity. As Sims et al. (1990) argue, "Bayesian models do not need to take special account for non-stationarity for forecasting, therefore classical problems with unit roots (inconsistency of asymptotic variances and test statistics) do generally not apply to Bayesian estimation". We begin the discussion of BVAR by giving the general form of a stationary Vector Autoregressive (VAR) model with p dimensions:

$$y_t = \delta + \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + \epsilon_t \tag{2.1}$$

where y_t for $t = 1, \cdots, T$ is an $M \times 1$ vector containing observations on M time series variables, ϵ_t is an $M \times 1$ vector of errors, δ is an $M \times 1$ vector of constant intercepts and Φ_p is an $M \times M$ matrix of coefficients. ϵ_t is $iid \sim N(0, \Sigma)$.

Equation 2.1 can also be simplified in form of:

$$y = (X \otimes I_k)\beta + e \tag{2.2}$$

where y and e are the $T \times M$ matrices, $(X \otimes I_k)$ is a $T \times K$ matrix and $k = Mp + 1$, and β is a $K \times M$ coefficient matrix, e is $iid \sim MN(0, \Sigma \otimes I_T)$. When the parameter vector β has a prior multivariate normal distribution with known mean β^* and covariance matrix V_β, The likelihood function takes the following form:

$$\ell(y|\beta) = (\frac{1}{2\pi})^{kT/2}|I_T \otimes \Sigma|^{-1/2} \times \exp[-\frac{1}{2}(y-(X\otimes I_k)\beta)'(I_T\otimes\Sigma^{-1})(y-(X\otimes I_k)\beta)] \quad (2.3)$$

The prior density for β is written as:

$$f(\beta) = (\frac{1}{2\pi})^{k^2p/2}|V_\beta|^{-1/2}\exp[-\frac{1}{2}(\beta-\beta^*)V_\beta^{-1}(\beta-\beta^*)] \quad (2.4)$$

From equation 2.3 and using Bayes' rule, the posterior density for β is derived as:

$$f(\beta|y) \propto \exp[-\frac{1}{2}(\beta-\bar{\beta})'\bar{\Sigma}_\beta^{-1}(\beta-\bar{\beta})] \quad (2.5)$$

and the posterior mean for β is:

$$\bar{\beta} = [V_\beta^{-1} + (X'X\otimes\Sigma^{-1})]^{-1}[V_\beta^{-1}\beta^* + (X'\otimes\Sigma^{-1})y] \quad (2.6)$$

and the posterior covariance matrix is:

$$\bar{\Sigma}_\beta = [V_\beta^{-1} + (X'X\otimes\Sigma^{-1})]^{-1} \quad (2.7)$$

The prior of Σ^{-1} takes the form of:

$$f(\Sigma^{-1}) = fW(\Sigma^{-1}|\underline{H}, \underline{v}) \quad (2.8)$$

where W denotes a Wishart distribution. According to Wishart property, $E(\Sigma^{-1}) = \underline{vH}$ and the non-informativeness is completed by setting $\underline{v} = 0$ and $\underline{H}^{-1} = 0_{M\times M}$.

The posterior for Σ^{-1} conditional on β is:

$$\Sigma^{-1}|\beta, y \sim W[(\underline{H}^{-1} + (y - (X \otimes I_k)\beta)'(y - (X \otimes I_k)\beta))^{-1}, T + \underline{v}] \tag{2.9}$$

According to Litternman (1986), the gain in efficiency of the BVAR models can be achieved by estimating all equations together via a Seemingly Unrelated Regression (SUR) procedure that uses the information contained in the covariances of residuals across equations. (Litterman, 1986 & Koop, 2007).

2.2.2 Gibbs Sampling

Gibbs sampling is a common method in Bayesian Econometrics and is widely used to simulate posterior distributions. As a type of Markov Chain Monte Carlo method (MCMC), the purpose of Gibbs Samplers is to assuage the difficulties of directly taking random draws from the unknown posterior distribution using a conditional posterior, which is the distribution that defines a posterior for each block conditional on all the other blocks. The implementation is normally commenced with choosing a start value for β and Σ. In the case of using non-informative or diffuse priors, zero means with uniformed variance-covariance are used to begin the sampling unless informative priors are available. For example, with the particular starting value for β^0 and Σ^0, the k^{th} draw from the Gibbs sampler (β^1, Σ^1) is gained using the following steps:

1. Draw β^k from $f(\beta|\Sigma^{k-1}, y)$.

2. Draw Σ^k from $f(\Sigma|\beta^k, y)$.

Then the draws are taken given the conditional posterior p.d.f's.[1] The Markov Chain created by the draws converges after a set of "burn-in" iterations. The continuing draws are draws from the marginal posteriors[2] for both β and Σ. Numerous methods are developed to identify the occurrence of convergence. One can examine the sequence of draws by graph or test whether the chains have the same mean and variance. (Cowles and Carlin, 1996).

2.2.3 Derivation of Marginal Likelihood - "Model Probability"

The Marginal Likelihood shows how the data looks like before the collection given the priors and the likelihood function. It is also know as "Prior Predictive Density". The generic form of the Marginal Likelihood is given in equation 2.10:

$$p(y) = \int p(y|\beta)p(\beta)\, d\beta \tag{2.10}$$

For any model using informative priors, we can convert the marginal likelihoods into "Model Probability" by evaluating their prior predictive densities. The larger $p(y)$ is, the better the data agrees with the priors. This "Model Probability" is an important component of the "Model-Averaging" framework, it defines the "Model Weights" of each BVAR estimation and shapes the "Model-Averaging" procedure. The marginal likelihoods are traditionally derived by using an algorithm developed by Chib (1995). The basic steps of the Chib Method is as follows:

Given $p(\beta|y)$, $p(\beta)$ and $p(y|\beta)$ as the posterior, prior and likelihood, Bayes Rule states:

[1]Normal distributed conditional posterior for β and inverted Wishart distributed posterior for Σ.
[2]$f(\beta|y)$, $f(\Sigma|y)$

$$p(\beta|y) = \frac{p(y|\beta)p(\beta)}{p(y)} \tag{2.11}$$

Rearrange the above, we have:

$$p(y) = \frac{p(y|\beta)p(\beta)}{p(\beta|y)} \tag{2.12}$$

Chib (1995) notes that the left hand side is not an explicit function of β, so the equality has to hold for any β, therefore, we may use the posterior mean say $\hat{\beta}$, substitute $\hat{\beta}$ into equation 2.12, we gain what Chib (1995) referred to as the "basic marginal likelihood identity":

$$p(y) = \frac{p(y|\hat{\beta})p(\hat{\beta})}{p(\hat{\beta}|y)}^{3} \tag{2.13}$$

According to the theory Chib (1995) proposes, the exact form of the posterior $p(\hat{\beta}|y)$ can be gained via a simulation procedure based on the fundamental rule of probability theory. Suppose β is split into two[4] components β_1 and β_2[5] from the sequential draws of Gibbs Sampler, the simulated posterior output β_1^r and β_2^r can be obtained for $r = 1, \ldots, R$, hence:

$$p(\hat{\beta}_1, \hat{\beta}_2|y) = p(\hat{\beta}_1|y)p(\hat{\beta}_2|\hat{\beta}_1, y) \tag{2.14}$$

The right hand side of equation 2.14 can be written as:

---

[3]The log likelihood is given in the form as: $\log p(y) = \log p(y|\hat{\beta}) + (\log p(\hat{\beta}) - \log p(\hat{\beta}|y))$

[4]The number of components that can be divided depends on the model.

[5]$\beta = [\beta_1', \beta_2']'$

$$p(\hat{\beta}_1|y) = \int p(\hat{\beta}_1|\beta_2, y)p(\beta_2|y)\, d\beta_2 \tag{2.15}$$

The integral in equation 2.15 can be approximated via Monte Carlo simulation as:

$$p(\hat{\beta}_1|y) \approx \frac{1}{R}\sum_{r=1}^{R} p(\hat{\beta}_l|\beta_2^r, y) \tag{2.16}$$

In equation 2.16, we use the draws of β_2^r generated by the Gibbs Sampler, and compute the conditional posterior $p(\beta_1|\beta_2^r, y)$, assuming $\beta_1 = \hat{\beta}_1$, and take the average of the resulting density values of $p(\hat{\beta}_l|\beta_2^r, y)$ and generate the approximation of $p(\hat{\beta}_1|y)$.

Finally, the conditional posterior $p(\beta_2|\beta_1, y)$ is calculable given $\beta_1 = \hat{\beta}_1$ and $\beta_2 = \hat{\beta}_2$. the log marginal likelihood function of equation 2.13 is:

$$\log p(y) = \log p(y|\hat{\beta}) + \log p(\hat{\beta}) - (\log p(\hat{\beta}_1|y) + \log p(\hat{\beta}_2|\hat{\beta}_1, y)) \tag{2.17}$$

The log marginal likelihood result is useful in measuring the weights of the posterior distribution in a multi-dimension model space. The proof is observed in the empirical implementations that is followed.

2.2.4 Posterior Predictive Distribution and Measurement of "Model-fit"

In Bayesian estimation, the Posterior Predictive Distribution (PPD) is often considered as a measurement of the "Model Fit". It is formally given as:

$$p\left(\hat{y}_p|y\right) = \int_\theta p\left(\hat{y}_p, \theta|y\right)\, d\,\theta = \int_\theta p\left(\hat{y}_p|\theta, y\right)\, p\left(\theta|y\right) d\,\theta = \int_\theta p\left(\hat{y}_p|\theta\right)\, p\left(\theta|y\right) d\,\theta$$
$$\theta = \begin{bmatrix} \beta' & \sigma^2 \end{bmatrix}' \tag{2.18}$$

where $p\left(\theta|y\right)$ is the posterior distribution with draws from original Gibbs Sampler and $p\left(\hat{y}_p|y\right)$ can be derived by drawing $\hat{y}_p$ from $n\left(x_p'\beta_r, \sigma_r^2\right)$, where subscript r indicates the r^{th} draw of our parameters in the retained series of draws from the original GS. To be precise, 1 draw of $\hat{y}_p$ per θ_r is sufficient to generate the PPD. Optionally, one can take several draws of $\hat{y}_p$ per θ_r for a "smoother" posterior density.

Once all draws of $\hat{y}_p$ are gained, the moments of the resulting PPD are obtained by placing Monte Carlo integration. The Posterior Predictive Mean is given in equation 2.19:

$$\left(\hat{y}_p|y\right) = \int\limits_{\hat{y}_p} \hat{y}_p p\left(\hat{y}_p|y\right)\, d\,\hat{y}_p \approx \frac{1}{R}\sum_{r=1}^{R} \hat{y}_{pr} \tag{2.19}$$

As an alternative measurement of "Model Fit", "Posterior Predictive P-value" is originated from PPD and is useful when the marginal likelihood is difficult to derive. Generally, it functions as follows: First, choose a statistic of interest that is a function of the actual data y, then simulate a posterior predictive density for the same statistic using simulated or "predictive" data instead of y. Second, examine the location of the original statistic (The statistic that depends on actual data y) in this distribution. If it is far out in the tail, it is very unlikely that observed data could have been generated by specified modeling structure.(i.e. the p-value, is small.) In most empirical work, a p-value of 0.05 or less would be interpreted as evidence against a given model.

The final step is to plot the distribution density and locate the predicted outcomes in this distribution. The closer the mean locates to the observed measure of interval, the more appropriate the regression model is. The numerical derivation of the "PPP" value that equals to the above steps is shown in equation 2.20:

$$PPP = \min(x, 1-x) \qquad \text{where} \qquad x = prob\,(y > E(y)) \tag{2.20}$$

This section summarizes the general form of the Bayesian Vector Autoregression Model and the methodologies use in the development of the "Model-Averaging" framework. The next section continues with the empirical implementations using a small fiscal dataset of Nevada counties.

2.3 Empirical Analysis

2.3.1 Data and Model Specification

The datasets underlying the estimation consist of 17 time-series of Revenue and Expenditure per capita for each county in Nevada. All numbers are expressed in U.S dollars. Revenue and expenditure per capita are calculated based on each region's population between 1995 and 2007, all variables are converted to logarithm form to control the variance and possible outliers.

In regional fiscal planning system, the revenue and expenditure budget always come from the same system of decision making. A BVAR model of two equations with one lag is shown in equation 2.21 to highlight the revenue and expenditure inter-temporal linkage in Nevada:

$$
\begin{aligned}
y_t^r &= \beta_{01} + \beta_{11} y_{t-1}^r + \beta_{21} y_{t-1}^e + \epsilon_{r,t} \\
y_t^e &= \beta_{02} + \beta_{21} y_{t-1}^e + \beta_{22} y_{t-1}^r + \epsilon_{e,t}
\end{aligned}
\tag{2.21}
$$

y_t^r and y_t^e are the revenue and expenditure per capita of each time period denoted by t, y_{t-1}^r and y_{t-1}^e are the one lagged revenue and expenditure per capita.

As mentioned above, if equations are stacked together, the equation system 2.21 is equivalent to a Seemingly Unrelated Regression (SUR) model. Next section explains the estimation process with results of this BVAR model.

2.3.2 BVAR Estimation

2.3.2.1 Defining Diffuse and Informative Priors

In this section, the BVAR model in equation 2.21 is estimated using a Seemingly Unrelated Regression suggested by Litterman (1986). The first step is to generate the posterior density of coefficients for all 17 counties using diffuse and informative priors respectively. For each county model, the two key elements of the estimations are the coefficients matrix β and error term matrix Σ. For the diffuse priors of each county model, the β assumes zero mean and a vague covariance matrix with 100 on the diagonal and zero covariance; the mean of Σ is the number of equations contained in the system, and the covariance matrix is a 2×1 identity matrix.

For the informative priors used in each county model, the β means are the mean of the posterior coefficients from another county's estimation using the diffuse priors, and the covariance matrix is the covariance matrix of the posterior coefficients of the same estimation. The mean and the covariance matrix of Σ are as same as under diffuse priors.

2.3.2.2 Posterior Distribution Comparison - Diffuse and Informative Priors

Douglas county is used as an example to indicate improved posterior distribution by using informative priors. The combination models[6] use $2,000$ burn-in draws and $3,000$ retained draws in the Gibbs Sampler. Among all the explanatory variables in equation 2.21, the coefficients for lagged revenue and expenditure per capita (Figures 2.1 and 2.2) are selected to demonstrate the reduced variance of posterior distributions using informative priors of neighbor counties.

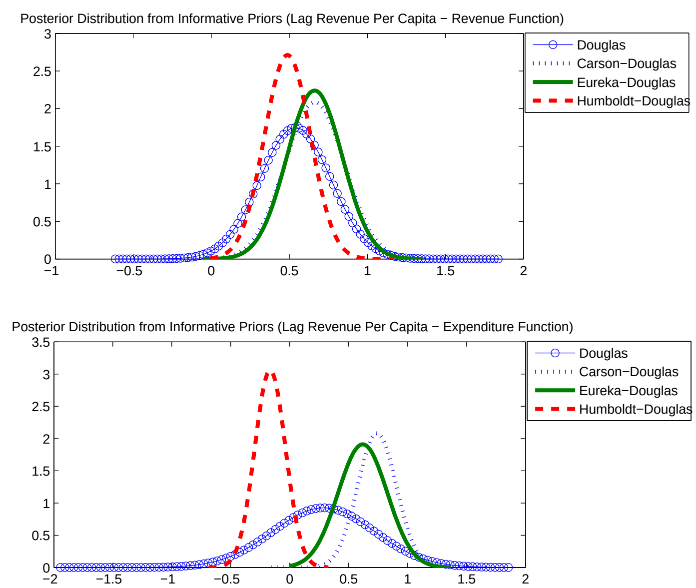

Figure 2.1: Marginal Effect Posterior Distribution - Lagged Revenue in VAR equations

The figures imply that by fitting informative priors from other counties into Douglas's VAR estimation process, the posterior of the marginal effects distributions

[6]Models uses Douglas data set and informative priors from other counties, i.e., Carson-Douglas model uses Douglas data with posterior information from individual Carson VAR estimation as the informative priors.

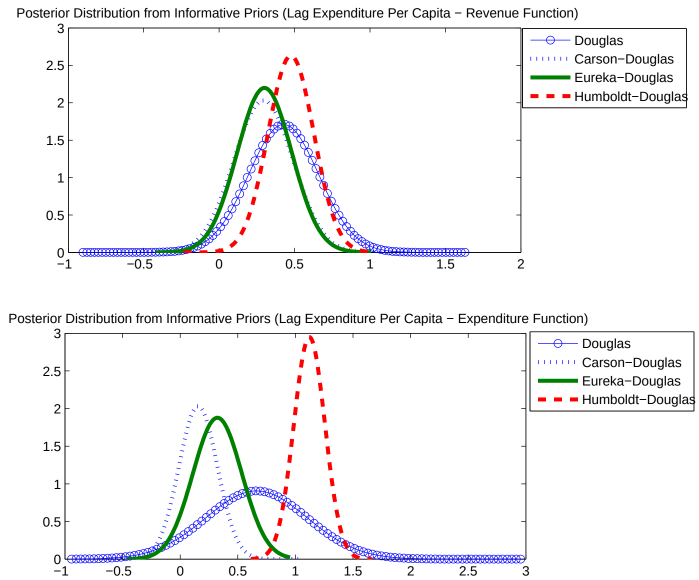

Figure 2.2: Marginal Effect Posterior Distribution - Lagged Expenditure in VAR equations

exhibit reduced variance. Given the primary concern of the BVAR model to produce accurate predictions of the future revenue and expenditure fluctuations, the predictive posterior distribution from the BVAR estimation is explained next.

2.3.2.3 Predictive Posterior Distribution - A conditional approach

The coefficients of the VAR estimations of each county yield a solid base for generating the predictive posteriors distributions. Specifically, the predictive posterior distributions of the variables of interest (Revenue per capita (RPC) and Expenditure Per capita (EPC)) are generated in two steps:

First, we use the originally drawn posteriors to capture the predictive value of RPC and EPC for one-year ahead among all county combination models[7], and label them as

[7] 3000 draws from Gibbs Sampling

"RPC12" and "EPC12". Given that the original datasets of each county only has 13 observations, we feed the one-year ahead predictions into two-year ahead predictions, the target variables become "RPC13" and "EPC13", in that way it captures the added uncertainty that arise from using predicted values as regressors. Since this has to be done for each lagged parameters from the Gibbs Sampling, this would yield $3000 \times 3000 = 9$ million draws, that is more than what is needed and required additional computing memory. hence every $30th$[8] draw of "RPC12" and "EPC12" are used, which reduce the final number of draws to $300,000$. Second, we compare the predictive values of the revenue and expenditure per capita for year 12 and year 13 with the actual figures using PPP values (see equation 2.20). A higher PPP value means that the predictive distribution is centered more closely around the true value. For each of the 17 counties in Nevada, 16 county-specific Posterior Predictive Distributions (PPD) are generated, that produces a total of 272 sets of predictive posterior distributions for Revenue and Expenditure per capita. Next section reveals how these 16 county-specific Posterior Predictive Distributions are converted into one model-averaged Posterior Predictive Distribution for each target county.

2.3.2.4 Model Probability and Weighted Average Predictive Posterior Distribution

For each model, the logarithm of the model-conditioned marginal likelihood (i.e. $pr(y|\pi_i)$) is computed using Chib's method shown in equation 2.17. Following Moeltner and Woodward (2009), the posterior probability of each model, denoted as $pr(\pi_i|y)$, can be expressed using Bayes' rule as equation 2.22:

[8] This number can be changed.

$$pr(\pi_i|y) = \frac{pr(y|\pi_i)pr(\pi_i)}{p(y)} \tag{2.22}$$

where $pr(y|\pi_i)$ is the model-conditioned marginal likelihoods of each individual county model using informative priors of other counties, $pr(\pi_i)$ represents the "Prior Model Probability", and $p(y)$ is the unconditional marginal likelihood, which is the probability that y is generated by any of the individual models. Given that all counties in Nevada are included in the estimation, we may assume that the sum of the posterior probabilities from each combination model equals to 1, i.e., $\sum_{i=1}^{N} pr(\pi_i|y) = 1$. Therefore, each combination model's posterior weight equals to the proportion of each model's conditioned marginal likelihood to the sum of all 16 conditioned marginal likelihoods. i.e.,

$$pr(\pi_i|y) = \frac{pr(y|\pi_i)}{\sum_{i=1}^{N} pr(y|\pi_i)} \tag{2.23}$$

As a result, we produce a table that shows the "Model Weights" of each county-specific model in Table 2.1.

In Table 2.1, the columns represent the probability weights for each target county. For example, 65% of the predictive posteriors of Carson county are drawn from the Nye-Carson combined model, 10% of the predictive posteriors in Carson comes from Humboldt-Carson combined estimation, etc.

Now we may build the "Model-Averaging" framework based on the BVAR estimation results and the "Model weights" listed in table 2.1. To achieve this, we initiate a random drawing process from the standard uniform distribution (i.e., $pr(\pi_i|y) \sim [0, 1]$) according to the weights of each county combination. For instance, each column in table 2.1 is arranged into a vector say ω, then 3000 random draws for year 12 and

Table 2.1: Posterior Model Probability - All county combinations

	carson	churchill	clark	douglas	elko	esmeralda	eureka	humboldt	lander	lincoln	lyon	mineral	nye	pershing	storey	washoe	whitepine
carson	.	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.6%	0.0%	0.0%	0.1%	0.0%	0.6%	0.0%	0.0%
churchill	3.0%	.	3.0%	5.7%	0.1%	0.4%	0.0%	0.0%	0.1%	18.1%	0.1%	0.1%	6.7%	1.6%	20.6%	80.2%	0.8%
clark	0.7%	1.2%	.	3.9%	1.5%	0.1%	2.4%	3.0%	2.0%	1.4%	8.1%	0.8%	2.6%	0.4%	7.7%	1.5%	1.3%
douglas	4.6%	98.8%	58.2%	.	96.8%	99.3%	0.0%	14.1%	6.5%	16.2%	0.0%	80.1%	4.4%	2.1%	37.6%	5.6%	97.5%
elko	3.6%	0.0%	3.5%	5.1%	.	0.0%	3.1%	27.5%	17.8%	0.7%	0.1%	0.3%	18.9%	8.0%	0.1%	1.0%	0.0%
esmeralda	0.1%	0.0%	0.3%	0.5%	0.0%	.	39.8%	4.1%	1.0%	0.1%	0.0%	0.0%	1.0%	0.0%	0.0%	0.1%	0.0%
eureka	0.5%	0.0%	0.5%	0.0%	0.0%	0.0%	.	0.0%	0.0%	7.1%	0.0%	0.0%	0.6%	0.1%	0.2%	0.9%	0.0%
humboldt	10.2%	0.0%	1.5%	1.4%	0.0%	0.0%	33.2%	.	53.7%	0.3%	0.0%	1.1%	1.1%	0.4%	0.2%	0.0%	0.0%
lander	0.7%	0.0%	7.7%	9.3%	0.2%	0.0%	5.8%	12.0%	.	1.7%	0.0%	1.9%	1.7%	0.6%	0.1%	0.0%	0.0%
lincoln	0.6%	0.0%	0.2%	1.2%	0.0%	0.0%	0.0%	0.0%	0.0%	.	0.0%	0.0%	0.4%	0.3%	0.6%	0.6%	0.0%
lyon	3.7%	0.0%	11.3%	25.0%	0.7%	0.0%	0.7%	28.5%	11.8%	2.8%	.	15.4%	4.2%	5.3%	1.0%	0.8%	0.2%
mineral	3.5%	0.0%	0.9%	2.8%	0.1%	0.0%	0.1%	2.2%	1.1%	1.6%	89.7%	.	45.3%	5.3%	0.1%	1.3%	0.0%
nye	64.8%	0.0%	0.5%	18.2%	0.0%	0.0%	0.0%	0.9%	0.5%	4.8%	2.1%	0.1%	.	72.7%	0.1%	3.2%	0.0%
pershing	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.2%	0.0%	0.0%	0.0%	.	0.3%	0.0%	0.0%
storey	0.5%	0.0%	2.4%	1.6%	0.1%	0.0%	14.9%	7.6%	5.1%	1.1%	0.0%	0.1%	5.4%	0.4%	.	0.1%	0.0%
washoe	1.1%	0.0%	7.3%	1.6%	0.5%	0.2%	0.0%	0.1%	0.2%	9.3%	0.0%	0.1%	2.0%	0.3%	30.6%	.	0.0%
whitepine	2.5%	0.0%	2.7%	23.7%	0.1%	0.0%	0.0%	0.1%	0.2%	31.0%	0.0%	0.1%	5.8%	2.6%	0.4%	4.7%	.
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

$300,000$ draws for year 13 are taken and compared with the cumulative sum of ω, this allows a random selection of the predictive posteriors of all county-combinations based on their "Model Weights".

The 17 weighted average predictive posterior distributions from the "Posterior Model Probability" produce an overlook of how the VAR models fits the explanation of the revenue expenditure inter-temporal linkage. The predictions accuracy are compared between the results from "Model-Averaging" framework and the predictive posteriors using "diffuse priors". Among all the counties, Carson, Lander, Pershing, Storey and White Pine have the most improved prediction from the "Model-Averaging" method (See Appendix A). For Pershing county, significant improvements in prediction for year 12 and year 13 are found in both revenue and expenditure equations[9]. The revenue equation predicts that a 1% increase of previous year's expenditure per capita will likely to generate a 0.54% increase of next year's revenue per capita, and expenditure equation shows that a 1% increase of previous year's revenue per capita implies a 0.28% increase of next year's expenditure per capita. For Carson city and Lander county, year 13 predictions in both revenue and expenditure equations are significantly improved .

The result from Carson city estimations states if the expenditure per capita of previous year increase by 1%, revenue per capita of forthcoming year will increase by 0.8%, conversely, an increase of previous year's revenue per capita will cause a 0.2% increase in expenditure per capita in the current year. In Lander county, these changes are 0.42% and −0.1% respectively. Year 12 prediction for the "Expenditure per Capita" (EPC12) is improved in the case of Storey county and White Pine county. Storey county results shows that a 1% increase of previous year's revenue per capita is likely to cause a 0.06% decrease in next year's expenditure per capita, and a same

[9]Revenue Per capita for Year 12 and 13, Expenditure Per Capita for Year 12 and 13.

unit of increase would cause a jump of 0.51% in White Pine's coming year expenditure per capita. The graphical illustration of the prediction improvements are displayed in figure 2.3 — 2.14. In each figure, The black dotted bell curve is the Posterior Predictive Distribution (PPD) of "Expenditure per Capita (EPC) for the predicted years. (i.e., "epc13" is the Posterior Predictive Distribution of "Expenditure per capita" for year 13.) The black solid bell curve is the Posterior Predictive Distribution (PPD) of "Revenue per capita (RPC)" for the predicted years. The black dotted line is the predictive posterior mean for "Expenditure per capita" of the predicted years, and the black solid line is the predictive posterior mean for "Revenue per capita" of the predicted years. The red dotted and solid lines are the actual "Expenditure per capita" and "Revenue per capita" respectively for either year 12 or year 13.

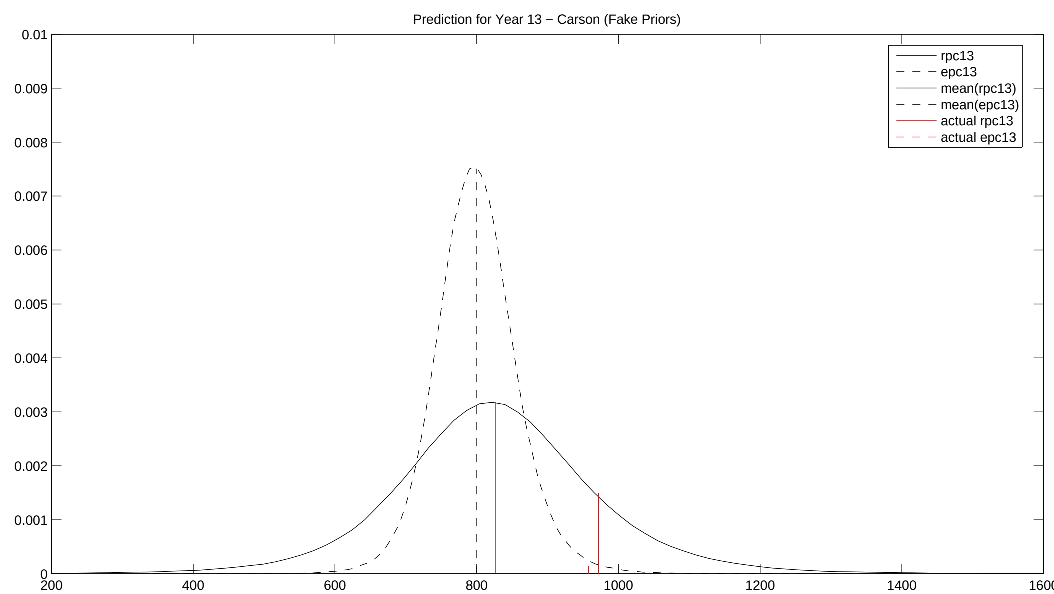

Figure 2.3: Posterior Predictive Distribution - Carson (Diffuse Prior)

The results also indicate that the random selection of the predictive posteriors from the county combination models are unevenly distributed. For example, 73%

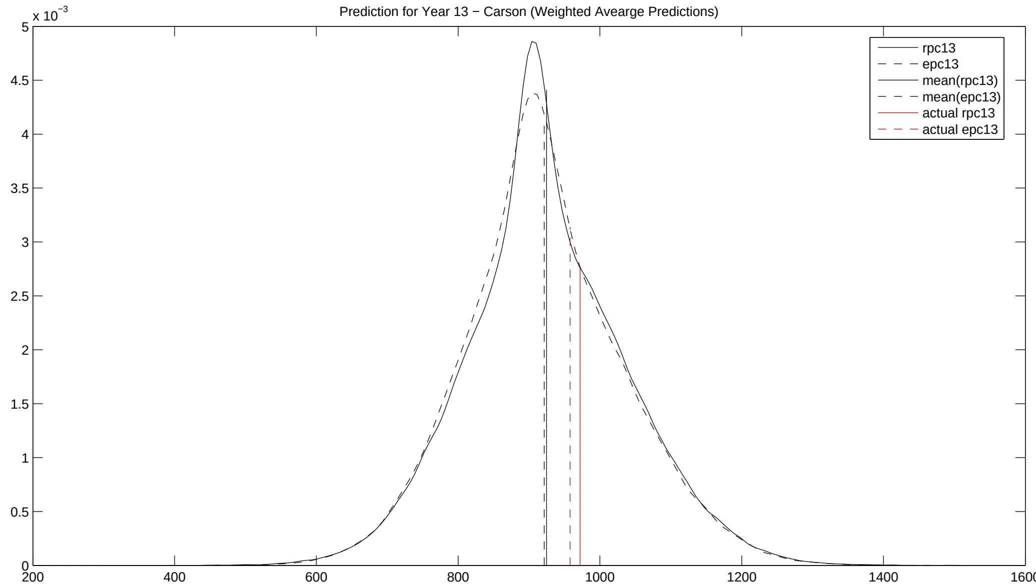

Figure 2.4: Posterior Predictive Distribution - Carson (Weighted Average Prediction)

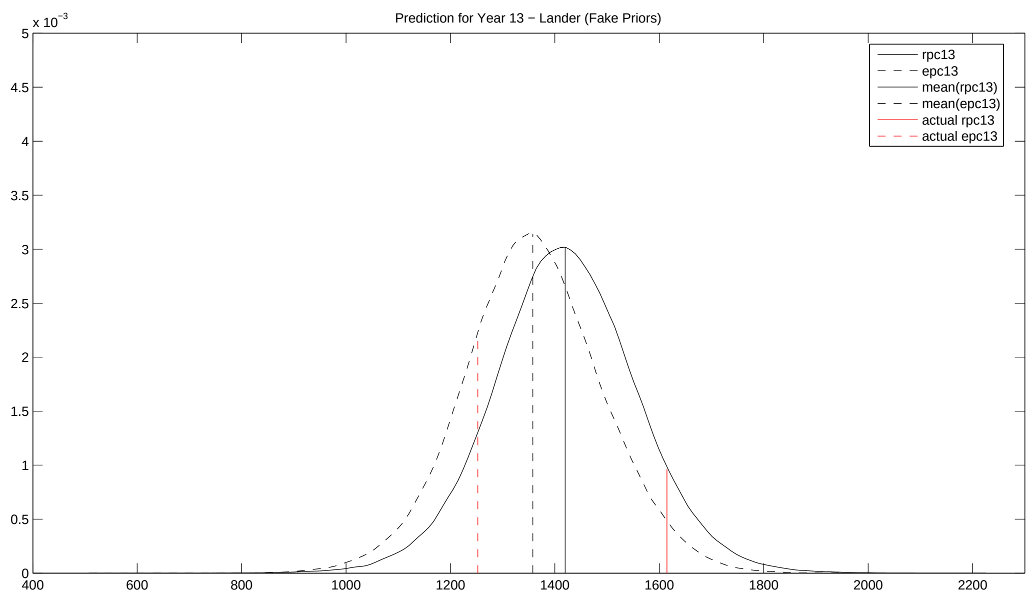

Figure 2.5: Posterior Predictive Distribution - Lander (Diffuse Prior)

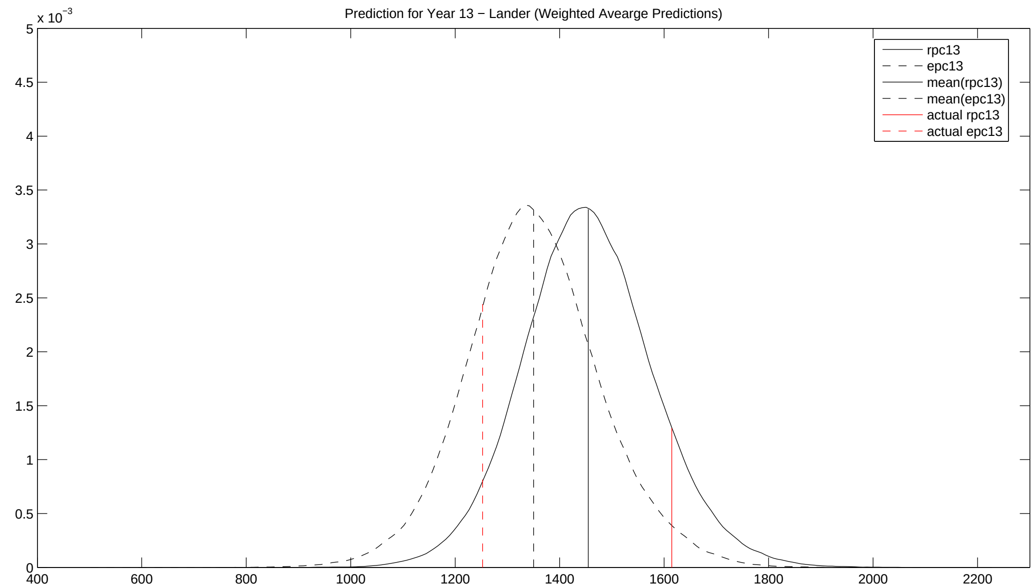

Figure 2.6: Posterior Predictive Distribution - Lander (Weighted Average Prediction)

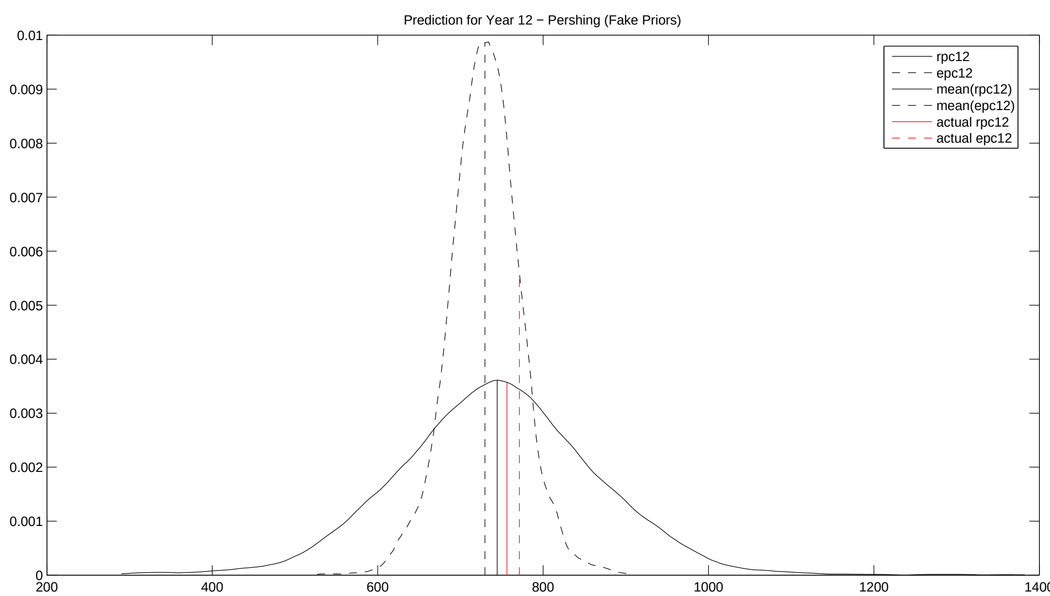

Figure 2.7: Posterior Predictive Distribution - Pershing (Diffuse Prior)

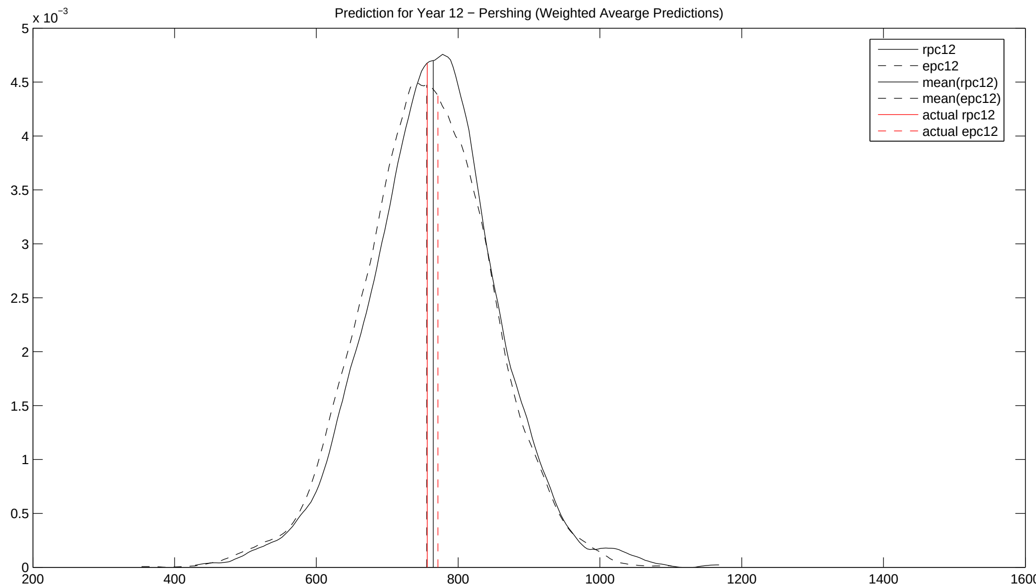

Figure 2.8: Posterior Predictive Distribution - Pershing (Weighted Average Prediction)

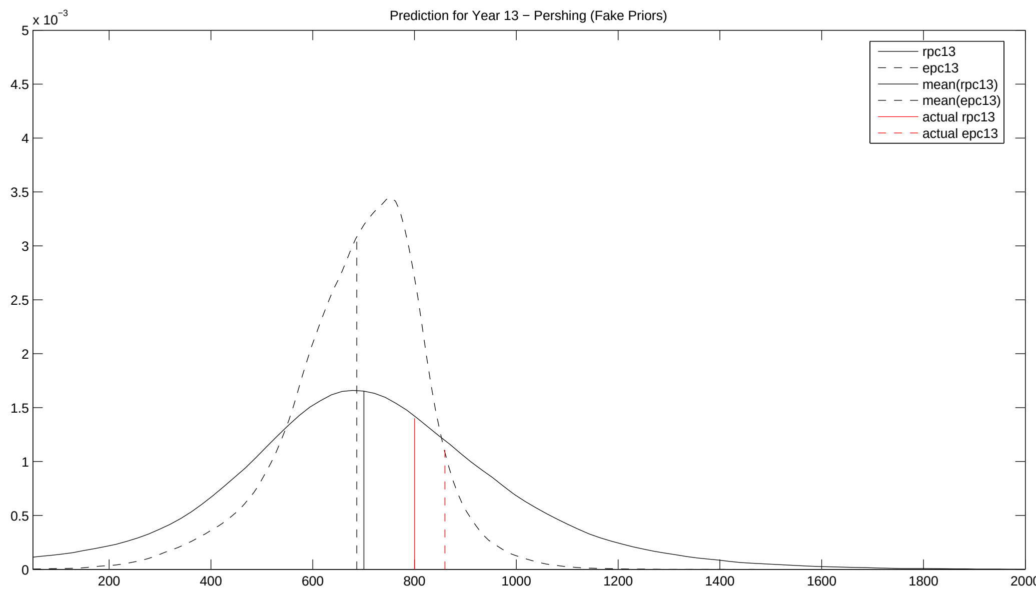

Figure 2.9: Posterior Predictive Distribution - Pershing (Diffuse Prior)

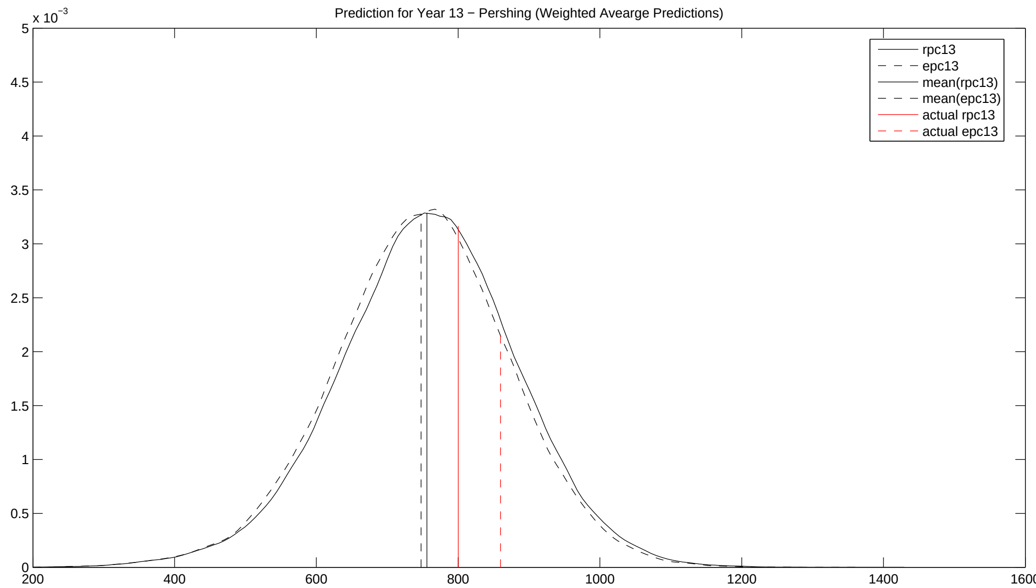

Figure 2.10: Posterior Predictive Distribution - Pershing (Weighted Average Prediction)

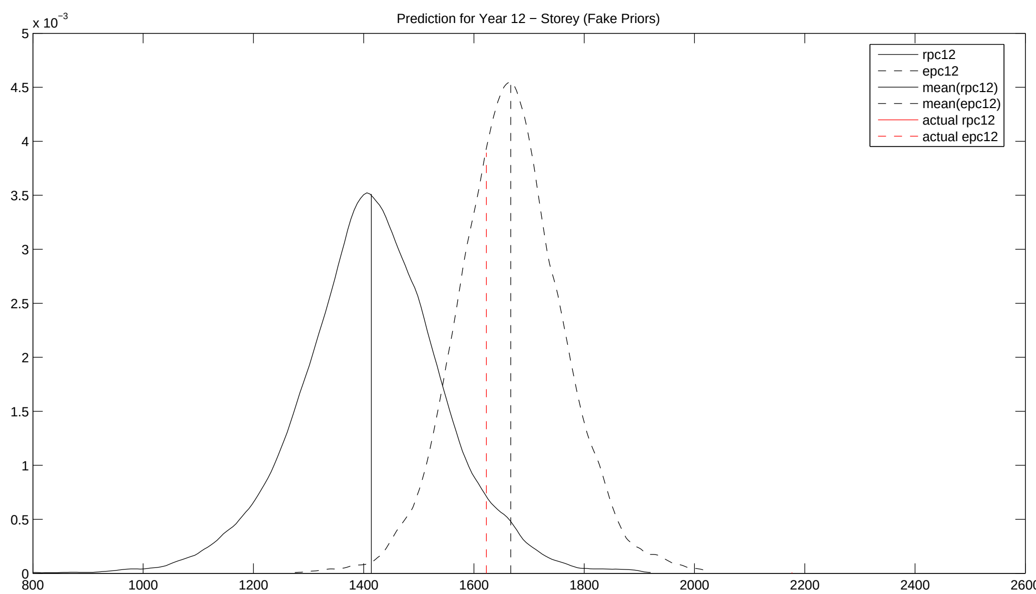

Figure 2.11: Posterior Predictive Distribution - Storey (Diffuse Prior)

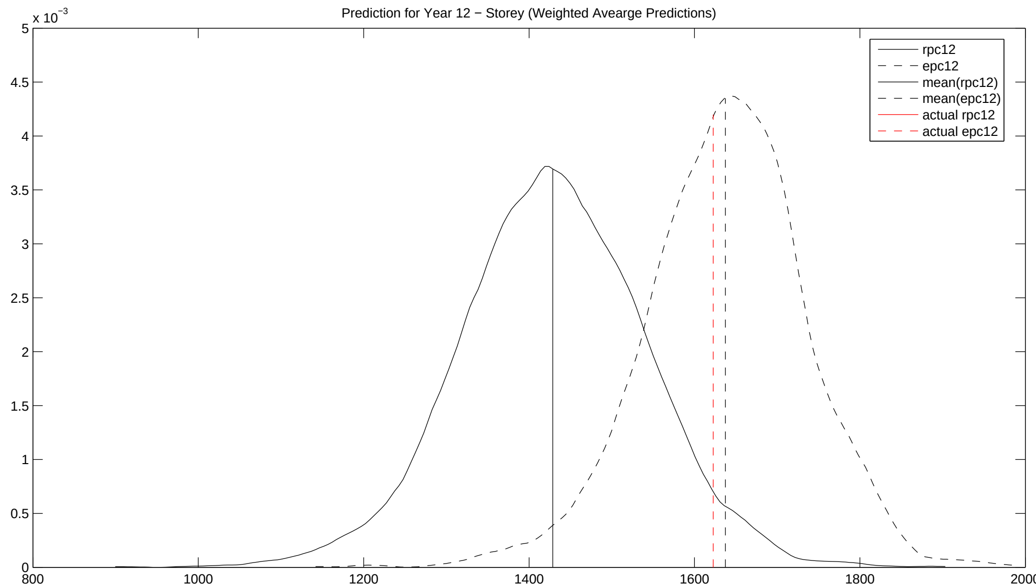

Figure 2.12: Posterior Predictive Distribution - Storey (Weighted Average Prediction)

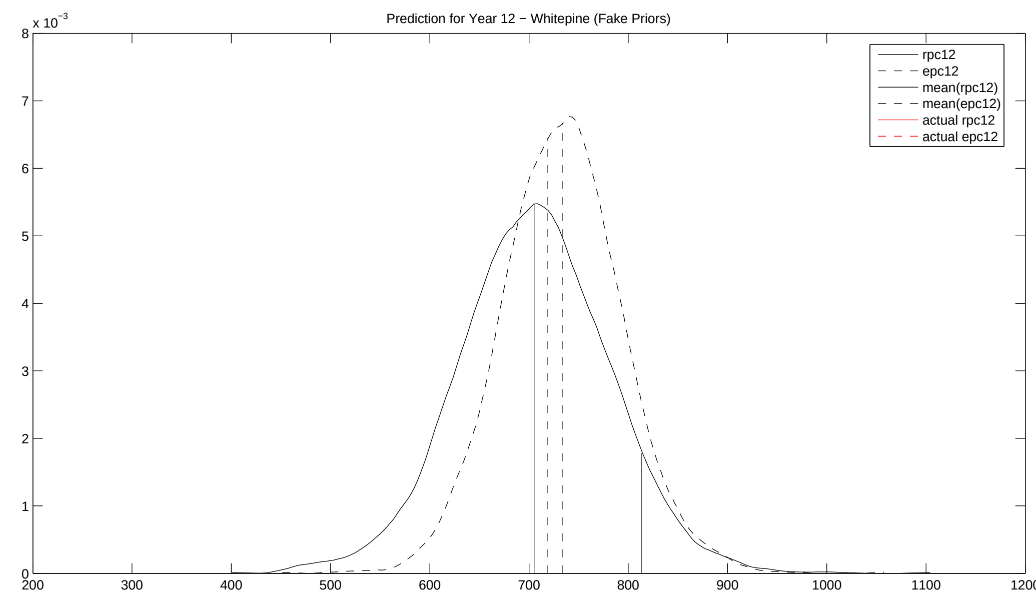

Figure 2.13: Posterior Predictive Distribution - White Pine (Diffuse Prior)

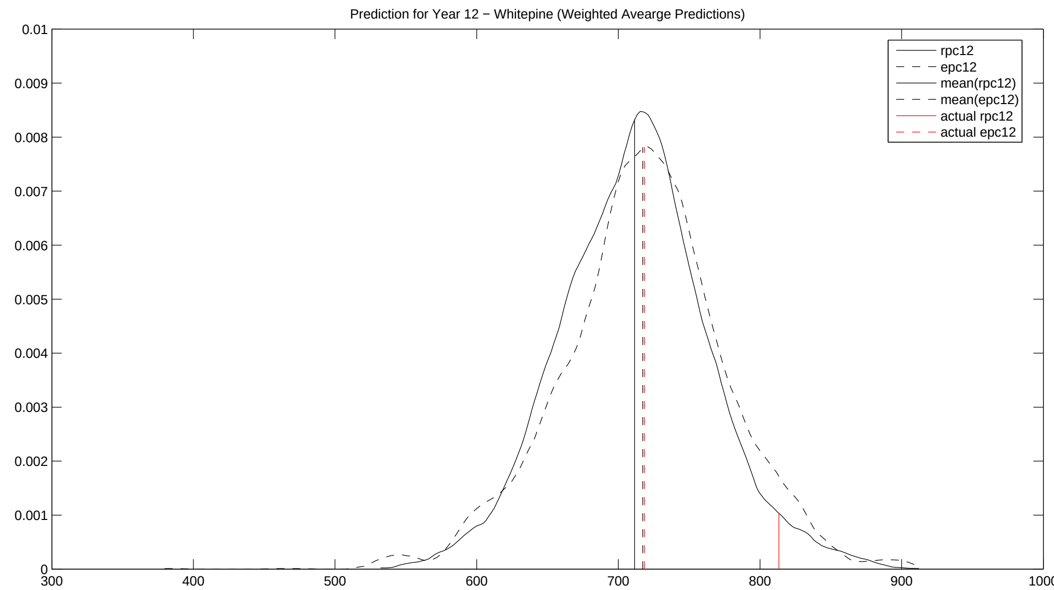

Figure 2.14: Posterior Predictive Distribution - White Pine (Weighted Average Prediction)

of the weighted average predictive posteriors of Pershing county comes from the estimation using informative priors of Nye county, similar cases are found in several other counties. By plotting the raw data of "Revenue and Expenditure per capita" of these counties, we find the weight dominance is associated with the similarities of the county fiscal level. Alghough nearly all 17 regions exhibit parallel flow pattern between the revenue and expenditure, the fiscal levels are different. Figure 2.15 compares the revenue-expenditure time series of four counties: Nye, Pershing, Carson, Clark, and it shows that Pershing county is more closely related to Nye county than to Carson and Clark, The "Model Weights" from table 2.1 displays the dominance of Nye county in the estimation of Pershing county's BVAR model. The weight also explains that majority of the model-averaged predictive posteriors of Pershing counties comes from Nye county and other similar cases. This shows that in the counties with improved predictions via the "Model-averaged" approach, i.e., Pershing, Storey, Carson, White Pine, Lander, the priors from regions of closer fiscal level to these counties are more informative.

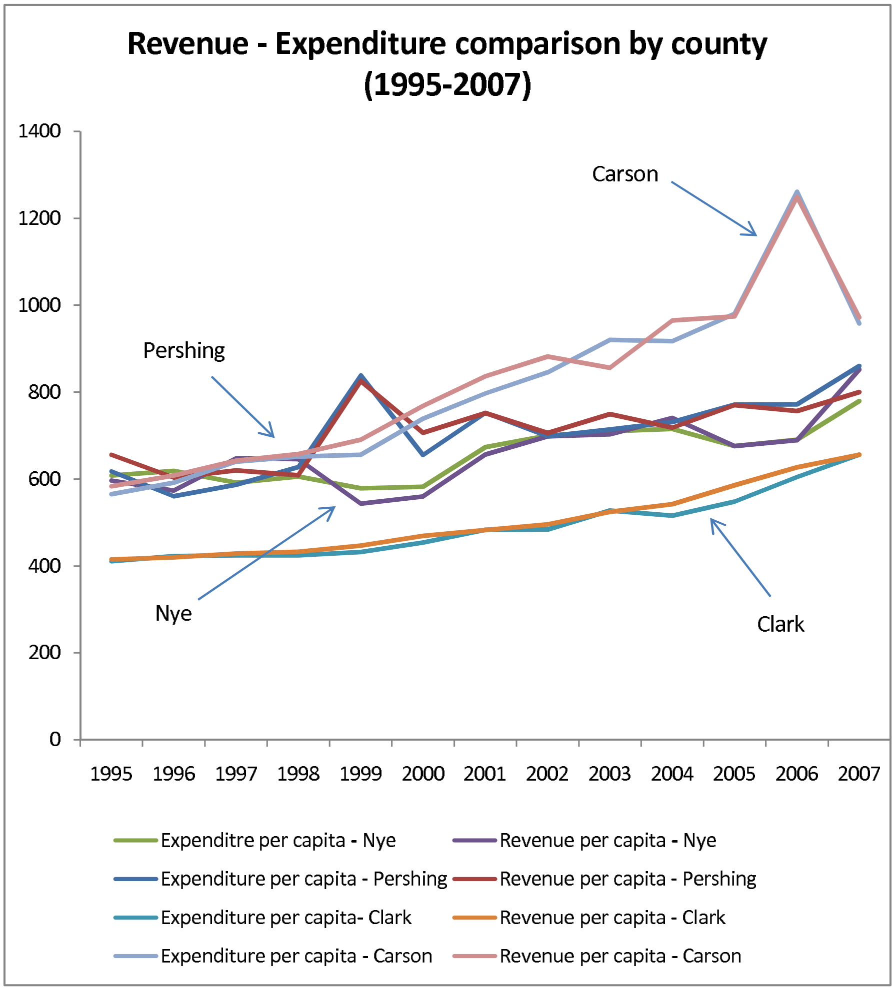

Figure 2.15: Revenue-Expenditure comparison by county (1995-2007) - Pershing

2.4 Summary and Conclusions

The applied research presented by this chapter develops a Model-Averaging Framework via a Bayesian Vector Autoregressive (BVAR) model, which attempts to address the inter-temporal linkage between county-level revenue and expenditure per capita in the state of Nevada. The study uses the small fiscal datasets of all counties in

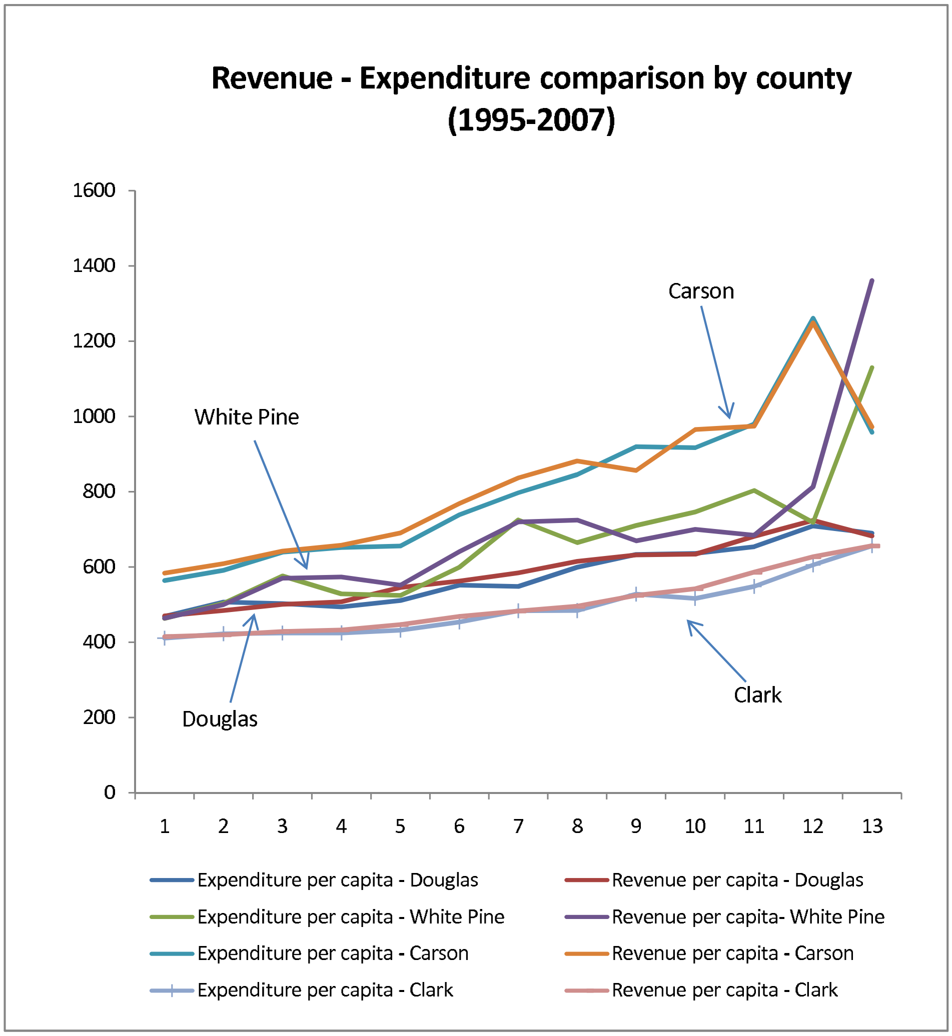

Figure 2.16: Revenue-Expenditure comparison by county (1995-2007) - White Pine

Nevada to address whether the proposed “Model-averaging” method is an effective tool in improving the regional economics forecasting. A number of results emerge from this analysis.

First of all, the application of the BVAR model allows the estimation to use informative priors from neighboring counties given the small data sets, and the results reflect that the variance of the coefficients’ posterior distributions are reduced. By adding the “Marginal Likelihood” and “Predictive Posterior Density” into the estimation, an internal examination of each county-combination’s “Model Probability” is completed. These “Probabilities” are then used to produce a “Weighted Average Predictive Posterior” distribution for each county. The overall results show significant prediction improvements of 5 counties, therefore, the “Model-Averaging” approach via marginal likelihoods is effective in refining both regular posterior distribution and the predictive posterior distribution.

In contrast to the results of Holtz et al. (1989), the BVAR estimation used in this chapter suggests an interdependence and inter-temporal linkage between local revenue and expenditures in Nevada. We find that the one-direction assumption that “past revenues help to predict current expenditures, but past expenditures do not alter the future path of revenues” is not universal among Nevada counties. In the case of Pershing, Carson and Lander county, historic revenue and expenditure information bilaterally predict each other’s future, and in Storey and White Pine county, revenue is a strong indicator of the expenditure, but not reversely.

By comparing the prediction accuracies, we find that the “Model Weights” are not evenly distributed among 17 counties of Nevada. This is manifested by that the weighted average posteriors and the posterior distribution of one or two counties from the combined models are very similar. For instance, 97% of the weighted predictive posteriors of expenditure per capita of White Pine county come from Douglas–White Pine[10] BVAR estimation; 73% of Pershing county's predictive posteriors of both revenue and expenditure per capita come from Nye–Pershing estimation. The time series comparison between the counties with improved predictions and their dominant regions (i.e., Pershing and Nye) show that the fiscal level similarities are the reasons for the weight dominance, and the priors from counties with similar fiscal levels are the major factors for the forecasting improvements. However, for counties that do not have improved predictions from the model-averaging approach, this relationsip is not found and further investigation is needed.

Nevertheless, the Model-Averaging approach this chapter addresses is only tested on a BVAR model, more experiments and field studies are suggested in future research to test whether the gained efficiency is sustained or enhanced in different models with larger set of regional units.

[10]Using Douglas Informative Prior in White Pine VAR estimation.

CHAPTER 3

Estimating "Jump-bidding" Impact in National Wild Horse and Burro Internet Adoptions

3.1 Introduction

The wild horse roaming is one of the major resource management issues for federal land agencies. In recent years, federal expenditure for maintaining captured horses is climbing, at the same time, adoption rate for animals are receding.

Thousands of horses are rounded up through the use of helicopters each year. Federal law limits wild horses and burros to areas assigned by the 1971 law[1]. However, the public lands allotted to free-roaming have been reduced by nearly 40 percent over the past decades. The current Bureau of Land Management (BLM) figure shows that 37,000 wild horses and burros roam on more than 32 million acres in 10 Western states, and about half in Nevada. An additional 32,000 of them are being held in government funded corrals and pastures, and the care and feeding of the captive animals is expected to reach 35 million in total. In recent years, federal land agencies such as the Bureau of Land Management (BLM) are promoting authentic valuation of these animals among interested adopters, via both on-site and Internet adoptions.

[1] Wild Free-roaming Horse and Burro Act

For on-site adoptions, the procedures are similar to the outcry ascending auctions. Animals are shown individually to all adoption participants. After the announcement of the reserve price and minimum increment, interested adopters display their bids in ascending order until no further bid is submitted. The adoption fee is the highest bid by the time each auction ends. Internet adoption, on the other side, performs the same bidding mechanism as the on-site auction, except adopters can only view the pictures of animals via the Internet and each session has a fixed end time. Therefore, winner of the auction is the bidder who has the highest bid by the end of the auction.

In recent years, unsatisfactory adoption rates have become a major problem for the Bureau of Land Management (BLM), only a small group of animals with particular features are receiving competitive bidding, rest of the animals are either adopted at the starting reserve price or stay unadopted. Bidders tend to adopt animals which give them visual attractions. This is more obvious in Internet Adoptions. Among those popular animal groups, the field data shows aggressive bidding is extremely common, and the bid increments submitted each round for these animals are much higher than the minimum requirement. This behavior is referred as “Jump-bidding”.

In addition, the BLM gives each bidder different adoption allowance based on their herding capacities. This allowance determines how many animals he can bid on simultaneously at each session. Given these factors, the primary concern of this chapter is to provide an empirical analysis of the aggressive bidding behavior based on current adoption activities. First, it addresses what animal groups are more favorable than others in terms of the ability to attract competitive bids; Second, it measures the impact of the bidding allowance on bidders’ aggressiveness; Third, it reveals if the aggressive bidding influences the auction revenue, in this case, the final selling price of each adopted animal.

By identifying the bidder adoption preference and the motivations for aggressive biddings, the results from the above investigations aim to generate some policy recommendations that could mitigate the current problem of unsatisfactory adoption rate and rising maintenance costs of unadopted animals that the BLM is facing.

The theoretical and empirical literature on the motivation of "Jump-Bidding" demonstrate various conditions of when jump bidding is expected, and its impacts on auction efficiency in terms of the level of competition and auction revenue. McAfee and McMillan (1987) indicate that the dominant strategy in response to jump bidding is to remain in the competition up to one's true value. Raviv (2008) shows the strategic reason of Jump-Bidding behavior by grouping the sequence of jump-bids in open-outcry car auctions. He finds that jump-bidders place fewer bids, and the prevalence of jump bidders in the bidding pool tends to conclude auction quickly. The same result is found in the independent private value setting. Daniel and Hirschleifer (1998) show the existence of a Jump-Bidding equilibrium, and the non-existence of revenue effects unless the bidding cost is substantial; In an extremely costly bidding environment, such for a take-over target, they found that repeated jump-bids communicate bidding information rapidly, and hence can conclude the auction in a small number of bids.

However, Avery (1998) argues that Jump-Bidding can be economically rational and has a negative impact on the expected revenue of the seller. In recent studies, this opinion is challenged. Issac et al. (2006) show that neither irrationality nor signaling is required to generate jump bidding. By allowing jump bidding in auctions, especially in auctions with significant underlying values, revenue can be increased. Also they display the expected utility from participating should be improved given the value distribution and level of impatience among bidders in similar settings.

In Internet auctions, where the bidding environment is uncertain, Goeree et al. (2002) claim that bidders lower the cost of "Jump-bidding" by behaving "as if" they are risk averse. In further discussions, Easley and Tenorio (2004) extend the concern to the cost in Internet auctions, where it appear to be an important factor that influences aggressive biddings. They suggest that jump-bidding emerges along with positive bidding costs, and the size of jump bids relates to the size of the competition. Therefore, in some sense, the level of competition and the bidding costs[2] are correlated with the size of jump bids and the auction revenue. Furthermore, Gunderson and Wang (2005) illustrate the Jump-Bidding signaling effect using both single subject and multiple subject models. Under single subject model, only one item is auctioned, and they find that by concealing the identity of the bidders (i.e., Internet bidding environment) permits the jump bidder to signal more information through the jump bids; In an auction of multiple items, a jump bid signals a high valuation, and causes a discrete change in the bidding behavior of other bidders. Brusco and Lopomo (2002) also prove that in multiple subject auctions, it is possible for bidders with larger demand to use jump bids to inhibit bidders withe smaller demand.

Given the previous literature in studying aggressive bidding behavior, in this chapter, we are interested in addressing how "Jump bidding" is associated with the level of competition in the Internet Wild Horse and Burro adoption, which is a typical multi-objects auction; and in what direction is the revenue driven by the aggressive bidders.

The rest of this chapter is structured as follows: section 2 provides the background of auction in general and an overview of prior theoretical explanation of signaling and aggressive biddings ("Jump Bidding") in both on-site auction and Internet auction settings; section 3 describes the empirical data; section 4 develops several regression

[2]In Internet auctions, the bidding cost is equivalent to Monitoring cost.

models intended to evaluate the aggressive bidding behaviors of wild horses and burros adopters, and contains the results of the analysis; section 5 concludes.

3.2 Theoretical Review of Auction and "Jump-bidding"

3.2.1 Auction - What is it?

An auction is a traditional way of selling goods via bidders' competition. It has been practiced for thousand of years. The range of objects sold by auction never stops to grow. With the emergence of modern technology, such as the Internet, the interactions among bidders are shifted from face to face basis to a virtual platform. Generally speaking, there are four types of auctions that are regularly used: English, Dutch, First-price Sealed, Second-price Sealed. The English auction, also known as "Open-outcry ascending price auction", is the most popular auction format. This type of auction allows continuous bidding in an "ascending order", starting from the reserve price which is set by the auctioneer. The transaction is either in the form of First-price or Second price. In the former, the winner pays the highest bid, where in the latter, the winner pays the second highest bid by the end of the auction. The notable example of an Internet based English Auctions is eBay; A Dutch Auction is conducted via the descending order of bidding. The auction starts with a relatively high price, which is gradually lowered by the bidder until the item is claimed. This format is not widely adopted as English Auctions, but is still in use in agricultural produce and flower sales in Europe.

The First-price and Second-price sealed bid auctions are different from English auctions in terms of the bidding processes. In both of these sealed bid auctions, only one bid is required to be submitted from each bidder. Similar to an English auction, a first-price sealed bid auction winner pays the highest bid and a second-price sealed bid winner pays the second highest bid. The National Wild Horse and Burro Internet Adoption of this chapter uses a First-price Ascending Auction.

3.2.2 Prior Theory on Signaling and "Jump-bidding" in Ascending Auctions

3.2.2.1 Types of Signaling Strategies in Ascending Auctions

To better understand the motivations of aggressive bidders in wild horse and burro auctions, it is necessary to gain an overview of the theory on signaling in ascending auctions in general. Ordinary auction theory suggests that in a private-value English auction, where players' valuation of the item are not known by his opponents, the winner will be the bidder with the highest valuation for the object. As a reasonable bidder, his strategy is to increase each bid by the minimum bid increment, this is also known as "Ratchet Solution" (Raviv, 2008) or "Straight Forward Bidding (SFB) (Issac et al., 2007); but a "Jump-bidder" in these auctions submits bids higher than what is required by the auctioneer. Such behavior is normally attributed to irrationality or to bidders' signaling of their valuations. Two types of signaling strategies are commonly found in ascending auctions: *Bluffing* and *Sandbagging*. (Cassady, 1967) *Bluffing* occurs when a weak player pretends to be strong, while *Sandbagging* occurs when a strong player wishes his opponent thinking he is weak. In some cases, players with moderate valuation *bluff* by making a high bid and drop out if his bluff is called; and players with a high valuation *sandbag* by bidding low, to induce lower bids from the opponents. Suppose an auction with bidders A and B, each player knows what the object is worth to him, and this valuation is held private. In the first round, the opening bidder, say bidder A submits first bid b_A, his rival bidder B can choose to match the bid or drop out based on: A submits a high bid or a low bid (Raviv, 2008).

If bidder A submits a high bid, bidder B may drop the auction if this bids is higher than his true valuation of the object. This allows bidder A to win with no further bidding. If bidder A is a weak player, his *bluffing* strategy succeeds; Second, if the bid is answered with the inference from bidder B that he has to bid aggressively in the second round to secure the winning, a high bid from A costs him more to win; If A is a weak player, the *bluffing* fails.

As an alternative option, a low opening bid from bidder A may have a *sandbagging* effect. Let us assume bidder A is a strong player with a high valuation, if bidder B interprets the low bid from bidder A as a sign of weakness, he may keep his own bids in the second round as low as possible to minimize the cost of winning, therefore, bidder A's *sandbagging* strategy succeeds. In standard auctions, the opening bidder always tries to convince their opponents that he is strong, in another words, he has a high valuation regardless of his true valuation. However, Hőrner and Sahuguet (2007) declare that players with high valuations can choose from either bidding high or low in their opening bids, enjoying the "deterrence effect" from the high bid and "sandbagging effect" from the low one. Therefore, the true valuation of a opening "Jump-bidder" is hard to measure, but it can be certainly associated with the overall number of bids he submit for the object.

3.2.2.2 Jump-bidding in Ascending Auctions

In general, the process of jump bidding in an ordinary ascending auction game is explained by Avery (1998) as following: Assume a bidding scenario with two risk-neutral bidders i and j, with valuations of v_i and v_j. These valuations are supposed to be affiliated. In another word, bidder i's value depends on his own signals and signals he receives from his opponent or vice versa. Let η be the value function that consists of the private and common components. The private part contains each bidder's own valuation of the good, and the common part can be treated as observations each bidder makes about his opponent's valuation during the biddings. For the private observation, we have $\eta(v_i, v_j) = v_i$ or v_j; For the common observation part, we have $\eta(v_i, v_j) > \eta(v_j, v_i)$ or vice versa. The inequality is derived based on the assumption that a "bidder's own observation is more important to his valuation than his opponent's observation". (Bikhchandani and Riley, 1991) Now consider a two-stage ascending auction with a pair of continuous bidding strategies $(B_a(x), B_A(x))$, where $B_a(x)$ is the bidding strategy for an "Ordinary" bidder, and $B_A(x)$ is denoted as the bidding function of an "Aggressive Bidder" in the second-stage confrontation who may have been triggered by a jump-bid from the first stage. They satisfy the relationship with the equilibrium strategy $B^*(x)$ as $B_a(x) < B^*(x) < B_A(x)$ (see Avery (1998)).

If we then define the valuation of both bidders as identically distributed over $(0, \bar{V})$, where $\bar{V}$ is the average observation of the two bidders that is uniform and $\bar{V} > 0$, then the bidder with valuation close to $\bar{V}$, say bidder i, is highly likely to commence the battle with a jump-bid J, which aims to shift his or her opponent from $B^*(x)$ to $B_a(x)$. Bidder j either responds with an ordinary bid b or a jump bid J. If she submits b, then strategy $(B_A(x), B_a(x))$ holds, otherwise, equilibrium is reached. Table 3.1 summarizes the effects of both ordinary bid and jump bid on future strategies:

Table 3.1: A two-stage auction game with Jump-Bidding (Avery, 1998)

Bidder i	Bidder j	
	J	b
J	$(B^*(x), B^*(x))$	$(B_A(x), B_a(x))$
b	$(B_a(x), B_A(x))$	$(B^*(x), B^*(x))$

Table 3.1 suggested by Avery (1998) reflects the outcomes of a jump bid J in the coming stages of bidding, but the assignments of strategies are uncertain. As Avery (1998) argues, "The open exit bidding selects the equilibrium $(B^*(x), B^*(x))$ for each possible combination of bids".

The motivation and impact of "Jump-bidding" in ascending auctions are shown in both the theoretical and empirical literature. For example, Avery (1998) demonstrates that a jump bid can serve as a communicating device among bidders of each other's valuation. Adding signaling stages such as *bluffing* or *sandbagging* to the game will reduce the average price; Daniel and Hirschleifer (1998) find that when a single good is auctioned to two bidders with private values and bidding costs are involved, such costs can lead to a jump bidding equilibrium, where both bidders submit jump bids and extend the game to the next stage.

Similarly, Easley and Tenorio (2004) find that the costs associated with entering the auctions can explain jump bidding in Internet ascending auctions. In addition, they claim that even if the bidders decide to drop out the auction, they will still suffer a positive transaction cost. Therefore, the best strategy would be staying in the game and respond to opponents' bids, either via a regular or a jump bid. Comparatively, the experimental literature on jump bidding is not as rich. Most of the empirical work focuses on the measurement of the revenue effect from jump bidding. For example, Plott and Salmon (2004) propose a method that allows the auctioneer to observe bidders' valuation during the auction process. Their conclusion is that Jump bids only facilitate the speed of the auction, but do not actually have an impact on the final prices and ultimately the auction revenue. Issac et al. (2005) subsequently test three alternative models of "Straightforward Bidding (Ratchet Solution)", "Signaling" and "Impatience and Strategic Bidding" in ascending auctions. Identical to Plott and Salmon (2004), they ascertain that jump bidding has either "neutral or positive effect"

(Issac et al., 2005) to the auction revenue. They also show that jump bidding observed in many field auctions is much more likely to be generated by some form of impatience rather than signaling.

3.2.2.3 Jump bidding in Internet Auctions

Different from on-site auctions, where bidders can enter the auction house and complete the transaction in a single visit if he wins, most Internet auctions can not be completed by a single visit to a website. Therefore, every time a bidder logs to an auction site and submits a new bid, he incurs a transaction cost $c \geq 0$, (Easley and Tenorio, 2004). This includes the time spent on searching the item and connecting to the Internet. This cost is common to all bidders who enter the site and join the auction. In addition, in a typical Internet auction, the bidding environment is uncertain: bidders do not know the number of bidders in an auction, or how many bids each participant submit.

In most Internet auction houses, bidders are free to review their bids during the auction.[3], and they will be automatically notified by email if they are outbid by their opponents. This implies the cost merely comes from the bidding process and is a pure transaction cost. According to Easyley and Tenorio (2004), for bidders who incur a positive cost each time they submit a bid, the "Straightforward Forward Bidding" which is to submit a new bid with the minimum increment may not be an optimal solution. If he chooses to bid low, he faces the possibility of further bidding and consequently further cost; If he chooses to bid high, he could be the current winner and save on bidding costs unless another bidder with higher valuation comes in, which depends on the probability distribution of other bidders' valuations.

[3]Most Internet Auctions have a fixed end time.

This can be better explained by a simple scenario with two risk neutral bidders: suppose we have an Internet auction with bidders i and j bidding for a single unit with minimum bid "b", where the private valuations of each bidder are positive and denoted as v_i and v_j.

If bidder "i" arrives at the auction site first, after observing the current situation, he has three options:

- Stay in the auction and submits a relatively low bid B_i^L, where $B_i^L > b$ and $B_i^L < v_j$.
- Stay in the auction and submits a relatively high bid B_i^H, where $B_i^H > b$ and $B_i^H > v_j$.
- Leave the auction with positive cost.

The first option, bidder "i" stays in and submits a partial bid as he wishes to extend the game further; while the second option allows bidder "i" to be the current or the ultimate winner; or the last option is the case that bidder "i" chooses to leave the site.

For the first option where bidder i stays in the competition with a low opening bid and waits for others, the probability that he wins the auction is low; If he submits a opening jump bid, a twofold effect emerges: First, a jump bid from bidder "i" could possibly deter other bidders from going further in the auction, gives him a higher probability of being the winner, and minimizes his or her potential bidding cost. This is specially beneficial to Internet adopters whose opportunity and search costs are relatively high; Second, the deterrence effect generates either a positive or negative impact to the sellers. The positive effect arises from the possibility that a high opening bid stimulates the level of competition among strong bidders (Bidders with high valuations); where as the negative effect stems from the possible discouragement of induced bidding.

This section reviews the background of signaling and jump bidding in ascending auctions in both ordinary and Internet settings with the conditions under how bidder participates in Internet auctions. Given the equilibrium strategy when facing a jump bid and positive transaction costs in Internet auctions, we may continue to discuss the impacts of "Jump bidding" in National Wild Horse and Burro Internet Adoptions, where some bidding rules and screening process from the Bureau of Land Management makes it a different selling interface to general Internet Auctions.

3.3 Field Data

The data for this chapter come from the Wild Horse and Burro on-line adoption program run by the Bureau of Land Management (BLM), Eastern Office in Virginia. A total of 2308 bids are recorded among 477 adopters for the 15 auction sessions that are held between March 2006 and July 2008. Each auction session lasts for 14 to 15 days. Prior to each session, individuals who are interested in adopting need to submit applications to participate in an session. The applications are then processed by the Internet Adoption office. The approval is based on the applicant's hosting facility, such as size of farm, herding equipment, etc. Selected adopters are informed and given the number of animals they are allowed to bid in each session.

Once the auction starts, bidders can only bid on the number of animals up to their assigned allowance, plus one. For example, assume that bidder "i" is approved to adopt 3 animals, he can only be the highest bidder of up to 4 animals simultaneously. If he wins all of the 4 animals, only 3 of them can be finally adopted. The remaining animal is passed to the second highest bidder for adoption. The highest bidder at the closing time of each session wins the auction and pays his final bid. One advantage of the screening process is the control of "noisy" bids that would otherwise comes from non-serious bidders. In addition, all adopters are required to pay a $125 deposit with their applications. The amount is refundable if bidders do not win the auction, but it deters random bidders from entering the auction. The main difference between the Internet adoption and on-site adoption is that bidders do not possess any information about the bidding environment, including the number of bidders in an auction, opponents' bidding time, number of bids each participant submitted, other bidders allowance or the number of animals his opponents are bidding on simultaneously.

The minimum increment per bid is $5. The mean of the bidding increment among all bids submitted is 10.7, with a standard deviation of 21.39, the maximum single increment is $325. Among all adopted animals, any single increment larger than $5 is treated a "Jump Bid'. There are total of 623 jump bids during 15 sessions. Figure 3.1 is the percentage distribution of the jump bid increments starts from $10, and each bar represents a $5 increase.

The magnitude of jump-bids across sessions, the total of number of bids submitted, the number of jump-bids (i.e., Bidding increments greater than $5) and the total auction revenue are listed in table 3.2:

Table 3.2 indicates that the sessions with more total number of bids submitted tend to have a higher proportion of jump bids. However, the sessions that have the least total number of bids do not produce the lowest revenue. Figure 3.2 shows that level of competition and occurrence of jump bidding are parallel and figure 3.3 draws the revenue trend over the 15 sessions.

There are total of 505 animals that are adopted by 477 bidders, and nearly half of

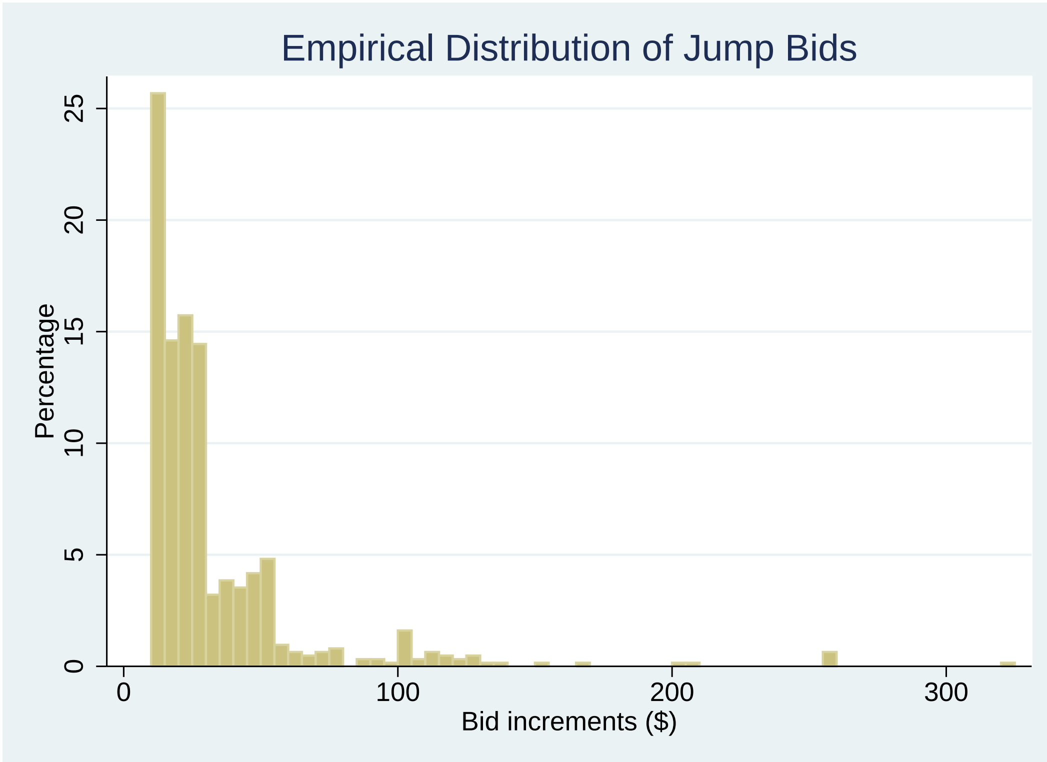

Figure 3.1: Jump bid Increments Distribution

Table 3.2: Summary of Number of bids and jump-bids in all 15 sessions

mm/yy	session	Total Bids	Total Jump Bids	Total Revenue ($)
Mar-06	1	255	72	8595
May-06	2	94	15	4280
Jul-06	3	149	53	3875
Sep-06	4	194	45	4755
Nov-06	5	207	65	7985
Jan-07	6	85	13	2855
Mar-07	7	156	51	4650
May-07	8	146	23	6865
Jul-07	9	83	29	4205
Sep-07	10	57	12	3255
Nov-07	11	63	13	3110
Jan-08	12	303	102	7710
Mar-08	13	64	19	3090
May-08	14	124	28	4395
Jul-08	15	328	83	10315

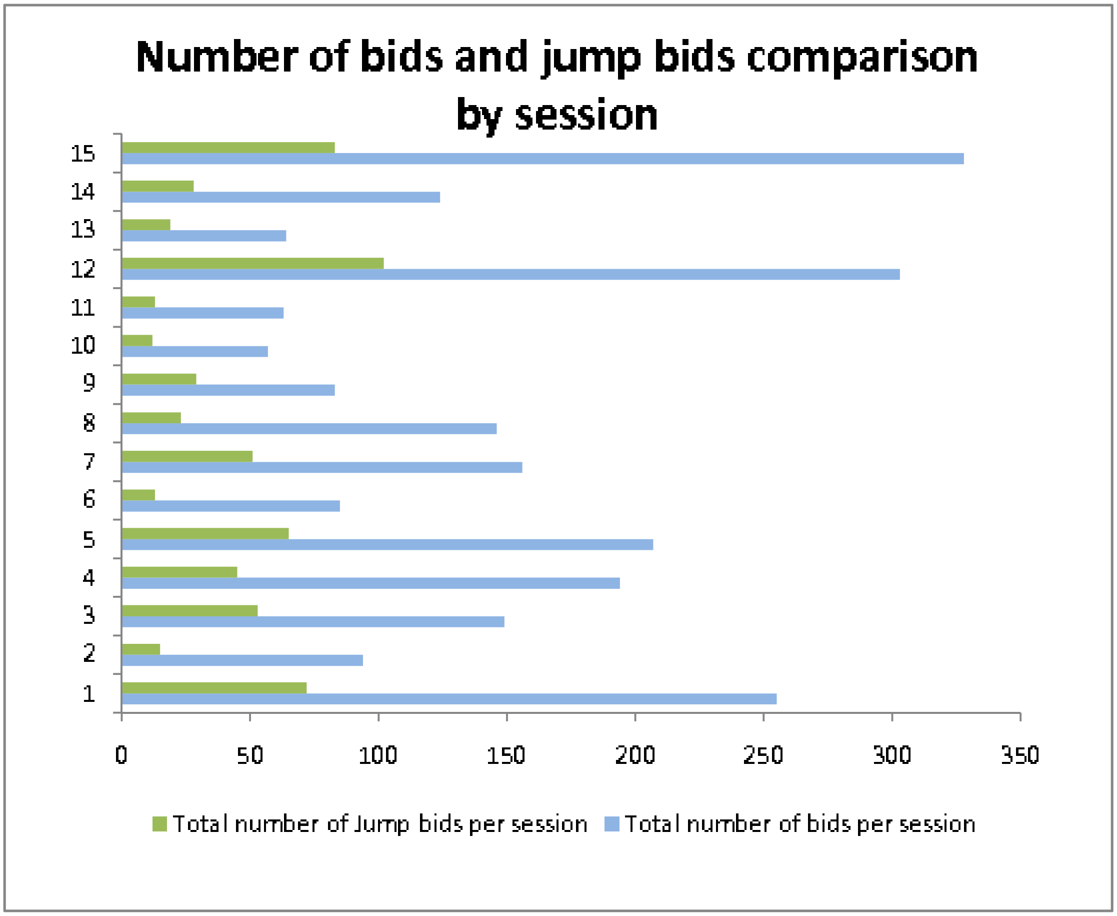

Figure 3.2: Number of Bids and Jump-bids of 15 sessions

them (238 of 505) are adopted at the minimum price of \$125 and received no second bid. 334 (70%) bidders adopt at leasat one animal. The percentage distributions of jump bids per animal are shown by Figure 3.4:

Figures 3.1 and 3.4 display a concentrated weight on the left end of each distribution. This indicates that bidders are seemingly bidding cautiously during these auctions. Interestingly, the magnitude of "Jump-bidding" increases towards the final minutes of each session. 840 (36%) bids are submitted within the last hour of the end of each auction, and 275 (33%) of these bids are "Jump-bids". In addition, 217 out of 275 Jumps are submitted within the last 10 minutes of each session, that is roughly 80% of the total Jump bids happen in the last 60 minutes of a session. The question

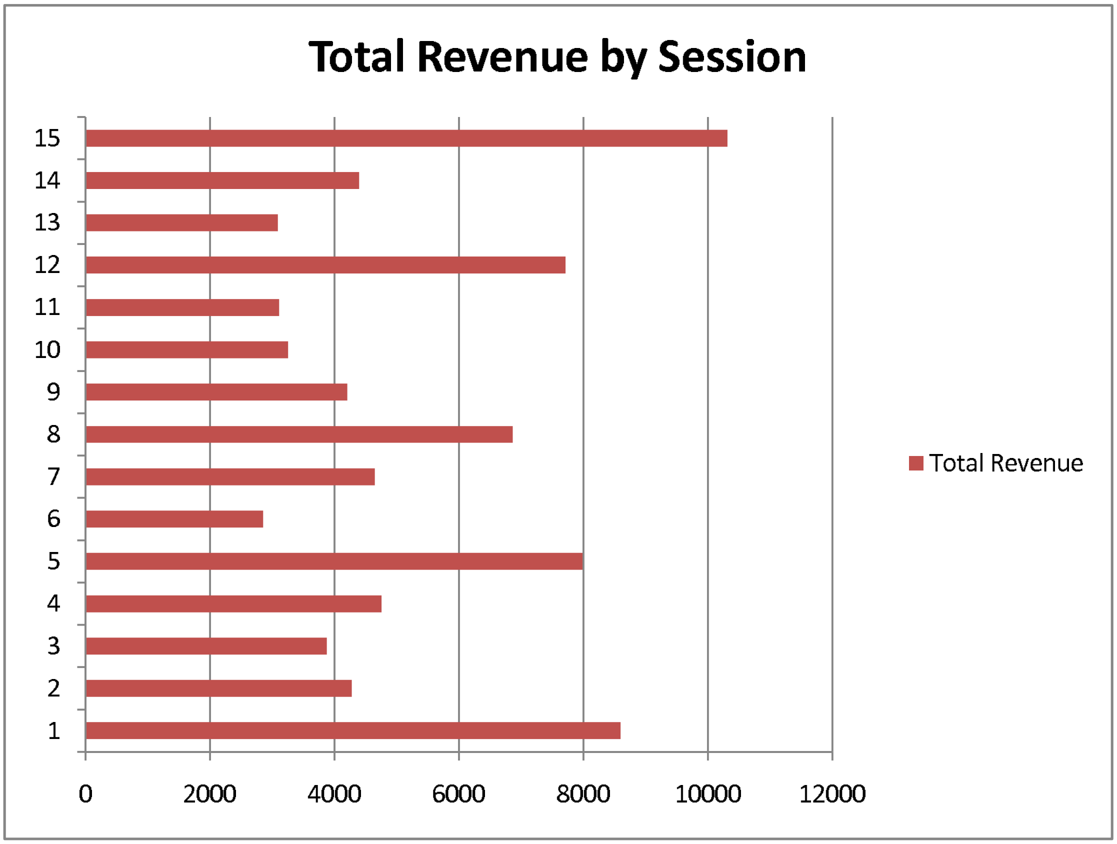

Figure 3.3: Total Revenue of 15 sessions

therefore is why bidders tend to bid more aggressive knowing the auction will end soon. This contradicts the ISZ model (Issac et al. 2005) where "Jump-bidding" is contributed to bidder's motivations to end the auction early.

Among the total of 505 animals that were adopted, 238 of them (47%) were only bid on once. However, that does not mean all of them were adopted at the minimum price of $125, 17 of them received an opening bid (also the only bid) of $130 or more, and 12 of these 17 animals are adopted with one bid only, including a "Jump-bid" up to $325. For the animals that are bid on more than once, the range of the number of bids they received is between 2 and 54, with an average value of 7.8, and a standard deviation of 7.7. This shows on average, animals are adopted within 10 bidding rounds if they draw the interest of more than one bidder. 21 of the 267 animals that receive

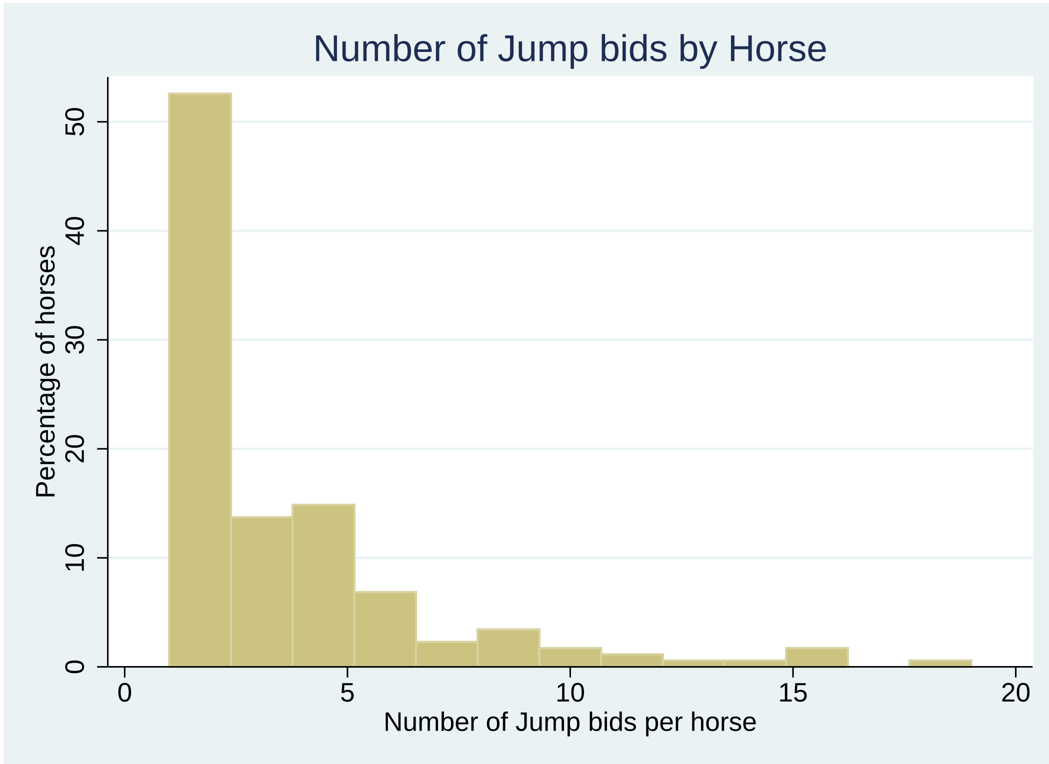

Figure 3.4: Jump bids percentage distribution per animal

more than one bid had an opening bid of $130 or more, and 12 of them are adopted with more than 3 rounds[4].

As mentioned above, another important feature of the Wild Horse and Burro auctions is the "Bidding Allowance". The BLM assigns the maximum number of animals each bidder can bid on before the auction starts, and this allowance ranges between 1 and 4. Among the 477 bidders that participated in these 15 sessions, 30% are allowed to adopt 1 animal, 27% are allowed to adopt 2, and 10% can adopt 3 or 4. For 32% no information on allowances could be obtained.

[4]The maximum number of bids received with an opening jump bid is 44.

3.4 Empirical Analysis

We are interested in three aspects of jump bidding in wild horse and burro adoptions: First, the level of competition and animal groups that are associated with jump bidding; Second, the relationship between jump bidding and bidding allowance; Third, jump bidding's influence on the adoption fee of each animal. The original data set only provides the age, type and color of the animals. In order to clarify the animal characteristics and generate corresponding variables for the ensuing analysis, table 4.1 and 4.2 are created to provide lists of specifications. Table 4.1 organizes the 17 different colors that are found among all adopted animals into 6 color groups based on their perceptual similarities. Table 4.2 contains basic specifications by animal types.

Table 3.3: Group of Colors

Color Grouping	Color
bbsc	bay, brown, chestnut, sorrel
bdgprs	buckskin, dun, grulla, palomino, red roan, strawberry roan
black	black
wcg	white, cremello, grey
pink	pink
pa	appaloosa, pinto
br	blue roan

Table 3.4: Animal Types

Type	Specification
colt	age<4, male, horse
filly	age<4, female, horse
stud	age≥ 4, male, horse
mare	age≥ 4, female, horse
jack	male, burro
jenny	female, burro
gelding	gelding, horse or burro

Given the over-dispersion of the jump bids and total number of bids, Poisson models are used to analyze the first two aspects. Ordinary Least Squares (OLS) regression is used to explore Jump bidding's impact on the final selling price of each adopted animal.

3.4.1 "Jump-bidding" and Level of Competition with Animal Features

3.4.1.1 Definition of Variables

The objective of this section is to examine the relationship between jump bidding and the level of competition within relevant animal groups. The dependent variable is the total number of bids each animal receives, the explanatory variables are the number of jump bids that are received by each animal, color and type each adopted animal belongs to and the number of bidders per animal.

3.4.1.2 Results

The results in table 3.5 demonstrate a positive relationship between the number of jump bids each horse received and the level of competition of the auction. An unit increase of the number of jump bids per animal indicate a 0.1% increase of total number of bids. The increase of bidders also has a signficant influence on the level of competition. An increase of one bidder drives the number of bids per horse by 0.23%. The results show animal types are less important than the colors in intensifying the bidding competition. Animals of brown or similar colors increases the number of bids by 0.24%, if the color is buckskin or similar, the increase is 0.17% and 0.31% if the animal is appaloosa or pinto. Black color on the other side, decrease the expected number of jump bids.

Table 4.3 is a two way summary of the color and types of all adopted animals.

Table 3.5: Poisson Regression of "Jump-Bidding" impact on level of competition with animal groups

Number of bids [a]	Coefficients	Standard Error	z-score	p-value
constant	0.531	0.156	3.390	0.001
Number of Jump bids	0.100	0.008	13.220	0.000
Number of bidders	0.230	0.013	18.270	0.000
colt	0.045	0.163	0.280	0.782
filly	-0.200	0.160	-1.250	0.212
gelding	-0.067	0.160	-0.420	0.673
mare	-0.174	0.165	-1.060	0.289
stud	-0.021	0.187	-0.110	0.912
jack	0.200	0.184	1.090	0.277
jenny	-0.310	0.192	-1.620	0.106
bbsc	0.244	0.051	4.770	0.000
bdgprs	0.178	0.063	2.840	0.005
black	-0.261	0.091	-2.880	0.004
wcg	0.015	0.060	0.250	0.806
pink	0.136	0.205	0.660	0.508
pa	0.313	0.095	3.300	0.001
br	0.129	0.170	0.760	0.449

[a] $\chi^2(16) = 2239.63$, pseudo $R^2 = 0.50$.

Table 3.6: Animal counts by Type and Color

	bbsc	bdgprs	black	wcg	pa	br	pink	Total
colt	22	10	9	18	3			62
filly	56	24	12	32	4	2		130
mare	20	16	5	14	6	2		63
stud	4	4	2	14	2			26
gelding	81	49	11	43	14	5		203
jack	2		1		2		3	8
jenny	4					1	1	6
Total	189	103	40	121	31	10	4	498[a]

[a] Animal features of 7 animals are missing.

The adoption rate of each category is not available due to lack of information of unadopted animals. Therefore, the total counts in table 4.3 is a relative reference of the popularity of each animal category. The combination of tables 3.5 and 4.3 shows that the level of competition in terms of total number of bids submitted does not have a strong connection with the number of animals adopted under each category. In another word, a higher number of adoptions for one category does not imply a higher level of competition for that category. For example, there are a total of 121 animals of "White", "Cremello" or "Grey" color that were adopted, but did not generate significant impact on the total of number of bids, which may imply this color group does not draw bidders' interest. For the "Black" group, there are only 40 adopted animals, but it generates a significant marginal effect that shows the negative relationship between this color group and the level of competition. The same situation is found among animals of "Appaloosa" and "Pinto" colors. Overall, higher level of competitions are perceived among certain animal groups.

3.4.2 "Jump-bidding" and bidding allowance

3.4.2.1 Definition of variables

This section attempts to address that at the bidder level, what is jump bidding's connection with the "Bidding Allowance". The dependent variable is the total number of jump bids submitted by each bidder regardless of the number of animals he adopts or bids on. (i.e., bidder A jump bid 30 times and adopted 3 animals, his total number of jump bid is 30.) the explanatory variables are the bidding allowance, the number of bidders per session and the number of animals adopted per session. The inclusion of the "bidding allowance" into the equation aims to measure how this quota variable affects bidder's overall aggressiveness in the auctions.

3.4.2.2 Results

The results in table 3.7 display the marginal effect of bidding allowance with respect to aggressive bidding, which reflects those bidders with larger herding facilities and farming capacities are more likely to jump bid. A bidder with 3 animal allowance is likely to have 0.38% more jump bids than bidders with 2 animal allowance. "Bluffing" by submitting a high bid in these auctions appears to be a superfluous strategy. On the contray, aggressive biddings actually intensifies the level of competition. (See result from table 3.5). The prevalence of strong bidders in the pool precludes the early conlusion of any auction started with jump bids.

Table 3.7: Poisson regression of bidding allowance impact on Jump bidding

Number of Jump Bids [a]	Coefficients	Standard Error	z-Score	p-value
constant	-0.713	0.154	-4.63	0
Number of bidders per session	0.034	0.007	4.93	0
Number of animals per session	-0.023	0.007	-3.32	0.001
Bidding allowance	0.386	0.043	8.94	0

[a] $\chi^2(3) = 103.37$, pseudo $R^2 = 0.07$

3.4.3 "Jump-bidding" and Auction Revenue

3.4.3.1 Definition of Variables

This section examines the relationship between "Jump-bidding" and auction revenue. Ordinary Least Squares regression is used to measure the jump bidding impact on auction revenue. Due to the fact that 238 of 505 animals receive only one bid and are adopted at the reserve price of \$125, the estimation takes the difference between the final adoption fee and the reserve price, and uses the log form of this difference as the dependent variable. The "Adoption fee" is the final amount paid by each animal's highest bidder by the end of each session. Panel data recording all the bidding history is not used because the final adoption fee is considered to be a better indicator of each animal's popularity, which also is more closely related to the number of jump bids and other bidding environment related variables, such as the number of bidders per animal, etc. The explanatory variables are similar to the ones used in previous sections. They are the total number of jump bids each animal received, the number of bidders, and the number of bids of each animal.

3.4.3.2 Results

Table 3.8 shows a significant positive relationship between jump bidding and the final selling price. If the number of jump bids increases by 1, the expected adoption fee increases by 0.22%. The results from the counts of bids and bidders per animal are consistent with standard auction theory. which predicts that the level of competition drives the induced preference and willingness to pay. This is somehow compatible with the results of ISZ (2006) model that aggressive bidding among group of strong bidders has at least no negative impact on auction revenue.

Table 3.8: Ordinary Least Square Regression - "Jump bidding effect on Auction Revenue"

Log revenue [a]	Coefficients	Standard Error	t-stats	p-value
constant	2.747	0.116	23.610	0.000
Number of Jump Bids per animal	0.222	0.036	6.160	0.000
Number of bidders per animal	0.036	0.052	0.680	0.495
Number of bids per animal	0.044	0.018	2.470	0.014

[a] $R^2 = 0.56$.

3.5 Discussion and Conclusions

As an empirical research on jump-bidding behavior, this chapter analyzes the impact of aggressive bidding on auction revenue, and explores the relationship between jump bids and animal features and bidder background, such as the bidding allowance. It divides the study of jump bidding behavior into two outcomes: Jump bids received by each animal and jump bids submitted from each bidder. This avoids the potential cross effects between bidders and adopted animals. For example, when studying the correlation between jump-bids and the number of animals approved, total number of jumps are counted on bidder basis instead of by each animal, and it helps to illustrate the true motivation and overall aggressiveness of the bidder with respect to his herding capacity.

The results from the bidding allowance and jump bidding behaviors display that bidders who are more likely to submit jump bids during the auctions are bidders with higher "Bidding allowance". The finding from the liaison between animal feature and aggressive bidding indicates that the visual attraction is the main factor that drives the competitive bidding. In these Internet based live animal auctions, adopters are more concerned with the personal connection with the animal they are going to adopt rather than the animal type, i.e., a Colt or a Mare.

The impact of jump bidding on revenue is consistent with previous models (Plott and Salmon, (2004); ISZ (2005)). The positive effect on revenue from jump bidding stems from the competition among strong bidders - bidders with high valuations. In the wild horse and burro auctions, strong bidders are also adopters with larger herding facilities. The jump bid does not cause early drop-outs or low adoption fee in the Internet auctions, instead, bidders with higher animal bidding allowance bid even more aggressively at an aggregated level. Based on the findings of animal feature section, the bidding competitions of certain color groups such as Brown, Buckskin, Appaloosa, Pinto are fraught with jump bids. These jump bids ultimately lead the animal to a higher selling price than the rest of animals from other color groups. It is uncertain the same results would emerge in regular commodity auctions where personal connection is less important, such as ipod, computer, etc.

To adoption program managers, this study raises several concerns: First, should they divide the auctions by animal color or types to improve the current adoption rate. For instance, initiate auctions by similar animal colors or type rather than mixing all the animals into a single pool. In the latter case, the attention of bidders are likely to be drawn to more attractive animals, which leaves other items in the auction pool unsolicited. Assigning animals of same color or type groups into the bidding pool can help to mediate this problem; Second, should they distribute bidders based on their herding facility and farming capacity instead of mixing all types of bidders in these Wild Horse and Burro Auctions. This may prevent weaker bidders from being discouraged by the aggressive bids from strong bidders, and it also ensures the revealing of maximum willingness to pay among similar types of bidders. Both of these recommendations are provided for policy makers to reconsider the current adoption rules in both on-site and Internet settings. The ultimate goal is to increase the adoption rate of these wild animals and mitigate the federal maintenance burden.

Regarding auction efficiency, there are many issues that remain unexplored on both the buyer and seller side in the Internet auction scenario this chapter uses. For instance, If the Bureau of Land Management (BLM) decides to initiate auctions by animal color or types, how will the aggressive bidding behavior change in this uniformed bidding pool holding other conditions constant, such as session duration, bidding allowance, etc. On the buyer side, if each bidder's search cost (opportunity cost) is incorporated in the empirical analysis, how different will the results be?

Though the dataset used in this chapter does not provide relevant information for such analysis, these could be fruitful topics for future research.

CHAPTER 4

Estimating "Sniping" Impact in National Wild Horse and Burro Internet Adoptions

4.1 Introduction

The Wild Free-Roaming Horses and Burros Act of 1971 states that the Bureau of Land Management (BLM) under the Department of the Interior and the U.S. Forest Service (USFS) under the Department of Agriculture has the authority to control the wild horses and burros on national public lands. However, the federal protection and lack of natural predators has resulted in a significant increase in wild horse and burro herd populations over the years. As the major federal land agency, the BLM is responsible to monitor the rangeland conditions and wild horse and burro herds to determine the number of animals that the land can support. The excess of wild horses and burros from areas where vegetation and water are scarce are offered for adoption to qualified people through the "National Wild Horse and Burro Adoption Program". Even though more than $220,000$ horses and burros have been placed into private care since 1971, low adoption rate is still an issue for the land managers given the rising maintenance costs.

The shape and size of the wild horses and burros for adoption are different. According to BLM figures[1], a typical wild horse stands about 13 to 15 hands high (52 – 60 inches) and weighs about 700 to 1,000 pounds. Wild burros average 11 hands high (44 inches) and weigh about 500 pounds. Most wild horses and burros put up for adoption are not accustomed to people. Therefore, the major challenge of an adopter is to develop a trusting relationship with these animals. Chapter 3 of this dissertation shows that bidders tend to adopt horses or burros that they are visually attracted to. For the Internet adoptions, this perception can only be completed by viewing the on-line pictures and brief information of these animals. As a result, only certain groups of animals are receiving attention in each auction session. The rest of them are either adopted at the minimum reserve price of $125 or stay unadopted. Like "Jump-bidding", late bidding is prevalent in field auction data from the BLM's Internet Adoption Program.

Late bidding is a practice commonly referred to as "Sniping", which often occurs in Internet auctions with a fixed end time, like eBay, where bidders submit their bids towards the very last minute or second of the auction. This behavior is regularly criticized for breaching the mechanism of ascending auctions. (Lucking, 2002) A late bidder or "Sniper" tends to bid late and low so as to minimize their payoffs, particularly for collectibles and antiques, where the true value is usually asymmetrically distributed among the bidding pool that is mixed by both experienced and inexperienced bidders. From a bidder's perspective, late bidding helps to avoid a bidding war, especially for the bidders who think they are more knowledgeable than their opponents of the item's true value, which is a popular phenomenon in the antiques market; From a seller's perspective, very late bids from bidders cause concern lowering the auction revenue if these bids are not being successfully transmitted due to

[1] www.blm.gov

slow Internet connections or other technical issues that may occur.

Over the years, various types of Internet auctions have generated new sources for the studies on how the bidding behaviors are shaped by different ending rules. For example, Roth and Ockenfels (2002) compare the ending rules between E-bay and Amazon, and show that there is a great deal of very late bidding on eBay, and considerably less on Amazon. eBay auctions have a fixed end time and Amazon allows the ending time to be automatically extended by some number of minutes. The "soft-close" rule of Amazon thus discourages the motivation to submit late bids.

Roth and Ockenfels (2002) also indicate that when the bidding environment is uncertain, "Sniping" is the response strategy from sophisticated bidders to incremental bidding by inexperienced bidders. Similar findings are also made by Barbaro et al. (2006). In the discussion of the "Sniping" impact on the auction revenue from a seller's perspective, Schindler (2003) shows "Late Bidding" produces a negative revenue impact using Yahoo auction data, where auctions are second-priced. Furthermore, Wang (2006) proves that bidders do not always bid their true valuation. Using a repeated e-bay auction model, he finds that the maximum willingness to pay in these fixed end-time Internet auctions is dependent on the type of other bidders they are competing with.

Given the literature on "Late bidding" and the BLM's concerns of unsatisfactory adoption rates and rising maintenance costs of unadopted animals, the main objective of this chapter is to provide some observations of how the "late bidding" affects the adoption rate and the expected revenue in the Wild Horse and Burro Adoptions. Specifically, we are interested in three aspects of "Late bidding". First, what type of bidders are more likely to be late bidders? The classification of the bidder type is based on the "bidding allowance" [2] assigned by BLM. Second, what type of animals

[2] See 3.1 for "Bidding Allowance" explanations.

in terms of colors, age, gender, etc are preferred by the late bidders? Third, what is the impact on the expected adoption fee of each animal if "Late bidding" dominates an auction? The results are expected to be used by the adoption program managers as a guide for refining the current auction rules.

The rest of this chapter is structured as follows: section 2 reviews the theoretical background of "Late bidding" phenomenon in a fixed time Internet auction setting combined with the explanations of bidders' underlying motivations to submit late bids; section 3 summarizes the data used for the empirical analysis, and section 4 estimates "Late bidding" behavior in the three aspects mentioned above via several regression models, section 5 concludes with suggestions on the current adoption policy and recommendations for further research.

4.2 Theoretical Review of "Late Bidding" - Motivation and Strategic Moves

4.2.1 A general model of bidding in Internet Auctions with a fixed end time

To understand the motivations behind submitting late bids in an auction with a fixed end time, we may use the strategic model by Ockenfel and Roth (2005). They assume a standard auction with N bidders($i = 1 \ldots N$). Bidder i bids at any time t, and $t \in [(0, 1) \cup (1)]$ from a continuous distribution within the total time period T. Bidder j bids at time $t' < 1$, and t' could be either smaller or greater than t as bidders can choose to enter the auction in the random order. Then reaction time given to either bidder is t'', where t' or $t < t'' < 1$. At $t = 1$, the winner of the auction is the highest bidder at that time. If multiple bids are submitted instantaneously at some

t including $t = 1$, they will be randomly ordered by the on-line system. Each bid has equal probability of being the highest bid at $t = 1$. The current bidding mechanism of Wild Horse and Burro Auction follows this very model.

4.2.2 Prior theory on "Late bidding" in Internet Auctions with Private Values

In fixed end time Internet auctions with private values, bidders enter the auction with private valuation of the good and a preset maximum willingness to pay. Under this circumstance, several theoretical conjectures on "late bidding" motivations are made. Assume an Internet auction with minimum initial bid h and minimum increments k among two bidders i and j. Ockfenfel and Roth (2006) suggest that as long as bidder's value is greater than $h + k$, then there are no dominant strategies.

For example, at any time $t \in [(0, 1) \cup (1)]$ from a continuous distribution within the total time period T, bidder i's strategy is to submit the minimum bid h at $t = 0$, then not submit any further bid as long as he remains the high bidder, but to increase his bid by k when he perceives that he is not the high bidder. The best response from his opponent, bidder j, is not to bid until $t = 1$. This assumes that $p(v_j - h - k) > 0$, which is the maximum payoff he could obtain at $t = 1$, where p is the probability that bidder j's bid at $t = 1$ is transmitted successfully.

If bidder i changes his strategy and remains inactive, then the bid from bidder j at $t = 1$ yields an expected payoff $p(v_j - h) < v_j - h$, this equals the payoff that bidder j could have chosen at any $t < 1$. Hence bidder j does not have dominant strategy during the bidding process. Similarly, Ockenfel and Roth (2006) claim that in any ascending Internet auctions, if bidders have valuations higher than $h + k$, bidding at $t = 1$ is the best response.

Regardless of the bid increments, an early bid in Internet auctions may induce a bidding war and decrease the final payoffs to the early bidder. On the contrary, a late bidder leaves no time for his opponent with a potentially high valuation to drive the competition. Therefore, in fixed end time Internet auctions, bidding late is common among bidders whose goal is to maximize payoff even though late bids entail the risk of not being transmitted successfully due to possibley slow Internet connection.

4.2.3 Late Bidding in Wild Horse and Burro Adoptions

As mentioned before, the National Wild Horse and Burro Adoption program uses a First-Price Ascending Auction with a fixed end time for its Internet auction sessions. Adopters need to get registered on-line before they can submit bids and only one account is allowed per adopter, this eliminates the possibility of "Shill bidding", which means the same bidder uses different accounts to raise up the bid and manipulate the auction. The collected data shows that the late bids were found in all 15 sessions between the years 2006 and 2008.

The following setting is given to illustrate the strategic motivations of late biddings in the Wild Horse and Burro Adoption scenario. We assume two bidders i and j with valuations of v_i and v_j for an animal, bidder i is a rational bidder and bidder j is the incremental bidder. The reserve price is \$125, and the minimum increment k is \$5. Suppose both bidders valuate this animal more than \$125, where v_i and $v_j > 125 + k$, and this is common knowledge. For bidder i, bidding early when facing an incremental opponent has the possibility of inducing a bidding war, unless the early bid is a jump bid and higher than the valuations of all other bidders in the pool; Otherwise bidding late is the most reasonable response given the bid can be uploaded to the server on time with probability θ. In general, if $v_j > v_i + k$, where v_j is the valuation from the incremental bidder, the most reasonable reply from bidder i is to bid at $t = 1$[3], with payoff of $v_i - 125 - k$ and probability θ.

Any other bids less than v_i from bidder i at $t < 1$ would be outbid by j at any time before the auction ends; If $v_j < v_i + k$, then the outcome would be dependent on the distribution and values of θ, the reserve price and k (Ockenfel and Roth, 2005). B

Each bidder enters the auction with their private valuations, which depends on factors such as the number of animals they are approved to adopt, the number of animals available at each session, the number of bidders, and some transaction cost $c \geq 0$ for every time he logs on the computer and submits a bid. Unlike eBay and many other Internet auctions, adopters of wild horse and burro auctions are responsible for checking their bidding status, in another word, they do not receive emails like other auction houses about their current bidding status. Thus, repetitive search costs may encourage late bids from adopters with higher opportunity costs.

In general, BLM's current rule of closing each auction session with a fixed end time allows bidders to take full advantage from submitting late bids on their targeted animals. In this case, the program managers may wish to gain more insight about how this hard close auction rule shapes the level of competition, and what types of animals are preferred by the "Snipers". The discussion is given in the following sections.

[3]The bid can be his true valuation, or anything below or above, if above, bidder i would have a negative payoff as the price he pays is higher than his true valuation, this is known as "Winner's curse".

4.3 Field Data

The dataset contains 2308 bid observations among 505 adopted horses and burros. A total of 477 bidders participate in the 15 sessions during year 2006-2008, 334 (70%) bidders adopt at least one animal. The average duration of these sessions are 15 days. For each bid that is successfully submitted, the time left to the end of each session are converted into minutes for better measurement of the late bidding behavior, and any bid that is submitted within the last 30 minutes is considered as a “Late Bid” given the average total duration of each session is 21600 minutes. 763 (33%) of 2308 bids are submitted within the last 30 minutes [4] of each session with a mean of 7 minutes and a standard deviation of 7.23; Around 457 (19%) of the bids are submitted within the final 5 minutes of the session with a mean of 2 minutes and a standard deviation of 1.37. This is close to 20% of the total observations and more than half of the bids sumbitted within the last 30 minutes. Among the 238 animals that are bid upon only once and adopted, 33 (13%) of them receive their only bid within the last 30 minutes. Comparatively, among the 267 animals that receive more than one bid, 146 of them receive their bids within the last 30 minutes, which amounts to 55% of the animals that are competitively adopted.

Because each bidder can bid on more than one animal at a time, late bids of each bidder may be found among several animals. To distinguish this from the last bid received by each animal, figure 4.1 and 4.2 are generated to show the empirical Cumulative Distribution over time of bidder’s last bid and animal’s last bid of all 15 sessions.

Figure 4.1 and 4.2 indicate that a considerable share of last bids among both

[4] 30 minutes is chosen as a general reference and is changeable.

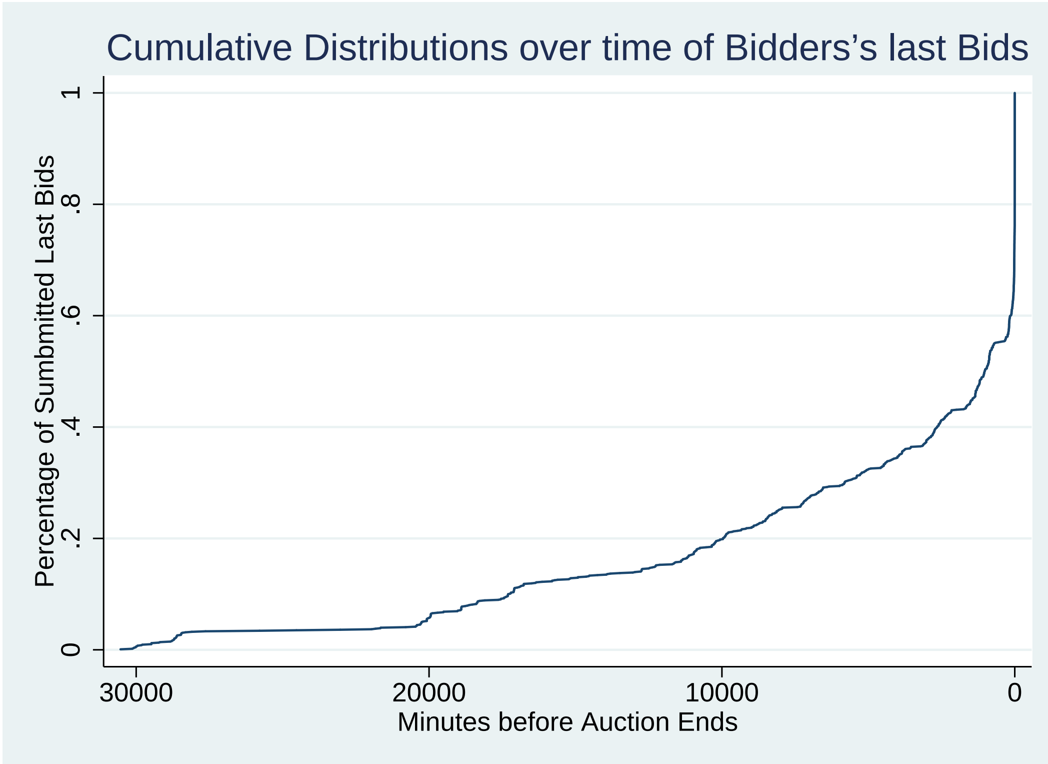

Figure 4.1: Cumulative Distribution over time of Bidder's Last Bids

bidder and animals are submitted near the end of the auction. Figures 4.3 and 4.4 are the histograms of the number of late bids submitted per bidder and per animal. All distributions are right-skewed, and the number of late bids submitted by significant portion of bidders is between $1-5$. This reveals that, although a considerable share of bidders submit their bid in the last 30 minutes, the number of late bids is related to the adoption allowance. Given the constraint of the number of animals for which each bidder is allowed to be the highest bidder concurrently[5], a low range of late bid repetitions is reasonable. That is, if bidder A chooses to bid late, and his bidder allowance is only 1, he will choose his favorite two animals and submit the bids, which limits his possibility of "Sniping" on other less preferred animals. In addition, the highest possible allowance is 4 animals, this may explain the high density of number

[5] Bidder with 1 animal allowance can not be the high bidder of more than two animals simultaneously.

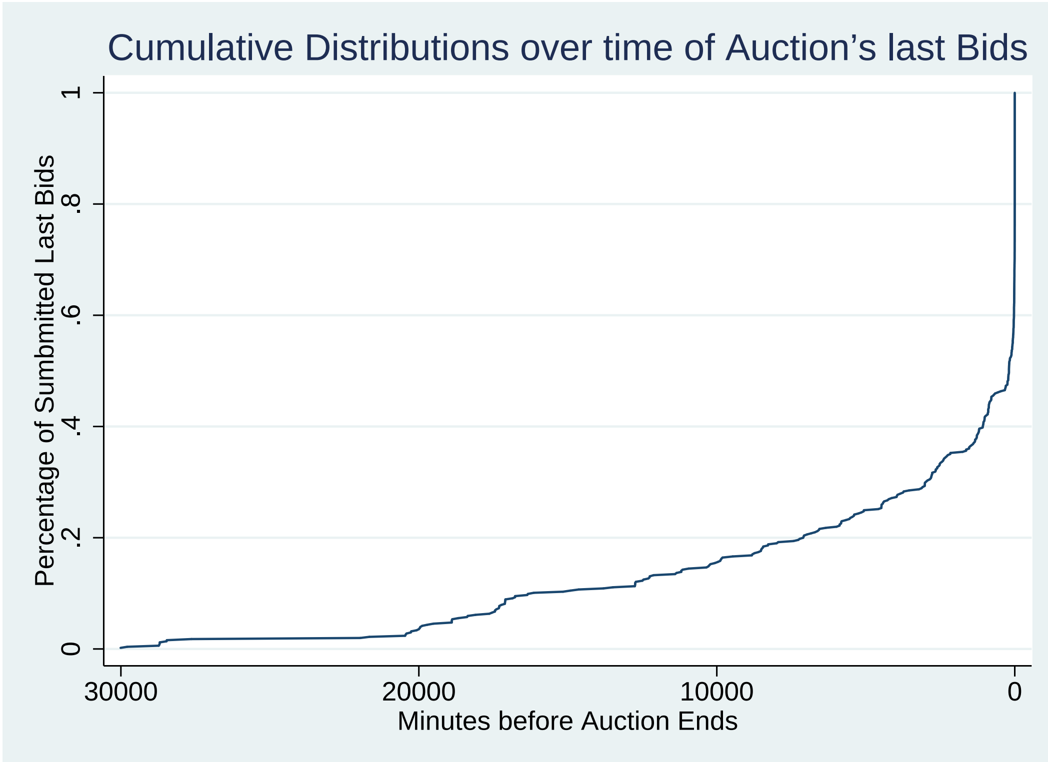

Figure 4.2: Cumulative Distribution over time of Each Animal's Last Bids

of late bids between 1 and 5 among bidders in figure 4.3.

4.4 Empirical Analysis

We are interested in three aspects of " Late bidding" in the Wild Horse and Burro Internet Auctions. First, the relationship between the "Bidding allowance" and the the late biddings. Bidding allowance is determined by auction participants' herding facilities and farming capacities; Second, the impact of animal features, such as colors, age, gender, etc on the motivation of "Late bidding" behaviors; Third, the influences of "Late bidding" on the adoption fee of the animals. The results of this section are expected to provide insights for project managers in determining whether a hard-close Internet auction is appropriate for the Wild Horse and Burro Adoptions Program.

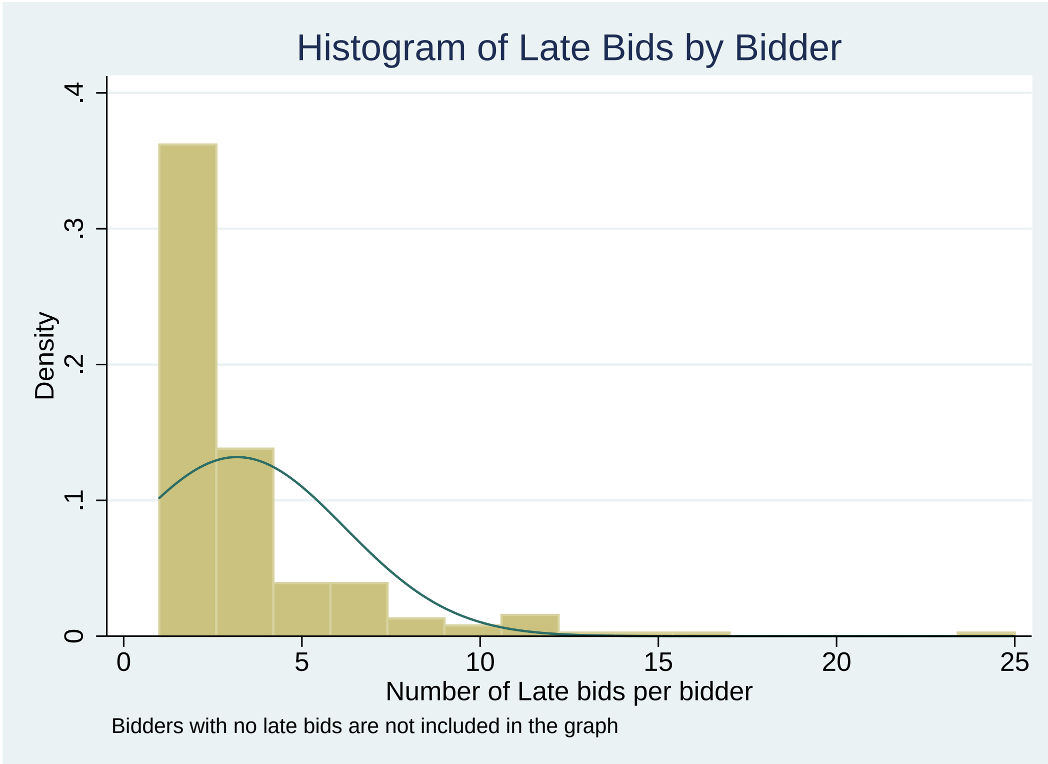

Figure 4.3: Distribution of Late Bids by Bidder

To specify the animal characteristics and generate corresponding variables for the ensuing analysis, tables 4.1 and 4.2 are compiled to present the summarized classifications of all adopted animals of the 15 sessions. 17 different colors that are found among all adopted horses and burros are divided into 6 color groups based on their perceptual similarities, the lists is displayed in table 4.1. Table 4.2 contains basic specifications by animal types.

Table 4.3 is a two way summary table for all adopted animals. The rows are the number of animals under each type and the columns are the number of animals under each color group.

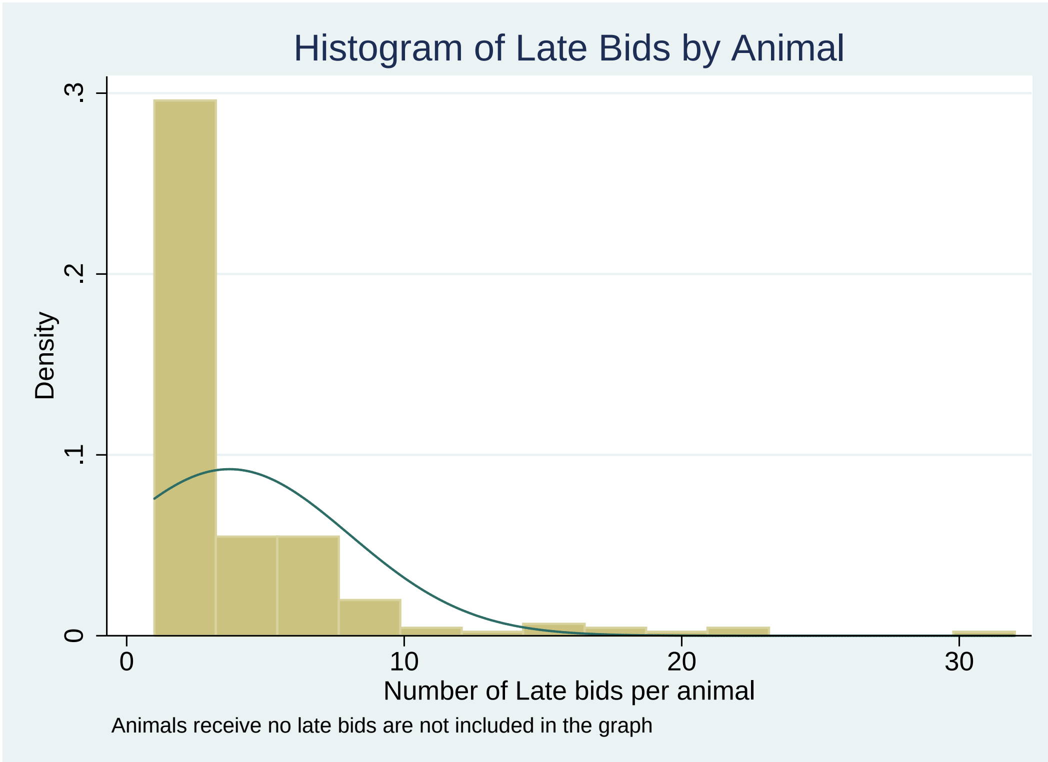

Figure 4.4: Distribution of Late Bids by Animal

Table 4.1: Group of Colors

Color Grouping	Color
bbsc	bay, brown, chestnut, sorrel
bdgprs	buckskin, dun, grulla, palomino, red roan, strawberry roan
black	black
wcg	white, cremello, grey
pink	pink
pa	appaloosa, pinto
br	blue roan

Table 4.2: Animal Types

Type	Specification
colt	age< 4, male, horse
filly	age< 4, female, horse
stud	age≥ 4, male, horse
mare	age≥ 4, female, horse
jack	male, burro
jenny	female, burro
gelding	gelding, horse or burro

Table 4.3: Animal counts by Type and Color

	bbsc	bdgprs	black	wcg	pa	br	pink	Total
colt	22	10	9	18	3			62
filly	56	24	12	32	4	2		130
mare	20	16	5	14	6	2		63
stud	4	4	2	14	2			26
gelding	81	49	11	43	14	5		203
jack	2		1		2		3	8
jenny	4					1	1	6
Total	189	103	40	121	31	10	4	498[a]

[a]Colors and types of 7 animals are missing.

4.4.1 Late bidding and bidding allowance

4.4.1.1 Definition of Variables

This section aims to investigate if any connection exists between each bidder's preassigned bidding quota (Bidding Allowance) and their motivations to submit late bids. The results is used to determine if bidders with larger herding facilities tend to be late bidders. Given the distribution of late bids that is shown by figure 4.2 and 4.4, a Poisson model is used to implement this estimation. The dataset shows over 50% of the "Late bids" [6] are submitted within the last 5 minutes. Therfore, two estimations are conducted. The two dependent variables are the total number of bids submitted within the last 30 minutes and the last 5 minutes of each auction session. Both variables are the sum of the late bids within each time interval from all the animals adopters bid on. The explanatory variables are: adopters' bidding allowance; number of animals he wins or adopts; total number of bidders of each session; total number of animals adopted at each session and total number of animals each adopter bid on regardless of the winning outcomes.

4.4.1.2 Results

Table 4.5 shows that the bidding allowance is inversely related to the number of late bids submitted within the last 5 minutes. Bidders with higher allowance are less likely to be "Snipers". This indicate the "Sniping" strategy is more widely used by bidders of lower bidding allowance to maximize their probabilities of winning towards the end of auction.

We also find that the number of animals an adopter bid on is positively related

[6] Bids submitted within the last 30 minutes

Table 4.4: Late bidding and Bidding Allowance - Last 30 Minutes

Number of late bids per bidder [a]	Coefficients	Standard Error	z-Score	p-value
constant	0.648	0.140	4.620	0.000
Bidding Allowance	-0.085	0.055	-1.550	0.121
Number of wins	-0.011	0.056	-0.190	0.847
Number of bidders per session	0.002	0.006	0.280	0.780
Number of animals adopted per session	-0.008	0.006	-1.290	0.197
Number of animals each bidder bid on	0.155	0.025	6.190	0.000

[a] $\chi^2(5) = 47.81$, pseudo $R^2 = 0.02$

Table 4.5: Late bidding and Bidding Allowance - Last 5 Minutes

Number of late bids per bidder [a]	Coefficients	Standard Error	z-Score	p-value
constant	-0.117	0.178	-0.660	0.509
Bidding Allowance	-0.152	0.070	-2.160	0.031
Number of wins	0.099	0.071	1.400	0.162
Number of bidders per session	0.007	0.007	0.980	0.325
Number of animals adopted per session	-0.003	0.007	-0.420	0.677
Number of animals each bidder bid on	0.116	0.034	3.430	0.001

[a] $\chi^2(5) = 24.97$, pseudo $R^2 = 0.02$

to the number of late bids submitted from this adopter.

4.4.2 Late bidding and level of Competition with Animal Features

4.4.2.1 Definition of Variables

Similar to the level of competition investigation in the jump bidding chapter, this section addresses what type of animals are most preferred by "Snipers" or "Late bidders". This serves as an information source for the project manager to decide whether to reform the bidding pool in future adoption activities, i.e., auctions with only brown animals, etc. The two dependent variables are the total number of "late bids" each animal receives within the last 30 minutes and the last 5 minutes. The explanatory variables are the total number of bids each animal receives, animal color and animal feature indicators listed in table 4.1 and 4.2.

4.4.2.2 Results

Table 4.6 and 4.7 show that the competition level of each animal directly influences the number of late bids submitted. This explains "Sniping" is used as a strategic move by adopters to bid on preferred animals. The color and type indicators generate identical results to the estimation of "Jump-bidding". "Brown", "Buckskin", "Appaloosa" and similar colors drive the late bids submission. The results are consistent for both 30 minutes and 5 minutes intervals.

The similarities between the results of this section and the results in the "Jump-bidding" chapter mirrors the fact that the competition stays in the same color groups, and aggressive biddings are more likely to occur in the very late stages of the auction session. Both findings state that the adoption rate needs to be discussed separately

Table 4.6: Late bidding and Animal Features - Last 30 minutes

Number of late bids per animal[a]	Coefficients	Standard Error	z-Score	p-value
constant	-0.571	0.282	-2.020	0.043
Number of bids	0.094	0.003	35.590	0.000
colt	-0.031	0.297	-0.100	0.917
filly	-0.128	0.289	-0.440	0.658
gelding	-0.170	0.290	-0.590	0.558
mare	-0.464	0.304	-1.530	0.127
stud	-0.274	0.356	-0.770	0.440
jack	0.002	0.321	0.010	0.996
jenny	-0.671	0.352	-1.900	0.057
bbsc	0.411	0.086	4.760	0.000
bdgprs	0.436	0.111	3.920	0.000
black	-0.214	0.171	-1.250	0.211
wcg	0.078	0.107	0.720	0.469
pink	0.783	0.291	2.690	0.007
pa	0.492	0.169	2.910	0.004
br	-0.173	0.421	-0.410	0.681

[a] $\chi^2(15) = 1071.28$, pseudo $R^2 = 0.40$

Table 4.7: Late bidding and Animal Features - Last 5 minutes

Number of late bids per animal[a]	Coefficients	Standard Error	z-Score	p-value
constant	-1.013	0.360	-2.820	0.005
Number of bids	0.095	0.003	27.620	0.000
colt	-0.135	0.382	-0.350	0.724
filly	-0.208	0.370	-0.560	0.573
gelding	-0.131	0.371	-0.350	0.725
mare	-0.485	0.389	-1.250	0.213
stud	-0.580	0.478	-1.210	0.225
jack	0.107	0.407	0.260	0.793
jenny	-0.492	0.440	-1.120	0.263
bbsc	0.264	0.112	2.350	0.019
bdgprs	0.398	0.146	2.720	0.007
black	-0.360	0.229	-1.570	0.115
wcg	0.157	0.140	1.120	0.263
pink	0.922	0.332	2.780	0.006
pa	0.482	0.214	2.250	0.025
br	-0.158	0.518	-0.310	0.760

[a] $\chi^2(15) = 654.71$, pseudo $R^2 = 0.35$

from the level of competition. Higher numbers of adoptions do not always indicate a higher valuation of the animals from a bidder's perspective, though improving the adoption rate is BLM's current top priority.

4.4.3 Late Bidding and Auction Revenue

4.4.3.1 Definition of Variables

Late biddings are commonly considered to have a negative impact on the selling price (Schindler, 2003). Therefore, this section addresses the connection between the final selling price of each adopted animal and the timing of the bids in the wild horse and burro auctions. Due to the fact that 238 of 505 animals receive only one bid and are adopted at the reserve price of $125, the estimation takes the difference between the final adoption fee and the reserve price, and uses the log form of this difference as the dependent variable to represent the final selling price. Ordinary Least Squares (OLS) regression is used to testify the late bidding impact on auction revenue because the dependent variable is continuous. The explanatory variables are: total number of bids with in the last 30 minutes and last 5 minutes, total number of bids per animal, number of bidders per animal and the timing of the winning bid, which is the percent of time left to the end of the auction when the winning bid is submitted.[7]

4.4.3.2 Results

The results in tables 4.8 and 4.9 indicate that in Wild Horse and Burro Adoptions, where significant animals are adopted at the reserve price, the timing of the winning

[7]The percent of time is calculated as the fraction between the minutes left when the winning is submitted and the total session duration in terms of minutes. i.e., if the winning bid is submitted when there are 5 minutes left till the end of the session, and the total duration of this session is 80 minutes, percent of time left = $5/80 = 6.25\%$.

Table 4.8: Late bidding and Auction Revenue - Last 30 minutes

Adoption fee [a]	Coefficients	Standard Error	t-stats	p-value
constant	2.797	0.137	20.440	0.000
Number of Late bids per animal	-0.034	0.023	-1.500	0.136
Number of bids per animal	0.141	0.018	8.060	0.000
Number of bidders per animal	-0.013	0.058	-0.220	0.828
Timing of the winning bid	-0.575	0.307	-1.880	0.062

[a] $R^2 = 0.50$

Table 4.9: Late bidding and Auction Revenue - Last 5 minutes

Adoption fee [a]	Coefficients	Standard Error	t-stats	p-value
constant	2.772	0.138	20.070	0.000
Number of late bids per animal	-0.007	0.033	-0.200	0.842
Number of bids per animal	0.126	0.017	7.540	0.000
Number of bidders per animal	0.005	0.058	0.090	0.926
Timing of the winning bid	-0.517	0.308	-1.680	0.094

[a] $R^2 = 0.49$

bid is inversely related to the final selling price. The later an animal is adopted, the higher a final selling price this animal receives.

This implies that the bidder's valuation for those popular animal groups, such as Brown, Buckskin are identical. Therefore, "Sniping" is not a useful strategy in Wild Horse and Burro auctions as it is in eBay antique market, where the asymmetric distribution of the expert knowledge may help more experienced bidders to succeed (Ockenfel and Roth, 2002). On the others side, the selling price is also driven by the overall competition of each animal, more bids an animal receives, the higher the final adoption price.

4.5 Discussion and Conclusions

In this chapter, we examine the late bidding impact on three aspects of the Wild Horse and Burro Auctions: *(i)* Bidder allowance; *(ii)* Animal features and *(iii)* Auction revenue. Late bidding intensity is divided into Bidder and Animal categories following the pattern used in chapter 3. The first set of result indicates that adopters with a higher animal allowance tend to submit fewer late bids.

In the animal feature investigation, the results are similar to the findings for "Jump-bidding". It appears that in Internet Adoptions where adopters can only view the pictures of the animal, the motivation to bid late is more associated with the colors than other factors.

For the revenue consideration, the adoption fee is inversely related to the timing of the winning bid. The less time left for the winning bid, the higher selling price of the adopted animal. Less preferred animals tend to be adopted earlier at a lower price, whereas more attractive animals draw more attention, and stimulate a group of "Snipers" to bid on. Hence, the competition among these late bidders hence elevates the price. The result clarifies the inhibition of competition by setting up the hard-close rule in the wild horse and burro auctions.

In contrast to common goods auctions, adopting an animal is likely to be an emotional investment as well as financial. Due to the randomness of the animal features in the bidding pool, an optimal solution of maximizing the adoption rate is difficult to produce. However, efforts can be made to increase the auction revenue from the existing Internet activities by setting up rules that encourage competition. For example, use the auto-extension rule like Amazon to discourage the late bids and extends the competition as necessary; or assign those popular animals into a single session rather than mixing them with other less preferred groups.

The hard close rule of the current adoption program has a negative impact on auction efficiency. The preset time frame hinders the process in revealing the maximum willingness to pay. For the Bureau of Land Management who expects to improve the adoption rate and cope with the rising maintenance costs, the results from this empirical research recommends some modifications of the Internet adoption ending rules. However, to better explore the relationship between strategic bidding and auction efficiency, lab based experiments using different treatments can serve the purpose more effectively than the field data this chapter is limited to.

CHAPTER 5

Conclusion

The three essays in this dissertation focus on empirical issues in regional economics forecasting and natural resource management. The first essay proposes a solution to the problem of using small datasets to predict regional fiscal conditions. I formulate a "Model-Averaging" framework and test it on a Bayesian Vector Augtoregression (BVAR) model using a small fiscal dataset of counties in Nevada. First I show that the informative priors from parallel regions are relative to diffuse priors in diminishing the variance of the posterior distributions in the estimation of individual counties. I then derive the model-weights based on marginal likelihoods of each estimations that use the informative priors, and develop a weighted average framework that integrates the model weights into the predictive posterior distributions. I compare the results of predictions from this model-averaging approach with the predictions using the diffuse priors and find improvements in 5 counties. I also show that counties with closer fiscal level to the target county dominate the predictive posteriors in the counties with improved predictions via the weighted average framework.

The second and third essay address the empirical observations of bidder behavior in the National Wild Horse and Burro adoptions. The second essay examines the level of "Jump-bidding" among adopters. I show that the level of competition in terms of the total number of bids submitted is determined by the level of jump bidding in the auction. I also find that the level of bidder allowance is a main factor that contributes to "Jump-bidding". Adopters with higher allowance are more aggressive bidders. Animals from certain color groups draw more attention and stimulate the competitive bidding. I show that the final selling price of each adopted animal is positively influenced by the level of jump bidding in each auction. The third essay examines the late bidding impact in the wild horse and burro auctions. I find that bidder allowance is inversely related to the level of late bidding. "Snipers" are more frequently found among adopters with lower allowance. Similar color groups are perceived to drive the late bidder crowd. I show that the timing of the winning bid affects the final selling price. Earlier adopted animals are sold at a lower price. Overall, this confirms that the fixed ending rule that is currently used by the adoption program inhibits the level of competition and hinders the auction efficiency. This research initiates considerations for the Bureau of Land Management (BLM) to refine the current adoption rules and policies in response to the problem of declining adoption rate and rising maintenance cost of herding unadopted animals. Relevant changes are recommended as follows:

1. Assign animals of similar colors into a bidding session to prevent bidders from being distracted by certain type of animals. i.e., session 1 with only black animals, session 2 with only brown animals, etc.

2. Use auto-extension rule instead of hard-close rule for the Internet auction to extend the underlying competitions. For example, set each session to be ended only if no bidding for a continuous 3 minutes after the last bid is submitted.

The first recommendation aims to improve the adoption rate of less preferred animal groups by separating them from the popular animal groups, and the second recommendation is provided to raise the final adoption price of popular animal groups.

All of them are designed to assuage the current adoption management issues that are confronted by the BLM.

APPENDICES

APPENDIX A

Model-Averaging Predictive Posteriors with P-value by County

Table A.1: Carson City - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson (Fake Prior)		896.66	103.65	882.61	36.84	826.96	149.93	799.37	58.56	0.001	0.000	0.139	0.009
churchill	0.03	927.98	72.99	905.95	62.76	867.13	99.61	846.56	90.68	0.001	0.000	0.139	0.106
clark	0.01	938.60	76.45	906.52	63.50	882.64	97.04	858.53	86.54	0.001	0.000	0.169	0.120
douglas	0.05	937.02	75.14	917.23	66.49	886.59	104.47	858.65	96.15	0.000	0.000	0.200	0.148
elko	0.04	947.03	80.79	921.81	72.73	881.05	109.50	896.29	110.16	0.002	0.001	0.194	0.280
esmeralda	0.00	911.15	75.50	888.26	66.84	834.71	99.78	826.98	98.19	0.001	0.000	0.080	0.086
eureka	0.01	898.89	72.98	886.80	61.37	825.08	95.70	805.99	83.49	0.000	0.000	0.055	0.031
humboldt	0.10	944.49	14.57	933.39	25.28	907.31	22.41	908.72	30.34	0.000	0.000	0.007	0.052
lander	0.01	921.25	72.62	905.89	66.29	851.03	91.40	839.93	88.25	0.000	0.000	0.091	0.088
lincoln	0.01	931.97	77.32	922.82	68.95	893.41	113.27	871.57	100.52	0.000	0.000	0.240	0.186
lyon	0.04	944.62	78.19	922.23	69.27	903.28	102.29	888.81	96.50	0.001	0.000	0.242	0.228
mineral	0.03	945.74	80.84	922.10	73.56	862.88	108.78	878.29	104.39	0.000	0.000	0.153	0.212
nye	0.65	968.68	89.50	950.26	82.40	945.72	119.31	944.82	118.43	0.005	0.000	0.409	0.451
pershing	0.00	924.07	86.45	918.75	76.56	873.83	128.64	842.25	103.59	0.001	0.000	0.216	0.126
storey	0.01	921.50	71.56	907.18	68.14	855.95	92.75	858.76	95.21	0.000	0.000	0.101	0.141
washoe	0.01	936.06	75.69	914.04	62.98	885.72	97.65	859.55	85.15	0.000	0.000	0.182	0.121
whitepine	0.03	923.58	72.54	909.52	66.25	867.89	95.21	851.06	89.08	0.000	0.000	0.132	0.111
Weighted Average		956.96	83.35	941.37	77.82	924.71	113.46	921.42	112.76	0.003	0.000	0.310	0.339
True Value		1249		1261		972		958					

Table A.2: Churchill County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0	492.37	9.66	481.36	20.36	461.16	16.29	453.04	23.92	0.000	0.001	0.000	0.000
churchill (Fake Prior)		493.69	15.98	490.28	19.77	468.62	24.12	465.79	25.83	0.000	0.002	0.000	0.000
clark	0.0118	496.96	9.78	489.48	19.04	468.89	15.82	463.67	20.88	0.000	0.001	0.000	0.000
douglas	0.9882	499.60	9.81	493.54	20.86	477.53	16.10	471.89	23.17	0.000	0.006	0.000	0.000
elko	0	494.02	10.01	506.51	24.47	483.54	22.23	472.13	25.44	0.000	0.031	0.000	0.000
esmeralda	0	492.85	9.81	495.30	22.40	468.70	21.44	464.31	24.47	0.000	0.010	0.000	0.000
eureka	0	493.75	9.49	490.33	20.22	468.04	16.59	465.76	24.36	0.000	0.001	0.000	0.000
humboldt	0	494.80	9.71	504.49	24.01	476.12	18.93	470.72	26.16	0.000	0.026	0.000	0.001
lander	0	496.17	9.79	499.06	22.47	472.79	14.68	470.56	23.48	0.000	0.015	0.000	0.000
lincoln	0	494.88	10.21	492.53	21.76	473.18	18.95	474.68	29.97	0.000	0.007	0.000	0.001
lyon	0	496.79	9.86	500.00	21.01	474.05	18.20	473.26	23.55	0.000	0.012	0.000	0.000
mineral	0	492.80	10.01	503.08	22.01	474.15	20.56	471.20	24.82	0.000	0.019	0.000	0.000
nye	0	499.62	18.76	506.75	18.61	489.44	26.16	487.56	24.97	0.000	0.039	0.000	0.001
pershing	0	496.16	10.20	484.51	24.28	465.74	17.51	454.08	36.20	0.000	0.004	0.000	0.000
storey	0	492.16	9.35	501.48	23.67	476.27	20.54	465.60	24.78	0.000	0.018	0.000	0.000
washoe	0	495.24	9.33	490.37	19.10	467.82	16.30	464.60	22.79	0.000	0.002	0.000	0.000
whitepine	0	494.17	9.72	493.89	20.61	468.91	16.07	469.13	23.98	0.000	0.004	0.000	0.000
Weighted Average		499.20	9.57	493.66	20.71	477.46	16.13	471.78	23.18	0.000	0.007	0.000	0.000
True Value		566		551.41		585		574.15					

Table A.3: Clark County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.0015	552.73	10.40	515.74	24.08	520.65	14.81	485.00	29.92	0.000	0.000	0.000	0.000
churchill	0.0297	552.92	10.53	533.39	22.04	527.07	17.92	511.27	26.81	0.000	0.003	0.000	0.000
clark (Fake Prior)		550.49	24.30	542.63	19.76	530.43	30.91	517.39	23.61	0.002	0.003	0.000	0.000
douglas	0.5822	550.77	9.60	550.07	26.31	533.20	18.44	524.96	24.39	0.000	0.018	0.000	0.000
elko	0.0345	546.81	9.66	572.74	21.43	549.93	20.78	523.96	21.84	0.000	0.064	0.000	0.000
esmeralda	0.0028	546.22	9.83	566.66	25.32	543.11	19.68	520.55	22.67	0.000	0.068	0.000	0.000
eureka	0.0048	555.14	10.32	527.63	24.28	525.55	16.03	501.84	30.20	0.000	0.002	0.000	0.000
humboldt	0.0149	547.05	9.28	571.64	21.74	544.69	16.57	522.11	21.40	0.000	0.059	0.000	0.000
lander	0.077	550.40	9.66	558.70	22.13	537.40	16.48	527.97	22.15	0.000	0.021	0.000	0.000
lincoln	0.0019	558.92	11.01	525.00	26.38	534.52	16.50	505.72	34.78	0.000	0.001	0.000	0.000
lyon	0.1128	550.44	9.42	558.86	22.91	539.65	17.32	530.20	21.93	0.000	0.027	0.000	0.000
mineral	0.0085	546.90	9.96	567.30	23.02	545.41	18.91	525.55	22.33	0.000	0.048	0.000	0.000
nye	0.0053	553.59	10.18	567.21	23.20	549.38	19.80	542.96	25.18	0.000	0.047	0.000	0.000
pershing	0	565.63	13.10	497.23	32.13	548.51	21.75	437.17	59.82	0.000	0.001	0.000	0.000
storey	0.0243	545.66	9.18	567.04	21.69	544.25	18.87	521.04	21.89	0.000	0.038	0.000	0.000
washoe	0.0731	554.60	9.92	531.67	22.27	530.91	15.25	514.39	25.76	0.000	0.000	0.000	0.000
whitepine	0.0267	553.95	9.85	538.09	23.85	530.43	14.83	518.60	25.85	0.000	0.004	0.000	0.000
Weighted Average		550.74	9.75	550.92	26.85	535.01	18.55	524.18	24.65	0.000	0.025	0.000	0.000
True Value		627		605		656		656					.

Table A.4: Douglas County - Revenue and Expenditure Per Capita Prediction with PPP Values Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.00	646.18	13.04	614.56	26.86	609.61	19.18	577.18	32.73	0.001	0.000	0.008	0.000
churchill	0.06	645.69	12.74	635.28	23.82	614.61	21.39	599.90	29.53	0.000	0.001	0.007	0.001
clark	0.04	647.11	12.40	635.28	12.40	619.85	19.94	607.27	25.91	0.000	0.002	0.003	0.001
douglas (Fake Prior)		647.47	13.51	642.02	30.25	625.24	22.88	616.52	31.96	0.000	0.017	0.014	0.014
elko	0.05	645.30	12.10	659.46	23.55	634.06	20.54	620.09	25.91	0.000	0.023	0.023	0.006
esmeralda	0.01	645.61	12.78	653.44	25.31	629.62	21.25	616.34	26.41	0.000	0.003	0.026	0.003
eureka	0.00	649.31	12.78	628.41	25.17	623.51	19.34	604.91	30.69	0.000	0.000	0.000	0.000
humboldt	0.01	646.90	11.83	659.92	24.07	635.38	19.91	620.63	27.43	0.000	0.004	0.026	0.004
lander	0.09	647.38	11.79	649.96	23.59	628.72	17.66	621.39	24.92	0.000	0.001	0.012	0.002
lincoln	0.01	650.96	13.25	627.44	25.55	623.55	19.08	602.93	34.42	0.004	0.000	0.032	0.001
lyon	0.25	648.05	12.01	649.04	22.97	630.31	18.85	623.85	25.31	0.001	0.003	0.028	0.013
mineral	0.03	645.05	12.29	656.26	24.29	632.55	21.20	617.39	25.88	0.002	0.003	0.052	0.004
nye	0.18	650.50	13.40	658.82	25.19	637.05	21.28	634.02	27.66	0.004	0.003	0.004	0.058
pershing	0.00	508.28	13.78	482.80	29.82	486.85	20.81	447.88	49.40	0.012	0.001	0.005	0.000
storey	0.02	643.00	12.81	655.44	24.76	629.58	24.48	613.42	26.73	0.000	0.002	0.023	0.002
washoe	0.02	648.81	12.55	628.85	23.72	617.57	19.46	598.98	28.81	0.000	0.002	0.004	0.002
whitepine	0.24	648.22	12.30	635.81	25.03	623.14	18.84	613.25	28.15	0.001	0.001	0.014	0.002
Weighted Average		647.74	12.47	646.20	26.19	627.40	21.32	618.50	29.17	0.000	0.010	0.007	0.008
True Value		723.67		703.81		682		690					

Table A.5: Elko County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13
carson	0	370.79	30.92	374.41	18.41	348.80	39.16	349.80	30.41	0.004	0.021	0.000
churchill	0.0012	632.31	28.40	646.34	18.64	619.83	33.90	601.37	33.61	0.001	0.001	0.032
clark	0.0152	375.85	26.32	386.24	15.68	373.60	32.63	363.83	30.17	0.004	0.059	0.000
douglas	0.968	376.50	26.08	387.54	15.25	370.77	31.59	361.62	28.78	0.003	0.067	0.000
elko (Fake Prior)		375.89	33.73	391.87	12.03	380.56	39.52	363.86	36.41	0.008	0.062	0.005
esmeralda	0.0001	376.61	28.31	390.64	16.74	377.08	35.74	361.10	33.13	0.003	0.111	0.002
eureka	0	376.80	29.75	379.12	19.72	367.94	38.59	367.66	33.72	0.006	0.047	0.007
humboldt	0.0003	378.53	28.12	389.72	15.67	374.14	34.23	364.08	34.30	0.003	0.093	0.001
lander	0.0019	377.68	27.00	385.55	15.95	370.14	35.97	367.83	33.22	0.003	0.056	0.001
lincoln	0	379.82	31.22	379.88	20.40	365.98	41.14	366.03	33.31	0.009	0.050	0.002
lyon	0.0067	380.90	27.07	388.54	15.81	374.34	34.64	369.15	31.73	0.005	0.083	0.001
mineral	0.0005	372.48	28.00	390.67	15.43	382.41	33.16	360.93	40.03	0.002	0.101	0.001
nye	0.0001	380.40	27.15	391.94	15.91	379.55	33.04	370.50	30.94	0.005	0.122	0.001
pershing	0	385.89	37.50	375.29	26.84	372.88	58.52	364.78	40.25	0.034	0.059	0.029
storey	0.0006	371.93	27.04	386.86	15.32	367.52	31.49	357.83	30.45	0.001	0.053	0.000
washoe	0.0048	376.06	27.71	383.02	16.61	366.07	33.80	362.10	29.99	0.004	0.050	0.000
whitepine	0.0006	374.90	27.26	383.09	17.15	366.77	32.93	363.39	27.46	0.002	0.050	0.000
Weighted Average		376.88	28.48	387.12	17.17	371.03	32.91	361.93	30.03	0.004	0.059	0.002
True Value		459.18		410.02		493.41		433.76				

Table A.6: Esmeralda County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0	2416.50	313.00	2136.00	249.82	2291.70	442.79	1998.40	345.21	0.103	0.071	0.033	0.047
churchill	0.0039	2328.80	296.66	2259.90	239.89	2257.20	400.83	2125.70	353.56	0.049	0.151	0.017	0.105
clark	0.0012	2359.80	303.66	2249.30	248.17	2260.30	390.85	2107.30	339.42	0.067	0.157	0.013	0.083
douglas	0.9932	2361.00	296.50	2386.60	248.23	2290.00	403.61	2182.50	366.41	0.064	0.331	0.020	0.135
elko	0	2350.30	298.88	2498.00	237.16	2511.60	395.49	2205.60	368.45	0.058	0.490	0.059	0.160
esmeralda (Fake Prior)		2363.9	435.13	2460	230.85	2531.1	820.61	2230	464.54	0.143	0.442	0.184	0.214
eureka	0	2416.60	325.21	2108.80	276.44	2259.70	437.17	1935.10	365.91	0.110	0.074	0.028	0.043
humboldt	0	2375.20	305.60	2479.80	235.41	2412.60	396.77	2239.60	373.22	0.078	0.478	0.035	0.192
lander	0	2387.00	298.52	2360.70	238.11	2339.20	388.36	2229.40	346.65	0.068	0.277	0.023	0.145
lincoln	0	2553.40	365.67	2276.60	290.14	2585.00	536.50	2302.20	432.10	0.216	0.209	0.150	0.253
lyon	0	2401.20	302.88	2392.00	248.00	2376.00	389.32	2267.10	351.47	0.082	0.324	0.030	0.173
mineral	0	2301.10	309.24	2496.70	240.66	2445.10	403.22	2152.50	419.63	0.052	0.497	0.045	0.150
nye	0	2443.20	311.34	2464.10	241.58	2522.70	426.85	2387.00	394.92	0.111	0.443	0.073	0.325
pershing	0	2704.10	477.19	2124.90	375.89	3027.80	929.61	1925.00	642.72	0.378	0.144	0.411	0.144
storey	0	2308.80	303.75	2422.00	237.01	2318.30	387.77	2145.70	370.66	0.049	0.378	0.020	0.127
washoe	0.0017	2418.50	291.27	2389.80	780.61	2522.00	1675.10	2338.10	1432.70	0.087	0.446	0.264	0.389
whitepine	0	2399.90	320.78	2297.80	251.69	2307.50	417.86	2195.20	361.28	0.093	0.205	0.027	0.148
Weighted Average		2315.60	355.92	2450.60	121.56	2328.50	413.68	2193.60	379.73	0.086	0.344	0.026	0.158
													.
True Value		2807.38		2494.16		3127.06		2569.39					

Table A.7: Eureka - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.0003	6044.60	706.53	6788.40	1240.00	5544.60	998.68	6201.70	1776.00	0.016	0.315	0.000	0.423
churchill	0.0002	6490.00	746.51	6914.90	1240.20	6135.00	1023.00	6320.90	1585.10	0.056	0.273	0.000	0.453
clark	0.0235	6441.40	720.29	6573.20	1246.50	6051.40	982.11	5939.30	1468.20	0.043	0.379	0.000	0.346
douglas	0.0003	6528.20	728.13	6824.80	1274.10	6261.10	1052.20	6357.10	1616.30	0.063	0.307	0.000	0.458
elko	0.0312	6689.30	823.70	6239.50	1459.50	6112.20	1230.80	6449.50	1652.90	0.112	0.490	0.000	0.482
esmeralda	0.3978	6334.70	766.69	6305.00	1306.10	5809.80	1112.40	5725.40	1580.60	0.041	0.470	0.000	0.302
eureka (Fake Prior)		6067.2	1494.2	6917.3	910.62	5283.5	2117.3	6262.3	1305.6	0.135	0.212	0.003	0.426
humboldt	0.3316	6614.80	792.60	6207.70	1493.00	6200.80	1167.80	6414.50	1631.30	0.082	0.498	0.000	0.473
lander	0.0582	6557.30	765.04	6394.60	1365.30	6078.20	1197.90	6142.30	1592.40	0.075	0.444	0.000	0.404
lincoln	0	6189.70	733.85	7506.60	1275.70	5653.40	1030.60	7491.50	1830.40	0.025	0.146	0.000	0.297
lyon	0.0065	6583.00	764.06	6578.40	1373.50	6255.10	1118.70	6305.00	1576.80	0.077	0.393	0.000	0.449
mineral	0.0013	6718.60	803.18	6468.50	1361.20	6395.20	1232.20	6519.80	1591.40	0.109	0.416	0.000	0.498
nye	0.0001	6605.40	735.93	6914.90	1264.30	6509.00	1030.70	6716.90	1533.30	0.075	0.272	0.000	0.447
pershing	0	5928.60	794.65	7791.70	1403.50	4900.10	1224.80	8382.80	2450.50	0.017	0.117	0.000	0.201
storey	0.1488	6654.80	808.65	6235.80	1411.50	5986.20	1194.20	6269.10	1584.70	0.100	0.499	0.000	0.440
washoe	0.0002	6288.70	708.32	6957.50	1218.20	6052.30	991.09	6563.30	1604.30	0.027	0.266	0.000	0.493
whitepine	0	6401.90	694.67	7132.20	1254.80	6085.10	1003.70	6621.10	1622.60	0.036	0.221	0.000	0.483
Weighted Average		6517.00	808.90	6269.80	1395.30	6000.00	1165.30	6092.90	1630.20	0.075	0.487	0.000	0.394
True Value		7663.4		6224.97		11237.59		6505.3					.

Table A.8: Humboldt County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.00	610.82	51.46	594.98	40.86	575.63	66.99	562.77	55.31	0.016	0.013	0.001	0.000
churchill	0.00	582.62	55.58	616.29	35.51	581.65	61.40	553.38	55.99	0.004	0.032	0.001	0.000
clark	0.03	608.07	47.55	625.31	31.87	596.70	62.34	578.86	60.98	0.006	0.038	0.001	0.000
douglas	0.14	603.00	47.63	637.87	31.18	601.80	57.24	577.48	59.88	0.009	0.089	0.000	0.000
elko	0.27	610.21	47.07	640.76	29.59	607.01	60.06	576.98	60.98	0.007	0.091	0.001	0.000
esmeralda	0.04	613.90	49.70	602.14	43.74	601.03	65.62	584.11	60.60	0.013	0.095	0.001	0.000
eureka	0.00	616.04	48.56	637.82	33.16	608.32	60.68	587.18	58.89	0.015	0.028	0.002	0.000
humboldt (Fake Prior)		615.63	52.87	638.88	36.99	609.58	72.64	588.75	71.29	0.018	0.128	0.004	0.000
lander	0.12	610.00	46.53	626.97	33.12	604.53	55.77	586.70	51.25	0.008	0.055	0.001	0.000
lincoln	0.00	622.13	50.83	613.43	43.52	602.29	67.94	592.22	61.10	0.023	0.051	0.003	0.000
lyon	0.28	616.39	45.78	636.84	31.53	602.64	60.41	586.89	60.91	0.009	0.087	0.005	0.000
mineral	0.02	603.47	50.26	639.43	30.54	607.02	59.99	575.06	67.53	0.007	0.093	0.001	0.000
nye	0.01	621.93	48.68	644.51	32.67	625.25	59.65	614.45	57.16	0.014	0.136	0.002	0.000
pershing	0.00	630.25	52.80	613.53	47.52	614.75	71.50	602.73	64.23	0.034	0.055	0.006	0.000
storey	0.08	594.95	50.52	632.82	30.76	588.17	62.58	552.87	64.81	0.004	0.058	0.001	0.000
washoe	0.00	608.82	49.17	617.57	34.84	598.47	61.58	588.46	57.58	0.008	0.026	0.002	0.000
whitepine	0.00	609.83	48.15	620.27	35.13	597.32	60.56	591.10	58.36	0.008	0.043	0.001	0.000
Weighted Average		610.63	47.90	636.45	31.06	603.29	59.82	580.05	60.67	0.010	0.081	0.002	0.000
True Value		730.27		678.98		804.84		899.38					

Table A.9: Lander County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.00	1420.00	102.37	1410.00	110.53	1350.00	132.44	1300.00	132.00	0.000	0.047	0.025	0.337
churchill	0.00	1380.00	100.14	1480.00	114.32	1380.00	115.78	1300.00	117.00	0.000	0.017	0.022	0.335
clark	0.02	1420.00	96.13	1500.00	113.11	1410.00	120.77	1330.00	122.70	0.000	0.013	0.049	0.246
douglas	0.07	1410.00	92.23	1560.00	101.43	1430.00	114.53	1350.00	118.83	0.000	0.001	0.055	0.196
elko	0.18	1400.00	98.80	1630.00	108.84	1460.00	130.05	1320.00	128.98	0.000	0.000	0.114	0.281
esmeralda	0.01	1410.00	99.58	1460.00	121.45	1380.00	120.64	1340.00	124.21	0.000	0.003	0.052	0.255
eureka	0.00	1420.00	97.68	1550.00	113.59	1410.00	123.79	1330.00	126.42	0.000	0.034	0.026	0.247
humboldt	0.54	1420.00	96.08	1620.00	103.03	1460.00	124.06	1360.00	125.10	0.001	0.000	0.112	0.193
lander (Fake Prior)		1417.7	111.48	1563.6	128.33	1419.7	139.01	1357.8	133.85	0.001	0.007	0.077	0.207
lincoln	0.00	1430.00	103.01	1500.00	113.15	1410.00	119.80	1380.00	124.82	0.001	0.015	0.046	0.146
lyon	0.12	1420.00	95.96	1580.00	104.65	1450.00	118.42	1380.00	128.04	0.000	0.001	0.084	0.143
mineral	0.01	1400.00	101.29	1590.00	101.58	1450.00	120.92	1360.00	120.13	0.000	0.001	0.080	0.184
nye	0.01	1420.00	95.40	1610.00	101.99	1480.00	120.74	1410.00	133.43	0.000	0.001	0.121	0.107
pershing	0.00	1440.00	101.74	1510.00	117.10	1420.00	126.89	1390.00	124.87	0.000	0.019	0.056	0.138
storey	0.05	1370.00	98.88	1590.00	102.58	1410.00	123.26	1290.00	124.20	0.000	0.000	0.046	0.370
washoe	0.00	1420.00	98.18	1480.00	105.09	1400.00	111.04	1350.00	118.48	0.000	0.015	0.029	0.200
whitepine	0.00	1420.00	97.08	1530.00	111.45	1400.00	125.92	1370.00	128.97	0.000	0.006	0.040	0.186
Weighted Average		1412.30	99.34	1604.90	108.65	1454.90	124.98	1350.20	127.76	0.000	0.000	0.100	0.213
True Value		1876.52		1222.48		1614.56		1252.52					

Table A.10: Lincoln County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.02	784.00	79.20	778.00	85.09	719.00	112.69	712.00	123.80	0.045	0.063	0.016	0.162
churchill	0.18	814.00	74.69	815.00	77.05	774.00	103.24	769.00	105.35	0.086	0.108	0.043	0.307
clark	0.01	822.00	71.67	806.00	84.21	788.00	108.98	769.00	115.57	0.097	0.095	0.053	0.299
douglas	0.16	823.00	69.33	817.73	76.67	793.30	89.28	782.08	96.96	0.094	0.117	0.040	0.299
elko	0.01	826.00	82.05	820.66	94.40	795.59	124.26	803.04	127.24	0.139	0.170	0.089	0.390
esmeralda	0.00	810.00	73.33	819.53	75.84	780.69	104.88	780.43	109.74	0.094	0.113	0.072	0.320
eureka	0.07	809.00	79.90	796.43	94.56	763.31	120.56	766.06	125.39	0.076	0.117	0.032	0.320
humboldt	0.00	823.00	74.05	810.65	92.86	786.37	110.47	787.06	119.70	0.104	0.141	0.063	0.368
lander	0.02	819.00	72.48	814.73	88.83	767.36	96.44	768.76	107.38	0.098	0.141	0.077	0.354
lincoln (Fake Prior)		816.96	103.02	836.41	51.99	781.71	165.87	815.87	77.78	0.158	0.084	0.114	0.437
lyon	0.03	824.00	72.69	819.76	81.09	793.21	99.34	790.74	107.25	0.105	0.138	0.050	0.355
mineral	0.02	821.00	84.10	818.77	89.22	798.34	114.99	806.20	111.53	0.135	0.159	0.092	0.407
nye	0.05	837.00	78.49	841.66	82.53	805.78	109.80	811.68	111.80	0.140	0.193	0.106	0.491
pershing	0.02	810.00	75.00	828.57	73.98	758.23	112.35	813.73	114.41	0.079	0.141	0.048	0.467
storey	0.01	810.00	76.04	801.99	92.87	757.85	114.83	764.39	121.88	0.092	0.129	0.055	0.311
washoe	0.09	812.37	70.49	806.35	73.74	771.00	99.35	758.36	102.06	0.074	0.083	0.031	0.250
whitepine	0.31	816.00	71.37	825.95	74.08	782.21	94.16	794.27	100.84	0.083	0.124	0.050	0.354
Weighted Average		816.67	75.00	820.19	76.92	779.46	102.77	781.69	106.51	0.090	0.120	0.048	0.331
True Value		913.04		906.61		949.4		825.99					

Table A.11: Lyon County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.00	512.48	24.54	491.54	24.02	490.02	30.45	475.16	26.39	0.037	0.077	0.009	0.000
churchill	0.00	496.78	25.29	504.20	20.88	481.80	28.65	477.75	24.77	0.007	0.190	0.002	0.000
clark	0.08	509.28	23.27	510.54	18.46	498.15	26.36	487.56	21.71	0.016	0.257	0.003	0.000
douglas	0.00	507.49	21.20	519.24	20.34	499.38	25.98	491.36	25.87	0.012	0.441	0.003	0.000
elko	0.00	508.96	23.80	535.59	19.33	510.29	30.94	490.10	33.30	0.022	0.237	0.020	0.000
esmeralda	0.00	512.05	23.91	502.48	22.69	493.94	29.63	484.11	26.50	0.032	0.383	0.015	0.000
eureka	0.00	512.68	23.77	529.38	21.70	505.45	31.23	490.01	29.75	0.028	0.170	0.006	0.000
humboldt	0.00	515.99	23.54	536.24	19.08	512.37	29.72	498.68	31.50	0.038	0.241	0.024	0.000
lander	0.00	510.83	21.65	525.24	18.34	504.72	25.63	495.09	23.86	0.024	0.435	0.006	0.000
lincoln	0.00	512.73	25.17	502.82	23.64	492.91	28.23	486.08	25.56	0.041	0.188	0.007	0.000
lyon (Fake Prior)		513.97	26.37	525.81	25.64	505.17	34.07	497.01	30.65	0.049	0.447	0.024	0.000
mineral	0.90	504.56	24.98	529.18	19.45	508.67	29.27	489.80	28.05	0.014	0.366	0.019	0.000
nye	0.02	510.89	23.70	529.97	19.11	508.85	30.25	502.73	29.81	0.025	0.341	0.017	0.000
pershing	0.00	514.31	25.84	494.55	29.09	494.35	35.67	482.65	33.57	0.056	0.146	0.010	0.000
storey	0.00	501.42	23.10	532.67	18.92	504.65	30.35	480.32	29.35	0.013	0.294	0.011	0.000
washoe	0.00	507.88	23.85	505.32	19.79	491.00	29.01	483.07	24.41	0.017	0.176	0.004	0.000
whitepine	0.00	508.39	23.43	510.14	20.99	494.13	28.24	488.50	25.11	0.019	0.293	0.005	0.000
Weighted Average		505.71	24.54	527.80	20.06	507.63	29.35	492.48	27.21	0.015	0.399	0.017	0.000
True Value		557.32		522.75		572.14		622.18					

Table A.12: Mineral County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.00	963.15	75.30	938.75	71.54	886.06	105.14	887.61	99.51	0.008	0.006	0.019	0.002
churchill	0.01	988.15	67.59	970.61	57.74	924.73	87.63	924.96	82.85	0.013	0.007	0.023	0.001
clark	0.01	1010.00	70.95	970.35	53.98	957.42	90.82	972.26	92.12	0.027	0.005	0.059	0.010
douglas	0.80	997.48	75.64	978.11	55.37	959.14	88.08	958.45	87.82	0.028	0.007	0.056	0.005
elko	0.00	1000.00	66.56	979.96	52.14	940.91	86.31	983.39	92.74	0.021	0.007	0.036	0.011
esmeralda	0.00	984.76	76.96	980.10	63.79	944.99	99.62	946.65	91.63	0.026	0.006	0.033	0.014
eureka	0.00	1000.00	69.51	975.70	53.72	934.21	88.53	969.09	99.34	0.021	0.019	0.061	0.007
humboldt	0.01	997.21	80.75	976.65	54.55	943.02	94.65	946.73	109.66	0.037	0.007	0.051	0.011
lander	0.02	992.88	81.74	979.71	55.25	944.00	100.40	943.06	97.48	0.030	0.012	0.062	0.004
lincoln	0.00	998.42	66.04	974.64	54.81	909.91	87.30	963.66	84.84	0.017	0.006	0.013	0.004
lyon	0.15	1000.00	77.89	984.68	54.77	958.00	95.18	966.02	94.38	0.038	0.009	0.069	0.008
mineral (Fake Prior)		1001.4	82.91	977.11	50.04	917.82	107.02	962.67	104.44	0.045	0.004	0.045	0.017
nye	0.00	1010.00	69.00	995.70	56.63	961.50	95.48	979.97	89.00	0.024	0.019	0.075	0.007
pershing	0.00	987.23	85.94	990.33	86.52	943.03	118.25	942.80	120.94	0.030	0.066	0.092	0.023
storey	0.00	984.50	71.06	972.12	54.79	929.03	91.37	952.25	94.56	0.011	0.009	0.035	0.012
washoe	0.00	1000.00	67.87	965.84	60.17	925.19	91.39	940.02	83.95	0.023	0.010	0.031	0.002
whitepine	0.00	986.73	73.33	984.14	63.05	946.55	92.67	954.61	85.74	0.018	0.020	0.053	0.008
Weighted Average		999.08	75.43	978.62	55.88	958.13	89.42	959.23	89.80	0.028	0.006	0.057	0.006
True Value		1143.89		1118.147		1097.79		1192.21					

Table A.13: Nye County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.00	622.25	67.84	626.91	51.65	574.71	93.66	580.43	78.81	0.150	0.095	0.001	0.004
churchill	0.07	649.47	53.87	651.27	38.63	626.43	64.63	628.17	55.95	0.212	0.136	0.001	0.003
clark	0.03	657.97	51.88	649.29	38.07	641.82	69.59	641.77	68.03	0.269	0.134	0.003	0.021
douglas	0.04	657.50	50.90	656.09	35.10	637.08	63.09	636.07	54.90	0.258	0.149	0.001	0.003
elko	0.19	661.08	51.70	662.08	36.23	643.63	62.40	643.35	64.82	0.283	0.204	0.001	0.023
esmeralda	0.01	658.47	56.93	661.58	37.42	651.17	74.51	652.52	56.41	0.298	0.214	0.003	0.044
eureka	0.01	661.65	56.50	660.45	38.87	646.21	69.55	648.00	75.40	0.283	0.211	0.005	0.013
humboldt	0.01	661.38	51.86	659.20	37.14	650.51	64.72	648.70	65.08	0.288	0.193	0.002	0.022
lander	0.02	660.66	53.19	662.09	35.95	647.02	68.52	649.06	63.39	0.281	0.202	0.002	0.013
lincoln	0.00	657.89	55.84	661.33	39.07	644.31	80.54	647.18	59.66	0.270	0.216	0.007	0.017
lyon	0.04	661.10	52.92	661.41	35.32	645.66	66.27	644.53	60.88	0.280	0.193	0.002	0.017
mineral	0.45	654.43	53.98	659.44	35.70	640.31	64.75	637.32	60.52	0.239	0.187	0.001	0.009
nye (Fake Prior)		664.88	68.73	667.29	25.06	657.49	88.62	661.69	71.46	0.343	0.161	0.018	0.040
pershing	0.00	652.77	65.29	654.05	46.68	628.99	110.20	638.85	69.04	0.278	0.199	0.016	0.017
storey	0.05	649.63	54.75	654.23	37.95	628.70	67.08	631.51	67.60	0.218	0.162	0.001	0.016
washoe	0.02	648.67	55.11	641.09	42.04	623.75	70.73	617.97	61.72	0.220	0.111	0.002	0.007
whitepine	0.06	655.74	53.16	661.24	35.44	643.21	65.09	648.02	51.95	0.253	0.190	0.001	0.008
Weighted Average		655.71	53.58	657.97	36.66	639.78	65.10	638.59	61.62	0.251	0.170	0.001	0.012
True Value		689.611		690.72		851.91		779.21					

Table A.14: Pershing County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.00	711.59	90.07	696.96	88.37	660.15	122.58	633.86	123.99	0.296	0.179	0.126	0.034
churchill	0.02	737.71	92.20	725.29	85.86	701.58	128.19	686.99	120.77	0.418	0.279	0.217	0.073
clark	0.00	745.35	88.46	728.46	89.28	724.54	132.56	707.03	130.61	0.441	0.302	0.276	0.122
douglas	0.02	743.69	87.30	732.10	87.17	714.38	113.91	698.87	113.89	0.428	0.314	0.220	0.078
elko	0.08	757.78	96.11	745.96	97.48	741.35	137.00	745.03	136.79	0.500	0.393	0.331	0.199
esmeralda	0.00	740.48	85.45	728.31	85.01	733.52	118.41	700.64	119.38	0.431	0.330	0.264	0.155
eureka	0.00	741.90	95.76	727.40	100.60	715.78	144.19	715.61	144.03	0.425	0.295	0.281	0.089
humboldt	0.00	749.63	89.24	738.08	96.20	723.57	126.65	722.59	127.90	0.467	0.358	0.264	0.133
lander	0.01	748.67	88.49	738.03	92.75	705.42	117.34	700.11	119.76	0.463	0.351	0.206	0.089
lincoln	0.00	754.44	80.37	744.55	78.29	738.46	115.40	713.10	109.96	0.484	0.357	0.287	0.086
lyon	0.05	751.32	87.27	740.31	89.73	745.25	123.76	736.45	124.61	0.477	0.357	0.328	0.153
mineral	0.05	754.98	100.53	742.47	98.70	702.72	139.39	709.56	143.03	0.492	0.368	0.239	0.140
nye	0.73	771.12	88.69	760.95	87.58	767.42	122.97	757.79	121.59	0.426	0.458	0.396	0.195
pershing (Fake Prior)		744.53	121.29	729.78	42.73	700.52	289.47	686.54	135.04	0.456	0.148	0.338	0.067
storey	0.00	737.06	93.42	725.35	96.20	688.90	137.02	689.04	138.56	0.411	0.307	0.211	0.109
washoe	0.00	740.78	84.49	725.78	81.56	709.93	127.62	684.69	118.52	0.420	0.270	0.234	0.067
whitepine	0.03	748.06	85.74	737.81	83.80	722.49	118.76	707.69	115.51	0.460	0.341	0.254	0.088
Weighted Average		764.91	90.77	755.65	90.23	756.03	126.76	747.59	125.32	0.456	0.434	0.364	0.180
True Value		756.39		721.42		800.21		859.79					

Table A.15: Storey County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.01	1417.1	114.5	1542	102.63	1386.9	135.76	1309.9	122.62	0.000	0.213	0.000	0.000
churchill	0.21	1399	109.07	1619.7	92.59	1498.4	133.15	1308.7	141.15	0.000	0.495	0.000	0.000
clark	0.08	1436.7	118.78	1638.4	91.1	1539.5	144.04	1343.7	131.98	0.000	0.421	0.000	0.000
douglas	0.38	1448.3	107.19	1676	87.39	1538.2	130.39	1352.6	138.83	0.000	0.269	0.000	0.000
elko	0.00	1418.9	110.98	1694	88.02	1520.4	145.61	1286.9	149.91	0.000	0.197	0.000	0.000
esmeralda	0.00	1415.7	113.48	1579.7	104.77	1396.4	154.68	1313.8	148.68	0.000	0.305	0.000	0.000
eureka	0.00	1423.4	111.54	1664.9	90.95	1485.8	144.98	1305.4	132.86	0.000	0.357	0.000	0.000
humboldt	0.00	1455.4	114.37	1692.2	83.48	1527.1	139.29	1349	142.43	0.000	0.197	0.000	0.000
lander	0.00	1477.1	113.38	1638.9	88.09	1474.3	132.54	1403	126.41	0.000	0.417	0.000	0.000
lincoln	0.01	1427.1	115.15	1617.7	98.56	1451.7	143.1	1346.8	141.28	0.000	0.497	0.000	0.000
lyon	0.00	1464	118.91	1676.5	90.21	1536	141.51	1398.2	140.27	0.000	0.271	0.000	0.000
mineral	0.00	1401.2	114.06	1688.8	86.39	1538.1	142.66	1300.6	146.51	0.000	0.216	0.000	0.000
nye	0.00	1430.6	114.53	1698.6	90.2	1557.1	150.36	1345.7	157.12	0.000	0.190	0.000	0.000
pershing	0.00	1440.3	122.27	1618	107.14	1458.6	152.74	1364.7	138.69	0.000	0.489	0.000	0.000
storey (Fake Prior)		1412.4	126.14	1666.7	93.25	1478.9	154.62	1318.5	153.49	0.000	0.314	0.000	0.000
washoe	0.31	1427.8	114.8	1611.4	92.3	1506.3	136.86	1351.1	137.69	0.000	0.478	0.000	0.000
whitepine	0.00	1422.4	113.79	1627.7	96.21	1455	135.52	1338	142.17	0.000	0.469	0.000	0.000
Weighted Average		1428.80	111.84	1637.50	96.78	1517.90	136.41	1342.30	139.80	0.000	0.418	0.000	0.000
True Value		2176.99		1622.62		2650.17		2282.02					

Table A.16: Washoe County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.00	686.15	20.89	654.84	28.89	637.6	29.26	611.85	35.24	0.001	0.000	0.000	0.000
churchill	0.80	689.14	18.89	668.05	26.4	649.51	30.2	631.59	33.82	0.000	0.001	0.000	0.000
clark	0.02	680.89	18.97	686.64	27.65	666.38	32.21	642.64	30.08	0.000	0.002	0.001	0.000
douglas	0.06	697.72	18.37	671.35	28.55	662.23	27.21	640.92	35.13	0.002	0.001	0.000	0.000
elko	0.01	674.63	19.85	715.91	27.62	705.29	41.91	636.19	32.62	0.000	0.039	0.053	0.000
esmeralda	0.00	694.13	19.93	669.44	27.8	657.28	29.44	637.6	34.92	0.000	0.027	0.035	0.000
eureka	0.01	677.13	20.01	707.03	29.42	687.45	40.96	640.41	33.96	0.002	0.000	0.000	0.000
humboldt	0.00	685.99	19.4	715.64	27.81	693.29	32.16	653.99	31.58	0.002	0.037	0.008	0.000
lander	0.00	694.26	17.83	698.71	26.71	674.01	28.36	660.46	30.41	0.002	0.009	0.001	0.000
lincoln	0.01	701.93	21.03	666.04	28.94	662.83	28.62	632.14	36.55	0.008	0.002	0.000	0.000
lyon	0.01	690.77	18.21	694.76	26.46	674.03	30.17	658.85	30.96	0.001	0.006	0.003	0.000
mineral	0.01	676.34	20.54	714.74	28.55	705.14	39.89	644.47	33.92	0.001	0.041	0.046	0.000
nye	0.03	690.59	22.33	712.52	30.62	705.76	36.7	678.06	34.74	0.005	0.040	0.041	0.001
pershing	0.00	716.55	23.42	628.86	34.06	691.08	39.17	539.3	66.29	0.041	0.000	0.028	0.000
storey	0.00	680.58	18.54	708.98	27	686.97	33.59	646.38	31.73	0.000	0.024	0.007	0.000
washoe (Fake Prior)		690.04	25.15	670.28	42.96	655.72	42.63	638.42	54.47	0.005	0.018	0.009	0.006
whitepine	0.05	692.69	19.3	676.12	26.54	661.35	28.63	646.29	32.71	0.000	0.001	0.000	0.000
Weighted Average		688.68	19.36	671.31	28.85	654.53	33.26	634.87	35.10	0.001	0.003	0.003	0.000
True Value		758.88		765.77		772.2		799.15					

Table A.17: Whitepine County - Revenue and Expenditure Per Capita Prediction with PPP Value Comparison

	weight	average_rpc12	std_rpc12	average_epc12	std_epc12	average_rpc13	std_rpc13	average_epc13	std_epc13	ppp_rpc12	ppp_epc12	ppp_rpc13	ppp_epc13
carson	0.00	686.09	60.96	709.14	63.15	654.24	74.65	652.95	79.68	0.016	0.439	0.000	0.000
churchill	0.01	718.99	52.32	724.3	58.68	684.86	66.78	681.7	70.88	0.036	0.451	0.000	0.000
clark	0.01	714.53	55.56	686.18	58.26	677.19	70.47	661.07	73.62	0.040	0.280	0.000	0.000
douglas	0.99	709.47	52.09	715.85	57.78	681.72	62.73	674.27	67.6	0.027	0.491	0.000	0.000
elko	0.00	738.26	59.57	648.31	67.92	642.45	81.5	714.31	88.59	0.101	0.133	0.000	0.000
esmeralda	0.00	688.55	58.08	734.23	59	671.67	66.81	691.53	68.26	0.052	0.149	0.000	0.000
eureka	0.00	716.25	60.02	653.8	63.99	647.85	78.89	672.81	89.38	0.016	0.378	0.000	0.000
humboldt	0.00	708.72	53.9	645.19	67.07	661.08	70.22	693.14	85.88	0.030	0.132	0.000	0.000
lander	0.00	703.39	52.56	669.76	62	654.48	67.71	662.38	79.91	0.021	0.198	0.000	0.000
lincoln	0.00	693.2	59.07	764.47	60.9	688.32	70.19	730.37	79.1	0.023	0.219	0.000	0.000
lyon	0.00	715.11	55.65	691.8	59.55	681.84	69.16	682.81	75.4	0.037	0.320	0.000	0.000
mineral	0.00	743.5	59.24	680.19	63.76	665.08	78.18	709.7	79.2	0.117	0.265	0.000	0.000
nye	0.00	731.79	59.56	718.28	60.07	704.2	72.84	718.85	76.35	0.082	0.500	0.000	0.000
pershing	0.00	679.44	63.56	788.99	69.09	669.98	86.08	767.57	99.23	0.016	0.140	0.000	0.003
storey	0.00	722.23	54.54	640.61	66.66	628.77	76.1	698.13	89.45	0.043	0.107	0.000	0.000
washoe	0.00	709.55	58.03	722.98	56.49	685.61	67.98	676.61	71.06	0.043	0.468	0.000	0.000
whitepine (Fake Prior)		705.09	75.85	733.48	60.00	679.86	84.09	691.19	72.42	0.071	0.402	0.000	0.000
Weighted Average		711.44	52.38	717.24	58.18	681.82	63.00	673.97	67.60	0.034	0.499	0.000	0.000
True Value		813.38		718.38		1361.69		1130.83					

BIBLIOGRAPHY

BIBLIOGRAPHY

Adkins, L.C., D.S. Rickman, and A. Hameed. 2003. "Bayesian Estimation of Regional Production for CGE Modeling." *Journal of Regional Science* 43:641–661.

Alsemgeest, P., C. Noussair, and M. Olson. 1998. "Experimental Comparisons of Auctions Under Single and Multi-Unit Demand." *Economic Inquiry* 36:87–97.

Ariely, D., A. Ockenfels, and A. Roth. 2005. "An Experimental Analysis of Ending Rules in Internet Auctions." *Rand Journal of Economics* 36:891–908.

Ausubel, L. 2004. "An Efficient Ascending-Bid Auction for Multiple Objects." *American Economic Review* 94:1452–1475.

Avery, C. 1998. "Strategic Jump Bidding in English Auctions." *Review of Economic Studies* 65:185–210.

Bajari, P., and H. Ali. 2004. "Economic Insights from Internet Auctions." *Journal of Economic Literature* 42:457–486.

Barbaro, S., and B. Bracht. 2006. "Shilling, squeezing sniping: Explaining late bidding in on-line second-price auctions." *Working Paper, University of Mainz*, pp. .

Beemiller, R.M. 1989. "Local area fiscal impact analysis using the Regional Input-Output Modeling System (RIMS II)." *Socio-Economic Planning Science* 23:261–269.

Bikhchandani, S., and J. Riley. 1991. "Equilibrium in Open Common Value Aucitons." *Journal of Economic Theory* 53:101–130.

Branscuma, A.J., T.E. Hansonb, and I.A. Gardnerc. 2008. "Bayesian non-parametric models for Regional Prevalence Estimation." *Journal of Applied Statistics* 35:567–582.

Brusco, S., and G. Lopomo. 2002. "Collusion via Signaling in Simultaneous Ascending Bid Auctions with Heterogeneous Objects, with and without complementaries." *The Review of Economic Studies* 69:407–436.

Bulow, J., and P. Klemperer. 1996. "Auctions versus Negotiations." *American Economic Review* 86:180–194.

Cassady, R. 1967. *Auctions and Auctioneering*. London, England: Berkeley: University of California Press.

Chib, J.I., S. 2001. "Marginal Likelihood from the Metropolis-Hastings output." *Journal of the American Statistical Association* 95:270–281.

Chib, S. 1995. "Marginal Likelihood from the Gibbs Sampler." *Journal of the American Statistical Association* 90:1313–1321.

Coppinger, V., V.L. Smith, and J. Titus. 1980. "Incentives and Behavior in English Dutch and Sealed-Bid Auctions." *Economic Inquiry* 18:1–20.

Cowles, M.K., and B.P. Carlin. 1996. "Markov Chain Monte Carlo Convergence Diagnostics: A Comparative Review." *Journal of American Statistical Association* 91:883–904.

Daniel, K., and D. Hirshleifer. 1998. "A Theory of Costly Sequential Bidding." *University of Michigan, Business School* No.98028:Working papers.

Doan, T., R.B. Litterman, and C. Sims. 1984. "Forecasting and Conditional Projections using Realistic Prior Distributions." *Econometric Review* 3:1–100.

Donald, S.G., H.J. Paarsch, and J. Robert. 2006. "An Empirical Model of The Multi-Unit, Sequential Clock Auction." *Journal of Applied Econometrics* 21:1221–1247.

Dréze, J.H. 1976. "Bayesian Limited Information Analysis of the Simultaneous Equations Model." *Econometrica* 44(5):1045–1075.

Dréze, J.H., and J.A. Morales. 1976. "Bayesian Full Information Analysis of Simultaneous Equations." *Journal of the American Statistical Association* 71:919–923.

Easley, R.F., and R. Tenorio. 2004. "Jump Bidding Strategies in Internet Auctions." *Management Science* 50:1407–1419.

Goeree, J.K., C.A. Holt, and T.R. Palfrey. 2002. "Quantal Response Equilibrium and Overbidding in Private-Value Auctions." *Journal of Economic Theory* 104:247–272.

Gunderson, A., and R. Wang. 2005. "Signaling by jump bidding in private values auctions." *Institute for Economic Research Working Paper 975, Queens University*, pp. .

Hansen, R.G. 1988. "Auctions with Endogenous Quantity." *Rand Journal of Economics* 19:44–58.

Harris, T.R., J.S. Shonkwiler, G.E. Ebai, and P. Janson. 2000. "Application of BEA Economic Areas in the Development of the Great Basin Fiscal Impact Model." *The Journal of Regional Analysis* 30.

Hendrick, K., and R. Porter. 1988. "An Empirical Study of an Auction with Asymmetric Information." *American Economic Review* 78:865–883.

Hőrner, J., and N. Sahuguet. 2007. "Costly Signalling in Auctions." *Review of Economic Studies* 74:173–206.

Holtz-Eakin, D., W. Newey, and H.S. Rosen. 1989. "The Revenue-Expenditures Nexus: Evidence from Local Government Data." *International Economic Review* 30:415–429.

Issac, R.M., T.C. Salmon, and A. Zillante. 2005. "An Experimental Test of Alternative models of bidding in Ascending Auctions." *International Journal of Game Theory* 33:287–313.

—. 2006. "A theory of jump bidding in ascending auctions." *Journal of Economic Behavior & Organization* 62:144–164.

Johnson, T., J. Ma, and J. Scott. 1996. "The conceptual basis of the Show Me models." *Presented Paper at the 26th Annual Meeting of the Mid-Continent Regional Science Association, St. Louis, Missouri.*, pp. .

Kagel, J., and D. Levin. 2003. "Behavior in Multi-Unit Demand Auctions: Experiments with Uniform Price and Dynamic Vickrey Auctions." *Econometrica* 69:413–454.

—. 1993. "Independent Private Value Auctions: Bidder Behavior in First, Second and Third Price Auctions with Varying Numbers of Bidders." *Economic Journal* 103:868–879.

Kamecke, U. 1998. "Dominance or Maximum: How to Solve and English Auction." *International Journal of Game Theory* 27:407–426.

Koop, G. 2004. *Bayesian Econometrics*. John Wiley & Sons Inc.

Koop, G., D. Poirier, and T.J. L. 2007. *Bayesian Econometric Methods*. Cambridge University Press.

Krishna, V. 2002. *Auction Theory*. San Diego, California: Academic Press.

Laffont, J.J., H. Ossard, and Q. Vuong. 1995. "Econometrics of First-Price Auction." *Econometrica* 63:953–980.

LeSage, J.P., and M.R. Dowd. 1997. "Analysis of spatial contiguity influences on state price level formation." *International Journal of Forecasting* 13:245–253.

LeSage, J.P., and A. Krivelyova. 1999. "A Spatial Prior for Bayesian Vector Autogregressive Models." *Journal of Regional Science* 39:297–317.

LeSage, J.P., and M. Magura. 1990. "Using Bayesian Techniques for Data Pooling in Regional Payroll Forecasting." *Journal of Business & Economics Statistics* 8.

—. 1991. "Using Indterindustry Input-Output Relations as a Bayesian Prior in Employment Forecasting models." *International Journal of Forecasting* 7:231–238.

LeSage, J.P., and Z. Pan. 1995. "Using Spatial Contiguity as Bayesian Prior Information in Regional Forecasting Models." *International Regional Science Review* 18:33–53.

List, J.A., and D. Lucking. Sep, 2000. "Demand Reduction in Multi-Unit Auctions: Evidence from a Sportscard Field Experiment." *American Economic Review* 90:961–972.

Litterman, R.B. 1986. "Forecasting with Bayesian Vector Autoregressions - Five Years of Experience." *Journal of Business and Economic Statistics* 4:25–38.

—. 1980. "Techniques for forecasting with vector autoregressions." *Ph.D Dissertation, University of Minnesota*, pp. .

Lucking, R.D. 2000. "Auctions On the Internet: What's being Auctioned, and How?" *The Journal of Industrial Economics* 48(3):227–252.

—. 1999. "Using Field Experiments to Test Equivalence between Auction Formats: Magic on the Internet." *The American Economic Review* 89:1063–1080.

Malakhov, A., and R.V. Vohra. 2009. "An optimal auction for capacity constrained bidders: a network perspective." *Economic Theory* 39:113–128.

Mcfee, R.P., and J. McMillan. 1987a. "Auctions and Bidding." *Journal of Economic Literature* 25:699–738.

—. 1987b. "Auctions with a Stochastic number of Bidders." *Journal of Economic Theory* 43:1–19.

Moeltner, K., and R. Woodward. 2009. "Meta-Functional Benefit Transfer for Wetland Valuation:Making the Most of Small Samples." *Environmental Resource Economics* 42:89–108.

Ockenfel, A., and A.E. Roth. 2002. "The timing of bids in Internet Auctions: Market Design, Bidder Behavior and Artificial Agents." *Artificial Intelligence Magazine* 23:79–87.

Ockenfels, A., and A.E. Roth. 2002. "Last-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet." *American Economic Review* 92:1093–1103.

—. 2006. “Late and Multiple Bidding in Second Price Internet Auctions:Theory and Evidence Concerning Different Rules for Ending an Auction.” *Games and Economic Behavior* 55:297–320.

Plott, C.R., and T.C. Salmon. 2004. “The Simultaneous Ascending Auction: Dynamics of Price Adjustment in Experiment and in the U.K. 3G Spectrum Auction.” *Journal of Economic Behavior and Organization* 53:353–383.

Raviv, Y. 2008. “The role of the bidding process in price determination: Jump bidding in sequential English auctions.” *Economic Inquiry* 46:325–341.

Rickman, D.S. 2002. “A Bayesian Forecasting Approach to Constructing Regional Input-Output Based Employment Multipliers.” *Papers in Regional Science* 81:483–498.

Rickman, D.S., S.R. M., and R. McKenzie. 2009. “Spatial and Sectoral Linkages in Regional Models - A Bayesian Vector Autoregression Forecast Evaluation.” *Papers in Regional Science* 88:29–41.

Rickman, D.S., and M.D. Partridge. 1998. “Generalizing the Bayesian Vector Autoregression Approach for Regional Interindustry Employment Forecasting.” *Journal of Business & Economic Statistics* 16:62–72.

Schindler, J. 2003. “Late Bidding on the Internet.” *Working Paper, University of Vienna*, pp. .

Shoesmith, G. 1990. “The Forecasting Accuracy of Regional Bayesian VAR Models with Alternative National Variable Choices.” *International Regional Science Review* 13:257–269.

Sims, C.A., J.H. Stock, and M.W. Watson. 1990. “Inference in Linear Time Series Models with some Unit Roots.” *Econometrica* 58:113–144.

Tenorio, R. 1997. “On Strategic Quantity Bidding in Multiple Unit Auctions.” *Journal of Industrial Economics* XLV:207–217.

Todd, R.M. 1984. “Improving Economic Forecasting with Bayesian Vector Autoregression.” *Federal Reserve Bank of Minneapolis Quarterly Review* 8:18–29.

Vickery, W. 1961. “Counterspeculation, Auctions, and Competitive Sealed Tenders.” *J. Finance* 16:8–37.

Wang, T. 2003. “Is last-minute bidding bad?” *Working Paper, UCLA*, pp. .

Wilcox, R. 2000. “Experts and amateurs: The Role of Experience in Internet Auctions.” *Marketing Letter* 11:363–374.

Zellner, A. 1962. "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests of Aggregation Bias." *Journal of American Statistical Association* 57:500–509.

—. 1971. *An Introduction to Bayesian Inference in Econometrics*. John Wiley & Sons Inc.