Effect of US Policies on Offshore Oil Leasing, 1983-2006:
A Random Parameter Logit Regression Analysis

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Abstract. The purpose of this study is to determine the effects of Minerals Management Service policy on Outer Continental Shelf leasing between 1983 and 2006. We apply a discrete choice model to a large, recently-developed spatial data set and examine factors that influence leasing such as royalty rates, policy, and exogenous land characteristics. In a time of soaring energy prices, we also focus on the effect of increased royalties on offshore production. We focus on offshore policies subsequent to 1983 with a flexible Random Parameters Logit model. Variables such as oil prices, net income, distance, geographical proxies and weather variables influence bidding in expected ways. We include the second moment of parameter distributions with the Random Parameter Logit model to avoid erroneous conclusions about the effects of government policy on bidding.

Keywords: *Random Parameter Logit, Oil Policy, Outer Continental Shelf*

Introduction

The Outer Continental Shelf (OCS) is thought to have great potential to supplement US long-term energy needs. The US Minerals Management Service (MMS) oversees the leasing and revenue collection for the OCS. For oil and gas specifically, offshore tracts of land are leased to private companies, giving them rights to explore, drill, and develop any petroleum resources. In the lease auctions, the bidding is by cash bonus, and later lessees pay royalties on any production. As a policy tool, the government is able to adjust the royalties, lease terms, and sale process.

With the surge in worldwide oil prices in the seventies, several studies emerged to bridge our understanding of optimal fiscal policy in the OCS. First, Reece (1978) developed a bidding model that analyzed various fiscal policies and corresponding effects on bidding. Due to lack of adequate pre-sale information, bidding in the OCS may not lead to a socially optimal outcome. As such, a government subsidy to mitigate presale uncertainty is recommended. Debrock et al. (1983) next investigated the effects of joint bidding and information pooling on petroleum lease auctions, finding that the pooling of information from joint bidding added to the value of tracts that received bids and provided industry with more accurate resources assessments. Although joint bidding reduced the number of participants, the increased a priori information resulted in more aggressive bidding and government revenues.

Moody et al. (1990) examined the welfare effects of switching from the tract-nomination sale process to area-wide leasing in 1983 with a discrete choice two-stage probit analysis. The analysis showed that the 1983 change to area-wide leasing, which increased the number of tracts offered, resulted in a higher supply of petroleum on the world market. The increased supply caused oil prices to drop- resulting in a transfer of wealth from onshore coastal to offshore producers. Also noted was the reduction in government revenues due to lower oil prices.

Hendricks et al. (1999) examined federal auctions for wildcat leases in the OCS by constructing a test of equilibrium bidding. The authors found that auction participants tend to bid less aggressively when they expect more competition, since the expectations for winning the given lease were perceived as lower with greater participation. More recently, Hendricks et al. (2004) investigated the effects of bidding rings and the winners curse. The authors provide insight on why there is a low occurrence of joint bidding on marginal properties in the OCS for federal auctions, providing empirical evidence that fear of the winner's curse may cause participants not to trade, and lead to inefficient outcomes.

The implications of the prior studies are, first, fiscal policy does indeed affect OCS bidding. Second, fiscal policy is necessary to ensure a competitive sale in a very concentrated industry such as oil and gas. Lastly, there are important distributional consequences when fiscal policy in the OCS is created, as some firms may benefit from regulation and some may not.

The purpose of this study is to determine the effects of MMS policy on OCS leasing between 1983 and 2006. We apply a discrete choice model to a large, recently-developed spatial data set and examine factors that influence leasing such as royalty rates, policy, and exogenous land characteristics. In a time of soaring gasoline prices, we also focus on the effect of increased royalties on offshore production. Our analysis adopts an approach similar to Moody; however, we focus on offshore policies subsequent to 1983 with a flexible Random Parameters Logit (RPL) model using newly available bidding data (IIC, Inc 2004). The RPL model allows not only for heterogeneity of choice across firms but also heterogeneity of all unobserved components (Louviere et al. 2001). Thus, modeling the unobserved component of choice increases the explanatory power of our bidding model, as well as provides further insights into the leasing process itself.

In the rest of the paper we present a conceptual model that shows how an individual firm would choose to bid on a given OCS tract based on observable and unobservable attributes. We next discuss the data used to develop an empirical model that predicts bidding in the OCS and present results. Lastly, policy suggestions are discussed.

Conceptual Framework

Consider the general case of the Random Utility Model (RUM). Let U_{qj} be the utility associated with the q^{th} firm for alternative *j*. The observable portion of utility, V_{qj}, is known as the deterministic component. Assuming Independently and Identically Distributed (IID) errors, we write the indirect utility function as

$$U_{qj} = \alpha_{qj} + \beta_q X_{qj} + \varepsilon_{qj} \tag{1}$$

where $V_{qj} = \beta_q X_{qj}$, X_{qj} are the attributes for the q^{th} firm for tract choice *j* and β_q is the associated parameter. The term ε_{qj} is stochastic and thus unobservable, but known to the decision maker; α_{qj} is the alternative specific constant for the q^{th} firm for tract *j*. The expression in (1) is useful because it allows us to dissect the random and nonrandom characteristics that influence utility; however, the IID assumption is a major shortcoming. Louviere et al. (2001) notes that IID based models assume that these random effects are constant, and do not vary among firms. Since probability distributions have more that one moment, it is reasonable to investigate the role of the unobservable component of utility on choice. The IID assumption restricts the utility of alternatives to be uncorrelated and have the same variance. In addition, the common value of error variance is not a function of individual characteristics so it is the same across firms. In effect, the IID based models assume that the distribution of the unobservable components are constant across firms, and cannot systematically influence choice.

We now consider a model that allows the distribution of unobservable effects to vary across individual firms. As such, now extend (1) to include heterogeneous preferences:

$$U_{qj} = \alpha_{qj} + \beta_q X_{qj} + \gamma_q X_{qj} + \varepsilon_{qj} \tag{2}$$

where $\gamma \sim N(\mu, \Omega)$ and β_q and γ_q are the nonrandom and random parameters in the utility function for firm *q*, respectively. All other parameters are previously defined. We can now write the associated probability model as,

$$P(j \mid \Re_q) = \frac{\exp(\alpha_{qj} + \beta_q X_{qj} + \gamma_q X_{qj} + \varepsilon_{qj})}{\sum_{q=1}^{J} \exp(\alpha_{qj} + \beta_q X_{qj} + \gamma_q X_{qj} + \varepsilon_{qj})} \tag{3}$$

where $\Re_q$ is an underlying function of the X_{qj} vector and is the individual specific random disturbance of the unobserved heterogeneity. The parameter γ_q illustrates the effects of individual specific attributes in the population that have a statistically significant effect on utility. The tastes and preferences of individual firms are embodied in this parameter.

The following is an example of how unobserved tract attributes can influence bid choice and be captured to better understand the behavioral choice process. Each firm will receive utility from bidding on a tract based on observable and unobservable characteristics. Suppose that q companies are bidding on the j^{th} OCS tract. Now consider that β_q is the parameter associated with water depth. Assuming IID, the probability that the q^{th} firm will choose j is based on the observable water depth and other unobservable influences. The second moment of β_q will be identical across firms.

However, consider the situation where the variance of parameter estimates are allowed to be 'free' over two firms, Firm 1 and Firm 2. The second derivative of γ_q is σ_{qj}^2 and can be a unique function of observed water depth Y_{qj} for the q^{th} firm. Notice this implies a unique distribution of utility for each Firm for each tract alternative. As such, the second moment of γ_q are uniquely distributed across Firms 1 and 2.

Now suppose Firm 1 is a much smaller company compared to Firm 2. Firm 1's individual specific attribute is their budget, which interacts with water depth (i.e., deeper water is a proxy for greater risk and a higher share of the budget and Firm 1 is less likely to bid). However, Firm 2 is very large and makes bidding decisions regardless of water depth. If IID is assumed, the parameter estimates will be inconsistent; an omitted variable will be correlated with observable water depth for Firm 1 but not for Firm 2- the second moment of water depth will vary across firms. The parameter obtained in the regression would be confounded with an additional parameter and the researcher may lead to erroneous conclusions. However, if the distribution of γ_q is allowed to be 'free' as a random parameter, it can be captured and used to better understand the behavioral process of choice underlying OCS tract selection.

Louviere et al. (2002) noted several practical considerations when taking into account the effect of unobserved effects on choice. First, variability in the stochastic component of utility is associated with numerous factors, and it is naïve to lump all unobserved effects into a single error term, assuming these differences are due solely to heterogeneity between individuals. Second, response variability is as much a behavioral phenomenon as response means. Third, coefficient estimates are confounded with error variance in the RUM, and empirical parameter estimates may actually be due to the mean of the response, the variability of the response, or both. The Random Parameter Logit (RPL) is one modeling approach that relaxes the assumption of IID errors, and allows all unobserved components of utility to predict bid choice. Using this approach we are able to model unobserved heterogeneity, as opposed to assuming it is a constant and treating it as a nuisance. Modeling the unobserved component of choice is hypothesized to increase the explanatory power of our modeling capabilities, as well as our insights into the behavioral choice process.

Data and Method

We utilize publicly available data for OCS issued leases, sold in 1983-2006. Data include various tract characteristics such as location, water depth, royalty rates, proven tracts, and any prior leasing or development at the same location. As a result of recent extensive spatial analysis conducted by the authors[1], relationships such as distance to nearest discovery and distance to nearest active lease are available for the first time and

[1] Data for the spatial analysis was obtained from the public website www.mms.gov.

included. A discrete choice model is applied to these data to identify the probability that a given tract will be bid on given its characteristics. Specifically, the RPL model is used to identify the probability the i^{th} firm will bid on lease alternative j with $J=1,\ldots, n$ alternatives in the choice set of tracts available.

The data consist of panels of bidding decisions between 1983 and 2004 for 15,308 tracts in the OCS. Each tract is associated with a set of attributes, and are discussed below in four categories: distance/geographical variables, tract specific attributes, economic variables, and other exogenous characteristics (Table 1). In the following paragraphs we specifically enumerate tract characteristics, and identify how we expect the characteristics to influence bidding. Each tract in the OCS is associated with a set of attributes.

Distance/Geographical Variables.

The following variables are hypothesized to influence bidding decisions due to the proximity of the given tract to other geological resources. The relevant units in the specification of these variables are the distance from one tract to another tract. As a result of recent extensive spatial analysis conducted by the authors, relationships such as distance to nearest discovery and distance to nearest active lease are available for the first time and included. For example, the distance of 7 is used to approximate the center of a given successful tract to another given area two tracts away. The unit of 30 is about ten tracts away. The closer the tract in question is to another successful area, we would expect a greater effect on firm bidding decisions.

We include the geographic/distance variables *Fields*, *Wells*, *Structures*, and *Discoveries*. Each variable is *unique* in physical characteristics and is expected to independently influence bidding. Since many of the following variables may appear similar, we tested the correlations of the following and found they were indeed positively related- however, the correlation coefficient for each relationship was not large enough to be concerned about multicollinearity in the regression analysis. As such, while the following geographic proxies appear similar, they do indeed represent unique attributes that we expect to contribute to explaining bidding. Also, a limitation of several of the leading independent variables is that while they are useful for explaining historical impacts of fiscal policy in the OCS they limit the forecasting capabilities of the model.

Distance is the linear distance from the given tract to another successful tract, which we would expect to positively influence bid decisions. The variable *Density12* is the count of active leases within a twelve mile radius, and should be a proxy for increased bidding. *Density30* similarly is a count of active leases, but is an approximation of the number of active leases that are between 12 and 30 miles. We expect the effect of the *Density30* variable to be positive and significant; however, the magnitude of the parameter should be smaller than the *Density12* parameter since leases closer to active leases may represent more profitable tracts. We used 12 and 30 mile increments because the distance from the center of a tract to another tract is 3 miles. As such, 12 miles represents four tracts out and 30 tells us the radius 10 tracts away.

VNField indicates that there is another successful field within 10 miles. *NField* is a tract that is between 10 to 31 miles of a successful field. We expect that the expected signs of both regression parameters will be positive. The distance of 10 is a proxy for three tracts away from the given tract, and 31 is about ten tracts way. A discovery is a field found in the OCS in that particular year. Specifically, *VNDiscovery* are the data for tracts within 7 miles, and *NDiscovery* are between 7 and 31 miles. A positive effect is reasonable to expect for both variables, since more bidding should occur closer to more profitable fields. As noted, 7 mile increments are approximately the distance from two tracts, and 31 mile increments are the distance from ten tracts.

A field is an area scientifically known to have oil and be economically recoverable, where economically recoverable is used in this vein to indicate that the firm *j's* opportunity costs are at least recovered for the given investment. *Field7* represents areas that are within 7 miles of a known resource, while *Fields31* are between 7 and 31 miles. We hypothesize a positive relationship between bidding and proximity to closer fields. Our prediction is that the sign and magnitude for both distance variables will be positive and significant; however, we expect the magnitude of *Fields7* will be greater than *Fields31,* as *Fields7* is the distance from two tracts and should therefore have a stronger influence on bidding than *Fields31.*

A well is an area where a hole has been drilled. *Well31Y4* is a hole that has been drilled within the past 4 years, within 7 and 31 miles of a known geological oil field. *Well7Y4 i*s a hole that has been drilled within the past 4 years, within 7 miles of a known geological oil field. It is likely that a positive regression parameter is obtained for these variables in our analysis. *DSY2D31* is the distance to a well that was discovered in the past two years within 31 miles. A positive relationship with bidding is expected. Structures are physical platforms in the OCS. Here we hypothesize that another structure within 7 miles, *Structures7,* would be a factor leading to increased bids.

Tract Specific Variables

Each one of the following variables represents unique information on the tract in question. We include information whether the tract was returned the last period, if it has successfully produced, the number of prior leases held, and if the reserve price was not met last year (bid rejection). *Returned(-1)* is a discrete lagged variable that indicates if the tract was returned last period. It is hypothesized that a returned tract would positively influence bidding. *PriorLeases* is the total number of prior leases for the tract and should be directly related to bidding. *Produced* is a variable that represents whether the tract produced in the subsequent year, and is expected to influence bidding in a positive fashion.

Bids that were rejected last period are represented by *Reject(-1)*. According to historical data at MMS, if a bid was not accepted in the prior time period there is a very likely chance that there will be a bid in the next period. As such, it would be reasonable to expect a positive sign on the regression coefficient for *Reject(-1);* a rejected bid means that government analysts believe that the tract is more valuable, and the winning bid should have been higher. However, the rejection could also be correlated with negative bidding in the subsequent period, since firms may have already decided in the prior period that the tract is not worth bidding on and therefore would not bid in the current time period. Plus, there are relatively few instances in the data where MMS rejected bids. The small amount of data for this occurrence may not be adequate to draw appropriate statistical inferences. As such, the estimated sign of *Reject(-1)* is ambiguous. An unexpected sign in the mean of the regression estimate could indicate that the estimated parameter is not representative of the entire population. As discussed in the conceptual section of this paper, closer examination of the second moment of the given parameter distribution could provide useful information to better understand the behavior process of bid choice.

Economic Variables

The following variables are included in the analysis to examine the effect of market influences on OCS bidding. Several of the following variables are indicators of economic phenomena, and present a limitation to this analysis- the model can only be used to explain historical effects of fiscal policy in the OCS, but not for prediction purposes. We include the price next year for oil, the produce price index, net income, and royalty rate.

SIC211(5) is the producer price index (PPI) for the oil and gas extraction industry. The PPI is a proxy for the overall level of prices in the industry, and hence should be positively correlated with bidding activity (Moody et al. 1990). We use a leading variable for 5 years to test the hypothesis that prices are important in the future at the end of the lease, as resource decisions are based on future periods and not in the current year. The real price of a barrel of oil next year, *OilPrice(1)*, should have a significant and direct relationship with bidding decisions.

NetInc(1) is a leasing variable for net income. Net income for an oil producer is defined as the difference between total revenue and total costs, and is hypothesized to correspond to bidding in a positive fashion. *Royalty* is the amount paid to the federal government for leasing of land in the OCS, and is defined as a percentage of gross production. *Royalty* is expected to pick up on the variation in the data as a result of Royalty Suspension Volumes (RSVs) imposed after the Deep Water Royalty Relief Act (DWWRA); i.e., the implicit subsidy to OCS companies for producing in deep water.

RSV's are part of the DWRRA and allow oil companies to produce specified quantities of oil royalty-free. The effect of increased royalty should decrease bidding, as royalty is a function of input demand for OCS producers. However, many factors in the regression analysis related to the RSV may be omitted. As such, the sign on *Royalty* is ambiguous due to the potential for omitted variable bias.

Other Exogenous Variables.

In a time of massive weather occurrences, the following data are included to test the effect of hurricanes on bidding. *USHUR* and *HUR* represent the annual number of hurricanes between 1984 and 2003 in the US and Worldwide, respectively. While it is obviously challenging to forecast the effect of hurricanes on resource decisions in the energy market, it is reasonable to hypothesize that the presence of hurricanes will either positively or negatively influence bidding. From one standpoint, the inevitable effect of extreme weather in the OCS is to reduce aggregate supply, push up prices, and hence increase bid activity. Following that logic, we would also expect that the magnitude of *HUR* to be larger than *USHUR*. However, increased hurricane activity could also wipe out many of the physical structures in the OCS and therefore reduce capacity and ability to acquire capital reducing the overall probability of bidding. As such, the expected effect of *HUR* and *USHUR* is ambiguous. The overall effect of *HUR* and *USHUR* may have to do with the relative increases in capital costs versus the change in the output price of oil due to supply restrictions. For example, if the price of factors of production increase by t and the exogenous price of oil increases by $2t$, then the overall effect on bidding will be positive. However, if the price of factors of production increases by $2t$ and the exogenous price of oil increases by t, then the isolated effect of *HUR* and *USHUR* on bidding will be negative. As such, the expected result of the exogenous weather parameters is indeed ambiguous and is an empirical question.

Estimation

The RPL model is a special case of the multinomial logit model (Train 1998). The RPL allows for parameters to vary across individuals in the population with the same characteristics. Another characteristic of the RPL is the relaxing of the assumption of IID errors, implying a completely unrestricted variance-covariance matrix. According to equation (3), γ_q is a vector of taste parameters for the q^{th} firm, and has its own unique distribution. In this case, preferences are observable to the firm but are random to the researcher. That is, tastes are known to the firm but unknown to the researcher and are a vector of random variables. By allowing for "free-variance", individual taste parameters differ from firm to firm. Following Morey et al. (1993), the unconditional probability of choosing alternative *j* is therefore:

$$\pi_q = \int_{-\infty}^{\infty} P_{qk}(\xi, X_q) N(\xi \mid \mu, \Omega) d\xi \tag{4}$$

Also according to Morey et al. (1993) we know $U_{qj} = \alpha_{qj} + \beta_q X_{qj} + \gamma_q Y_{qj} + \varepsilon_{qj} = \alpha_{qj} + \xi_q X_{qk} + \varepsilon_{qj}$ and $N(\beta | \mu, \Omega)$ is the normal *cdf* where $\gamma \sim N(\mu, \Omega)$ and ε_{qj} is a random draw from EV1 distribution of errors, and γ_q is the correlation across choices for the q^{th} individual.

In this model, a closed solution is not possible and π_q is generated by a randomly drawn process. The simulated probability (SP) for R random draws is given as:

$$SP_q = \frac{1}{R}\sum_{r=1}^{R} P_q(\beta_q^r, X_q) \tag{5}$$

where for the random draw r for the q^{th} firm from $N(\beta|\mu,\Omega)$, the coefficients are given as β_q^r. The estimator is simulated Maximum Likelihood and is given as:

$$SL = \sum_{q=1}^{N} \ln\left[\frac{1}{R}\sum_{r=1}^{R} P(\beta_q^r, X_q)\right] \tag{6}$$

Maximizing over (6), our dependent variable is the probability of a bid, in the current time period, as explained by tract specific attributes, economic variables, and other exogenous factors.

Results

We present two statistical models to investigate the influence of the DWRRA on bidding decisions. The DWRRA provided royalty suspension provisions for tracts in water greater than 400 meters. Table 2 presents the base model including geographic/distance proxies, tract specific attributes, economic variables, and presence of hurricanes. Table 3 shows the slope dummy model to examine the effect of the DWRRA. The dummy variable for DWRRA is equal to zero for the time period prior to the policy and equal to one subsequent to the policy. As with all slope dummy variables, the policy variable can only be multiplied by a continuous variable. As such, we are only able to estimate slope dummies for continuous parameters in the model. When the sloped dummy model is compared to the base model, the dummy variable can be used to suggest if the slope of the parameter is different after the DWRRA. A switching regression model would be more conclusive but the large number of parameters led to convergence problems in the RPL.

The first result is the high explanatory power of our bidding model (Table 2). Since the estimation is maximum likelihood, the appropriate measure of goodness of fit is pseudo r-square and the value of 54% is excellent. In fact, Domencich and McFadden (1975) indicated that a pseudo r-square of this value for maximum likelihood is comparable to about a 90% goodness of fit in a linear model with Ordinary Least Squares. As such, our RUM is a very powerful framework for explaining bidding in the OCS.

Most of the signs and magnitudes of the estimated parameters are consistent with our expectations. The means of estimated parameters for Geographic/ Distance proxies such as *PriorLeases*, *Distance12*, and *Distance30* are all positive and statistically significant at the 99% level. Also the magnitude of the parameter on *Distance12* is greater than the parameter on *Distance30,* indicating that closer active leases are more likely to receive bids.

It is critical to note the importance of the statistical significance of the second moment of the parameter distribution for *PriorLeases, Distance, VNDiscovery, Fields7, Fields31, Well7Y4, and DSY2D31.* That is, if a given researcher had assumed IID they would have led to erroneous conclusions about the sign, magnitude, or statistical significance of the given parameter. For example, consider the case of *Distance.* The first moment of the parameter distribution indicates there is no effect of this variable on bidding. The lack of statistical significance is counter intuitive, as we would expect distance and bidding to have a positive relationship. Due to the statistical significance of the second moment of the estimated parameter we see that the distribution of this parameter varies across decision makers in the data, and there is indeed heteroskedasticity present. As such, since non-constant variance in the IID based model leads to inconsistent parameter estimates, we cannot draw appropriate statistical inferences about the mean of *Distance,* but do indeed observe that the effect on bidding differs across firms.

Consider another example with the first moment of the parameter distribution for the geographic proxies *Fields7, Fields31, Well7Y4 and DSY2D31.* If one were to assume IID, the assumption would lead to the conclusion that the variables had no effect on bidding. However, according to the second moments, the mean of each parameter does not represent each data point and hence is incorrect. As such, *Fields7, Fields31, Well7Y4* and *DSY2D31* do indeed influence bidding, but the effects of each variable on the behavioral process of choice is different across tracts in the data.

The effect of the *Reject(-1)* variable is negative and significant, indicating that a given tract in the data is less likely to obtain a bid this period if the reserve price was not met last period. According to historical data at MMS, if a bid was not accepted in the prior time period there is a very likely chance that there will be a bid in the next period. A rejected bid means that analysts believe that the tract is valuable, and the winning bid should be higher. However, the rejection could also be correlated with negative bidding in the subsequent period, since firms may have already decided in the prior period that the tract is not worth bidding on and therefore would not bid in the current time period. Plus, there are relatively few instances in the data where MMS rejected a bid. The small amount of data for this occurrence may not be adequate to draw appropriate statistical inferences. The negative and significant coefficient for *Reject(-1)* seems reasonable given our data.

Generally speaking, our tract specific parameter estimates are statistically significant with the expected sign. As discussed, *Returned(1)* indicates that the given tract was going to be returned in the subsequent time period, and was hypothesized to directly influence bidding. The positive and significant coefficient confirms our hypothesis Also, as expected, *PriorLeases* is positive and significant, indicating that the more leases a given tract had the more likely it would be to receive a bid. The first and second moments of the *Produced(1)* variable are statistically insignificant in explaining bidding. This confirms that non-constant error variance is present in our data and ignoring second moments of parameter distributions would lead to erroneous conclusions.

The effects of the economic variables *NetIncome(5)* and *OilPrice(1)* are positive and significant. The positive sign on *NetIncome(5)* means that bidding decisions are based on Net Income in five years. As we discussed, many OCS leases have five year terms and we hypothesized that a given firm would make the decision to bid on what earnings were expected to be at the end of the lease. Both the first and second moments of the parameter distribution for *OilPrice(1)* are positive and significant. The statistical significance of the second moment of *OilPrice(1)* indicates that the effect of this variable is not constant across tracts. The first moment of the parameter distribution for *Royalty* is not significant, but the second moment is significant at the 99% level. The result indicates that the DWRRA increased bidding on some tracts, but not on other tracts.

The variable *HUR* is positive and statistically significant, indicating increased number of worldwide hurricanes has a direct impact on bidding. While that result may seem counterintuitive, we discussed earlier that the sign on this coefficient is ambiguous. While weather activity such as hurricanes could inhibit bidding, the reduced supply could also push up prices and hence be correlated with more business activity. Hurricanes push up prices, and since prices are directly related to bidding, hurricane activity actually increases the probability of a bid in the OCS.

Table 3 shows the results from our slope dummy model. Slope dummy models are useful because they are able to capture the effects of policy variables and the corresponding sensitivity in parameter estimates. Specifically the dummy variable for the DWRRA is multiplied by the continuous variables. If the estimated coefficient is positive bidding is more sensitive to oil prices after the policy.

The first interesting difference between the base and slope dummy model is the improved goodness of fit. Also, it is important to note the positive and statistical significance of many of the slope dummies. For example, *dPriorLeases*, *dDensity12*, *dDensity30*, and *dHUR* are positive and statistically significant indicating that the effects of these parameters on bidding are more sensitive *after* the DWRRA. Consider the case of *dPriorLeases.* The coefficient estimate of 2.69 indicates that if a tract had one more prior lease, the probability of a bid increases by about 2.69%, after the DWRRA.

The positive coefficient on the second moments of the parameters distributions for *dPriorLeases, Reject(-1) dOilPrice(1), dNetInc(5), Royalty,* and *dUSHUR* indicates an increased sensitivity to bidding. But, the behavioral phenomena are not equal across decision makers in the data. For example, consider the case of *dOilPrice(1).* The slope dummy suggests different magnitudes after DWRRA and the corresponding difference in probability of a bid. However, another interesting layer of complexity is that the distribution of this parameter is non-constant across tracts. As such, some tracts post-DWRRA are more likely to receive a bid with a one unit change in oil price tomorrow, but some tracts will not change bidding behavior whatsoever. Plus, if the distribution of this parameter were held constant under IID, the researcher would lead to the erroneous conclusion that the effect of prices are constant before and after government policy.

Conclusions

This paper has investigated the effects of government policy on oil leasing in the OCS. A discrete choice analysis is developed that identifies the probability a given tract would be bid on based on exogenous tract characteristics, economic variables, and weather. As hypothesized from our theoretical model, economic variables such as oil prices and net income directly influence leasing activity. Also, distance and geographical proxies and weather variables are shown to positively influence bidding. The analysis is unique because we focused on not only the first moment of parameters to effect bid choice, but also the second moment. By including the second moment of parameter distributions, the model is more robust compared to an IID based analysis. Relaxing IID in the discrete choice analysis is critical from a public policy perspective, as the econometric restriction may lead decision makers to erroneous conclusions about government programs.

For example, the first moment of the parameter *Royalty* indicates that the given Royalty Suspension Volume subsidy has no effect on bidding. However, upon closer examination of the data distribution and looking at the second moments we find that the effects of the *Royalty* does indeed affect the probability of a bid, but the effect is not equal across tracts Another feature of the RPL model is the avoidance of omitted variable bias. If non-constant error variance is assumed and heteroskedasticity is present, then variables in the model will be interacting with an omitted variable in the form of differences in the distribution of the error term across tracts.

One limitation of the model is that it is only appropriate for explaining the effect of the DWRRA, since we used several leading variables in the regression. An extension of this research is to incorporate oil price futures into the model so that it can be used for forecasting purposes. Also, an out of sample statistical validation procedure such as a jackknife may be used to examine the predictive capabilities of the model.

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Table 1. Variable Definitions

Variable	Mea n[2]	Definition
1. Dependent Variable:		
Prob_Bid	0.003 (0.058)	whether tract was bid on that year
2. Independent Variables:		
a) Geographical/ Distance Proxies[3]:		
Distance	785.996 (404.409)	distance in miles to nearest successful field
Density12	11.834 (14.040)	density of active leases in 12 mile radius
Density30	65.278 (67.228)	density of active leases in 30 mile radius
Reject(-1)	0.203 (14.127)	=1 bid was rejected last period, = 0 if was not rejected
VNField	0.186 (0.388)	tract is very near anther successful field, less than 10 miles
NField	0.467 (0.498)	tract is near anther successful field, less than 31 miles
VNDiscovery	0.204 (0.403)	tract is very near anther successful discovery, less than 7 miles
NDiscovery	0.217 (0.412)	tract is near anther successful discovery, less than 31 miles
Fields7	0.433 (0.992)	number of fields within 7 mile radius
Fields31	11.628 (19.086)	number of fields within 31 mile radius
Well31Y4	5.977 (46.102)	number of wells in 31 mile radius the past 4 years
Well7Y4	0.361 (3.823)	number of wells in 7 mile radius the past 4 years
DSY2D31	0.812 (1.705)	distance to well, within past two years
Structures7	1.458 (6.494)	number of structures in 7 mile radius
b) Tract Specific Attributes:		
Returned(1)	0.052 (0.221)	tract was returned last period
PriorLeases	0.242 (0.558)	number of leases in prior years for the tract
Produced	0.021 (0.143)	=0 if has not produced in past, =1 if has produced
c. Economics Variables		
SIC211(5)	81.931 (30.401)	producer price index in 5 years, when lease expires, for oil and gas industry SIC code 211
OilPrice(1)	28.812 (9.529)	leading oil price next year
NetInc(1)	13.557 (7.854)	leading net income next year
Royalty	0.155 (0.362)	before and after DWRRA
d. Other Exogenous/Weather Variables		
USHUR	1.862 (1.761)	number of hurricanes in US waters
HUR	8.115 (5.284)	number of worldwide hurricanes

[2] Standard deviations are in parentheses.
[3] According to the *Manual of Oil and Gas Terms*, a "field" is an area scientifically known to have oil and know to be economically recoverable; a "discovery" is a recently found field within two years; a "well" is where a hole has been drilled; and a "structure" is where physical platforms exists.

Table 2: Random Parameter Logit Regression Results- Base Model

Variable	Random Parameters in Utility Function		Derived δ^2 of Parameters Distributions	
	Coefficeint	St. Err.	Coefficient	St. Err.
a) Geographical/ Distance Proxies:				
Distance	-0.013	0.020	0.001***	0.001
Density12	0.161***	0.028	0.0218	0.027
Density30	0.017***	0.005	0.004	0.006
Reject(-1)	-5.586***	1.318	1.806	1.215
VNField	-1.530	1.005	1.254	0.889
NField	2.410	1.693	0.020	1.354
VNDiscovery	-1.074**	0.581	0.642*	0.380
NDiscovery	-10.722	19.848	0.401	0.363
Fields7	0.578	0.039	0.984**	0.524
Fields31	-0.004	0.038	0.108***	0.039
Well31Y4	-0.001	0.039	0.002	0.002
Well7Y4	-0.016	0.039	0.100***	0.041
DSY2D31	-0.057	0.072	0.435***	0.136
Structures7	-0.244***	0.114	0.129	0.167
b. Tract Specific Attributes				
Returned(1)	2.513***	0.294	0.870***	0.350
PriorLeases	2.160***	0.353	0.682**	0.359
Produced(1)	0.792	0.548	2.540***	0.952
c. Economics Variables				
SIC211(5)	0.007**	0.004	0.004	0.004
OilPrice(1)	0.030***	0.009	0.047***	0.018
NetInc(5)	0.016	0.015	0.0019	0.023
Royalty	0.649	0.473	4.036***	0.988
d.. Other Exogenous/Weather Variables				
USHUR	0.086	0.062	0.140	0.113
HUR	0.119***	0.019	0.015	0.031

No. of Observations	14436
Log-Likelihood at Zero	-1360.062
Log-Likelihood at Convergence	-618.981
Adjusted McFadden's ρ^2	0.5390

Note: ***, **, * significant at 99%, 95% and 90%, respectively.

Table3: Random Parameter Logit Regression Results- Slope Dummy Model

Variable	Random Parameters in Utility Function		Derived δ^2 of Parameters Distributions	
	Coefficeint	St. Err.	Coefficient	St. Err.
a) Geographical/ Distance Proxies:				
dDistance	-0.011	0.023	0.001	0.001
dDensity12	0.196***	0.035	0.001	0.038
dDensity30	0.018***	0.007	0.002	0.011
Reject(-1)	-11.040***	3.564	4.558***	1.997
VNField	-1.570	1.199	0.336	1.856
NField	2.778	1.954	0.061	1.804
VNDiscovery	-1.290	0.673	0.191	0.763
NDiscovery	-9.931	23.381	0.330	0.793
dFields7	0.761	0.553	0.005	0.005
dFields31	-0.002	0.045	0.005	0.005
dWell31Y4	-0.001	0.002	0.001	0.002
dWell7Y4	-0.022	0.037	0.004	0.049
dDSY2D31	-0.039	0.076	0.011	0.162
dStructures7	-0.305**	0.172	0.0435	0.306
b. Tract Specific Attributes				
Returned(1)	2.793***	0.359	0.007	0.667
dPriorLeases	2.692***	0.544	2.399**	0.606
Produced(1)	1.367	0.655	0.321	1.374
c2. Economics Variables				
dSIC211(5)	0.003	0.004	0.001	0.007
dOilPrice(1)	0.019	0.018	0.123***	0.049
dNetInc(5)	0.007	0.017	0.064***	0.039
Royalty	0.406	0.796	7.188***	2.926
d. Other Exogenous/Weather Variables				
dUSHUR	0.065	0.084	0.433***	0.152
dHUR	0.151***	0.024	0.008	0.082
No. of Observations	14436			
Log-Likelihood at Zero	-1360.0625			
Log-Likelihood at Convergence	-607.0045			
Adjusted McFadden's ρ^2	0.54880			

Note: ***, **, * significant at 99%, 95% and 90%, respectively.